Development Participation and Adoption Intention of ICT for Informed Decision-making in Urban Public Services: Dashboard for Jakarta Traffic Police Patrolling Allocations

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Abstract

This thesis investigates the development participation and adoption intention of Information and Communication Technology (ICT) for informed decision-making in urban public services, using a dashboard as an ICT example and Jakarta Traffic Police's patrolling allocation as the use case of decision-making. This research addresses the gaps in understanding Data-Driven Decision-Making (DDDM) in the public sector and the limited study of government-to-employee (G2E) ICT adoption. It also aims to investigate the underexplored role of user participation in the development and adoption of government ICT. Furthermore, this research underscores the need for qualitative insights to inform the development of quantitative hypotheses, particularly where traditional technology acceptance models like TAM and UTAUT may overlook key public sector contextual factors.

The study is divided into two phases: requirement elicitation and adoption intention examination. In the first phase, semi-structured interviews with Jakarta traffic police were conducted to explore their decision-making processes within a Data-Driven Decision-Making (DDDM) framework and identify preferred features for a user-centred dashboard, leading to the development of a tailored prototype. In the second phase, semi-structured interviews were conducted to develop original hypotheses, focusing on public sector-specific contextual factors. These were then quantitatively tested to examine the factors influencing the traffic police's behavioural intention to adopt the dashboard.

The novel contributions of this research include the development of the original contextual hypotheses and identifying new motivational factors influencing government employees' ICT adoption, such as interoperability expectations, social incentives, and user experience-related factors. The research also highlights the importance of user participation in enhancing the intention to adopt ICT tools in the public sector. The study provides practical insights for improving public service delivery through data-driven tools and contributes to refining ICT adoption theories in public sector contexts while offering evidence-based recommendations that integrate both technological advancements and human insights to foster more resilient and adaptive decision-making.

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List of Acronyms

AI - Artificial Intelligence

API - Application Programming Interface

AV - Autonomous Vehicle

AVE - Average Variance Extracted

BI - Behavioural Intention

CCTV - Closed-Circuit Television

CFA - Confirmatory Factor Analysis

CFI - Comparative Fit Index

COSS - College of Social Sciences (University of Glasgow)

CR - Composite Reliability

DDDM - Data-Driven Decision-Making

DOI - Diffusion of Innovation

EFA - Exploratory Factor Analysis

GIS - Geographic Information System

G2B- Government-to-Business

G2C- Government-to-Citizen

G2E - Government-to-Employee

GDPR - General Data Protection Regulation

GPS - Global Positioning System

HTMT - Heterotrait-Monotrait Ratio

ICT - Information and Communication Technology

IDT - Innovation Diffusion Theory

INTPC - Indonesian National Traffic Police Corps

IoT - Internet of Things

IRSMS - Integrated Road Safety Management System

ICT – Information and Communication Technology

IT - Information Technology

KPI - Key Performance Indicator

ML - Machine Learning

MT-ITS - Models and Technologies for Intelligent Transportation Systems

NHTSA - National Highway Traffic Safety Administration (US)

RMSEA - Root Mean Square Error of Approximation

RTC - Road Traffic Crash

SEM - Structural Equation Modelling

STATS19 - UK Road Accident Reporting Form

TAM - Technology Acceptance Model

TLI - Tucker-Lewis Index

TPB - Theory of Planned Behaviour

TRA - Theory of Reasoned Action

UI - User Interface

UTAUT - Unified Theory of Acceptance and Use of Technology

UEQ- User Experience Questionnaire

UX - User Experience

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“Orang boleh pandai setinggi langit, tapi selama ia tidak menulis, ia akan hilang di dalam masyarakat dan dari sejarah. Menulis adalah bekerja untuk keabadian.”

"A person may be as smart as the sky is high, but if they don’t write, they will disappear in society and from history. Writing is working for eternity."

- Pramoedya Ananta Toer (Indonesian novelist, political prisoner, and advocate for social justice).

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Author's Declaration

I declare that, except where explicit reference is made to the contribution of others, that this thesis is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

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Chapter 1 Introduction

1.1 Background

Urbanisation is rapidly increasing, especially in developing countries, which will see most of the future urban population growth (Eckert and Kohler, 2014; Majumdar and Chatterjee, 2020; Jedwab, Loungani and Yezer, 2021). This growth has intensified quality-of-life challenges, including in road transport, where traffic crashes and congestion cause significant human and economic losses (Hu, Zhou and Sun, 2014; McCann, 2017; Bhattarai and Budd, 2019; Sovacool, Kim and Yang, 2021). Economic growth has increased vehicle ownership (Dargay, Gately and Sommer, 2007; Kisiała and Kudłak, 2024), exacerbating crashes (Liddle, 2012), congestion (Sovacool, Kim and Yang, 2021), and pollution (Krausmann *et al.*, 2009; Espoir, Sunge and Bannor, 2023). Low- and middle-income developing countries struggle with sustainable urban development amidst rapid urbanisation and industrialisation (Rob and Talukder, 2013; Razia and Binti Abu Bakar Ah, 2022) and face severe road safety issues and disproportionate fatalities among vulnerable road users due to inadequate preventive measures (Mohan and Bhalla, 2016; Urie, Velaga and Maji, 2016).

Rapid urbanisation has led cities' stakeholders to use Information and Communication Technologies (ICT) to address the resulting economic, social, and environmental issues (Perera *et al.*, 2013; Anthopoulos, 2017). This approach, known as a smart city initiative, aims to enhance governance (Gil-Garcia, Helbig and Ojo, 2014; Scholl and Scholl, 2014), urban development (Anthopoulos and Reddick, 2016; Castelnovo, Misuraca and Savoldelli, 2016), and public services (Meijer and Bolívar, 2016; Pereira *et al.*, 2018) to achieve sustainable development and improve residents' quality of life (Ballas, 2013). Smart city initiatives focus on multiple domains, such as transportation, energy, health, education, and governance, to create interconnected and intelligent urban environments (Gracias *et al.*, 2023).

In addition, the electronic government (e-government) concept, or the government's use of ICT to provide public services to citizens and organisations, aligns closely with smart city governance. ICT is foundational for the government's digital transformation with a focus on urban management and the provision of relevant information (Joseph, 2017; Syväjärvi *et al.*, 2019; Chohan and Hu, 2020; Hardi and Gohwong, 2020; Mensah *et al.*, 2021). With the support of national governments, local governments play a crucial role in smart city initiatives that drive digital transformation (Snow, Håkonsson and Obel, 2016; Cranefield and Pries-Heje, 2020; Daniel, Wahid and Tan, 2020). To foster smart cities, governments must emphasise public service efficiency and transparency, utilising ICT in smart governance to enhance decision-making and collaboration (Rodríguez Bolívar, 2016; Pereira *et al.*, 2018).

One of the most fundamental roles of ICT in governments is improving the decision-making processes, especially by enabling data-driven approaches to governments (Rodríguez Bolívar, 2016; Pereira *et al.*, 2018; Abraham, 2020) by using data and its conversion into actionable knowledge, known as Data-Driven Decision-Making (DDDM) (Gates and Matthews, 2014; OECD/ITF, 2016; IRTAD, 2019; Choi *et al.*, 2021). ICT plays a vital role in DDDM by gathering, organising, analysing, and sharing data to make well-informed decisions (Beyers, 2016). ICT-supported decision-making processes have been effectively utilised in local government projects, showcasing their ability to improve strategic development activities (Kadoic and Kedmenec, 2016). This approach is especially advantageous in the public sector, where decisions can have significant and expensive outcomes (Shoara Akter, Milon Molla and S. M. Robiul Islam, 2019).

Governments have utilised ICT supported data-driven approach in implementing road safety measures such as informed patrol allocation (Al-Harthei *et al.*, 2017), real-time traffic monitoring (McTiernan, 2019), and electronic enforcement (Shrivastava and Shrivastava, 2019; Feng, Wang and Quddus, 2020; S. K. Ahmed *et al.*, 2023). These strategic uses of ICT for road safety have been shown to reduce crashes and improve safety (McTiernan, 2019; Shrivastava and Shrivastava, 2019; S. K. Ahmed *et al.*, 2023). These e-government integrations into the smart city concept are crucial to ensure optimisation of public service (Syväjärvi *et al.*, 2019) and play a crucial role in enhancing government transparency and accountability, especially in smart city development (Almuraqab, 2020).

However, the public sector in developing nations continues to face challenges related to digital transformation adoption failure (Syed *et al.*, 2018; Syed, Bandara and Eden, 2023) due to design-reality mismatches (Gómez and Heeks, 2016; Syed, Bandara and Eden, 2023), ineffective project management (Gil-Garcia, Helbig and Ojo, 2014), and unrealistic planning, often exacerbated by conflicts between technology and local contexts (Anthopoulos, 2017). Meanwhile, the actual value of ICT investments depends on their adoption and utilisation to achieve the intended goals (Russell and Meehan, 2014; Damoah and Kumi, 2018). Failure to engage intended users can render significant investments in technology development futile, where government ICT projects do not achieve their objectives due to low adoption rates (Aftab and Myeong, 2018). These risks underscore the need to understand the dynamics behind technology adoption and use, as a lack of uptake can result in wasted resources (Hashim, 2010), inefficiencies, reduced effectiveness in delivering public services (Afzaal and Masood, 2019), increased costs, and missed opportunities to improve public governance (Heeks, 2006).

Over several decades, studies underscore the importance of user participation in the ICT development process, highlighting that insights into their tasks and preferences are critical for successful adoption, acceptance, trust, and usage (Ives and Olson, 1984; Cavaye, 1995; Clavadetscher, 1998; Procaccino *et al.*, 2002; DeLone and McLean, 2003; Amoako-Gyampah, 2007; He and King, 2008; Chagas *et al.*, 2021). This long-term recognition emphasises the enduring relevance of user involvement, as each technological shift reaffirms the necessity of aligning ICT solutions with user needs and preferences (Callens, 2023). User participation in the development phase of a system can result in increased commitment (Barki and Hartwick, 1989), system acceptance (Alavi and Joachimsthaler, 1992), behavioural intention (Jackson, Chow and Leitch, 1997), adoption (Amoako-Gyampah, 2007), use, and satisfaction with the system (Díez and McIntosh, 2009). When people are part of the system development process, they are more likely to trust and embrace the system than systems built independently and presented to them (Surbakti *et al.*, 2020).

Finally, studies have developed several theories and frameworks to understand and examine ICT acceptance and adoption, such as the Theory of Reasoned Action (TRA) (Fishbein and Ajzen, 1975), the Theory of Planned Behaviour (TPB) (Ajzen, 1991), the Technology Acceptance Model (TAM) (Davis, 1986), the Innovation Diffusion Theory (IDT) (Rogers, 1962), and the Unified Theory of Acceptance and

Use of Technology (UTAUT) (Venkatesh *et al.*, 2003). These models link individual attitudes and behaviours to the broader adoption of new technologies, providing insights for successful ICT implementation. They have been applied in public sector studies to understand obstacles and ensure successful e-government and smart city initiatives (e.g., Kachwamba and Hussein, 2009; Srivastava, 2011; Ziemba, Papaj and Descours, 2014; Rasyid and Alfina, 2017; Idoughi and Abdelhakim, 2018; Khrais and Mahmoud, 2019; Al Nidawy *et al.*, 2020; Sarasati and Madyatmadja, 2020; Huda, Kurniasari and Ruroh, 2022).

1.2 Research gaps and motivations

Data-Driven Decision-Making (DDDM) in the public sector has received less attention than in the private sector, while scholarly discourse highlights its potential for organisational change. Future research is recommended to explore how DDDM is implemented in government organisations, focusing on the practical steps and challenges civil servants face (Brynjolfsson and McElheran, 2016; Dingelstad, Borst and Meijer, 2022). Additionally, examining various data types and analytics tools in decision-making can provide insights into the most effective tools for specific situations, complement theoretical propositions, inform practitioners, and refine DDDM theories and practices (Hino, Benami and Brooks, 2018; Silva, Junior and Lacerda, 2022).

These gaps motivated this research to contribute to the underexplored potential of DDDM in the public sector. By investigating the practical implementation of DDDM in public sector contexts, this research aims to uncover the specific steps and challenges civil servants face. Additionally, it seeks to identify the data types and analytics tools used in various decision-making scenarios, bridging the gap between theory and practice to refine DDDM theories, providing valuable insights for practitioners, and improving public administration's efficiency and effectiveness.

In addition, despite extensive research on government-to-citizen (G2C) and government-to-business (G2B) interactions and the adoption of e-government services, the study of interactions between government employees and ICT innovations in the government-to-employee (G2E) context remains limited (Rehouma, 2017; Rehouma and Hofmann, 2018). This study is motivated to address this gap by focusing on the G2E context, which has been identified as a valuable avenue for understanding the facilitators and barriers to employees' ICT adoption (Rehouma, 2017; Rehouma and Hofmann, 2018; Martins and Nielsen, 2020; Abdulkareem *et al.*, 2022; Dingelstad, Borst and Meijer, 2022). In addition, the role of employee participation in public sector IT projects has received limited attention despite its significance for effective system adoption and utilisation (Lopes, 2017; Rehouma, 2020; Lemke, Ehrhardt and Popelyshyn, 2021). Employee involvement is crucial for ensuring ICT systems' successful implementation and uptake (Bano and Zowghi, 2015; Lopes, 2017; Rehouma, 2020). Motivated by this gap, this study explores how employee participation and user involvement can enhance the development and adoption of ICT systems in government services.

Finally, current G2E ICT adoption studies were primarily quantitative and directly utilise existing theories such as the Technology Acceptance Model (TAM), the Theory of Planned Behaviour (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT), which might overlook the unique characteristics of public organisations and government employees (Venkatesh, Brown and Bala, 2013; Rehouma, 2017; Rehouma and Hofmann, 2018). Qualitative insights are valuable in understanding contextual factors of ICT adoption (Venkatesh, Brown and Bala, 2013; Barile *et al.*, 2018; Rehouma and Hofmann, 2018), which complement the study's quantitative examination of adoption intentions. Thus, this study is motivated to examine government employees' ICT adoption by using both qualitative and quantitative methods, which have been advocated to capture comprehensive and contextual nuance and insights (Gil-Garcia and Pardo, 2006; Venkatesh, Brown and Bala, 2013; Bano and Zowghi, 2015; Rehouma, 2017; Barile *et al.*, 2018; Rehouma and Hofmann, 2018).

1.3 Aims, questions, and objectives

This study's overarching aim is to provide insights into government employees' decision-making, participation in ICT development, and their behavioural intention to adopt ICT. The study has two phases to achieve this overarching aim: a requirement elicitation phase and an adoption intention examination phase.

Phase One: Requirement elicitation

The first phase explores government employees' decision-making and participation in ICT development. This phase will involve government employees developing an ICT tool to inform decision-making. During the development process, the study aims to understand how government employees make decisions and to determine what contents and features they prefer in an ICT tool. The results of this exploration will inform the subsequent ICT development, which will be the subject of the adoption intention examination phase.

This phase addresses two research questions:

RQ1: How do government employees conduct decision-making within the data-driven decision-making framework?

RQ2: "What features do government employees prefer in an ICT for decision-making, and how does their participatory involvement in its development provide insights into user-centred design practices?"

The objectives for this phase are:

O1: To explore how government employees conduct decision-making within the data-driven decision-making framework through qualitative semi-structured interviews analysed using thematic analysis.

O2: To identify the features government employees prefer for an ICT for decision-making through thematic analysis of interview data and participatory ICT development to provide insights into user-centred design practices.

The insights from this phase will inform the subsequent ICT development process, which will serve as the research subject for Phase Two.

Phase Two: Adoption Intention Examination

This study adopts an approach that leverages the researcher's familiarity with the study environment (Appendix F) to gain valuable insights into the factors influencing government employees' behavioural intention to adopt the developed

ICT tool. In this phase, qualitative interviews are conducted to explore employees' perceptions, followed by a quantitative survey to validate the identified factors. The researcher's professional experience, access to key personnel, and understanding of operational processes could provide a unique advantage in obtaining contextually rich data and fostering trust and openness during data collection (Appendix F). This familiarity could ensure a comprehensive exploration of ICT adoption challenges and contribute to the findings' applicability in public sector settings.

The research questions for this phase are:

RQ3: What factors are perceived as motivating government employees' adoption of ICT tools, and how can these insights inform the understanding of technology acceptance in the public sector?

RQ4: "What are the relationships between identified motivational factors and the behavioural intention of government employees to adopt ICT, and how do these findings contribute to the refinement of ICT adoption theories in public sector settings?"

The objectives for this phase are:

O1: To explore the factors perceived as motivating government employees' adoption of ICT tools through semi-structured interviews analysed using thematic analysis and to use these insights to inform the understanding of technology acceptance in the public sector.

O2: To examine the relationships between identified motivational factors and the behavioural intention of government employees to adopt ICT through a survey analysed using structural equation modelling (SEM) to refine ICT adoption theories in public sector settings.

These two phases are designed to gain insights into data-driven decision-making practices in the public sector and provide the evidence necessary to refine DDDM theories and practices. Second, this study will provide an understanding of the involvement of government employees in creating a practical and inclusive ICT solution, which is expected to address common issues like design-reality mismatches and unrealistic planning that have been emphasised in previous research. Finally, this study could also reveal the contextual factors that promote or hinder the adoption of ICT, which is essential for improving public service delivery and operational efficiency in urban government settings.

1.4 Scope

1.4.1 Decision-making in traffic police's patrolling allocation

Due to the research aim of understanding urban government employees' decision-making, this study focuses on traffic police's patrolling allocation as a key aspect of managing urban transportation effectively. Urban transportation management and governance are crucial parts of smart city development, affecting quality of life significantly (Giffinger and Gudrun, 2010; Chourabi *et al.*, 2012; Neirotti *et al.*, 2014; Peng, Nunes and Zheng, 2017). Among the urban transportation stakeholders, police have a crucial role, especially with their presence on the roads (Armour, 1984). Police presence on the roads has been found to reduce traffic violations and crashes (Rothengatter, 1982; Clarke *et al.*, 2010; Deangelo and Hansen, 2014), suggesting that strategic decision-making in patrol allocation could further enhance these benefits (Rezapour, Wulff and Ksaibati, 2018; Kamnik, Nekrep Perc and Topolšek, 2020; Sam, 2022).

Police presence remains crucial because while ICT tools, such as automated traffic enforcement systems, can deter violations, they lack the immediacy required to address offences posing immediate risks, underscoring the critical role of police in making decisions for patrol allocations and traffic regulation enforcement to compensate for these limitations (Eccles *et al.*, 2012; Ubaldi, 2013; Farmer, 2017; United Nations, 2018a). Optimising patrol allocations is critical to managing limited resources to maximise the impact on road safety (Singh *et al.*, 2011; Chen, Cheng and Wise, 2017; Chen, Cheng and Ye, 2019; Dewinter *et al.*, 2020). While existing patrol allocation studies have explored many methods for efficient officer deployment, such as spatial, temporal, and spatiotemporal, the lack of police involvement in research design and decision-making processes has been a notable gap, limiting the practical applicability of findings (Telep and Gross Shader, 2019). Engaging police in the research process is crucial for translating academic insights into practical policing strategies, bridging the gap between research and practice, and enhancing the real-world impact of these studies (Hartmann et al., 2018; Fyfe, 2019; Boulton et al., 2021).

1.4.2 Dashboard as an ICT example

This study, which will explore government employees' participation in ICT development and examine their intention to adopt ICT, has selected a dashboard as an example of an ICT solution. A dashboard is a software tool designed to integrate and visualise data across various applications, providing a concise representation that allows users to quickly understand the current situation and make informed, data-driven decisions (Beuschel, 2008; Kumar *et al.*, 2010; Wilbanks and Langford, 2014). The dashboard format is beneficial for several reasons. First, dashboards are inherently user-centric, intuitively consolidating and visualising essential information (Yigitbasioglu and Velcu, 2012; Few, 2013; Al-Kassab *et al.*, 2014). This quality aligns with the need to involve users in the ICT development process to gain insights into their tasks and preferences, which are critical for successful adoption, acceptance, trust, and usage (Ives and Olson, 1984; Cavaye, 1995; He and King, 2008; Abelein, Sharp and Paech, 2013; Rehouma, 2019). By engaging users early and often, developers can create more effective and accepted solutions (McCurdie *et al.*, 2012).

Second, dashboards can enhance decision-making by providing data visualisation and analytics (Provost and Fawcett, 2013; Contreras-Figueroa *et al.*, 2021). This provision can be beneficial for police decision-making when allocating their patrolling resources. For example, visualising crash data can help identify high-risk areas and optimise patrol routes, improving overall safety and resource management (Shuey, Mooren and King, 2020).

Third, dashboards are flexible and scalable, allowing them to be customised to meet the specific needs of different users and organisations (Richardson, Courtney and Haynes, 2006; Al-Kassab *et al.*, 2014). This flexibility ensures that a dashboard can be adapted as new requirements emerge, making it a sustainable solution for long-term use (Jackson, Chow and Leitch, 1997; Pauwels *et al.*, 2009). Customisability allows for ongoing relevance and effectiveness, accommodating evolving user needs and organisational goals (Vazquez-Ingelmo, Garcia-Penalvo and Theron, 2019). Integrating user feedback can continuously improve a dashboard, ensuring it remains relevant and practical (Surbakti *et al.*, 2020).

Therefore, this study will use a dashboard as an ICT example to develop a user-centred solution aimed at meeting the practical decision-making needs of government employees. It will also serve as a model for examining the broader impacts of user participation on ICT development and adoption in the public sector. Understanding these factors can help design better ICT solutions that are more likely to be accepted and effectively used by government employees.

1.5 Thesis structure

This thesis is structured into eight chapters, which are:

Chapter 1 introduces the research background, gaps, motivations, aims, questions, scope, and structure.

Chapter 2 reviews the literature on smart city governance, e-government, data-driven decision-making, dashboards, ICT development participation, user-centred design, ICT adoption, road traffic crashes, and police patrolling allocation.

Chapter 3 describes the overall research methodologies, the requirement elicitation phase's qualitative methods, and its ethical considerations.

Chapter 4 provides the results of the requirement elicitation phase.

Chapter 5 describes the qualitative and quantitative methods and ethical considerations for the second adoption intention examination phase.

Chapter 6 provides the results of the adoption intention examination phase.

Chapter 7 discusses the results of both phases.

Chapter 8 provides the conclusions.

Chapter 2 Literature review

This chapter provides a review of the literature related to this study. In line with the context of this research, the chapter describes the concepts of government's ICT adoption in smart city governance and e-government, followed by an overview of governments' data-driven decision-making and the roles of dashboards. The literature on employee participation in government ICT development and user-centred design is also reviewed. In addition, this chapter provides a literature review on government ICT adoption evaluation. Finally, the review of studies on traffic crash data analysis and police patrolling allocation, which is the scope of this study, is presented.

2.1 ICT and government

Integrating Information and Communication Technologies (ICT) in government plays a transformative role in modern urban management, mainly through smart city governance and e-government concepts. Smart city governance focuses on utilising ICT to enhance resource management, service provision, and citizen engagement, fostering sustainable development and improving quality of life. E-government, a key component of smart governance, modernises public administration by streamlining processes, enhancing transparency, and improving service delivery.

These technological advancements are especially crucial in developing countries, where addressing infrastructure gaps and leveraging ICT frameworks can significantly enhance governance and urban development. The following sections will further explain these concepts, describing the role of ICT in shaping smart city governance, the evolution of e-government, and the unique challenges and opportunities developing countries face in adopting these technologies.

2.1.1 Smart city governance

The concept of a "smart city" is multifaceted and constantly changing, with no explicit agreement on its essential components and standards (Dameri, 2013; Borsekova and Nijkamp, 2018). There is often confusion and criticism surrounding this term due to a lack of clarity and understanding (Hollands, 2008; Müller, Park and Sonn, 2023). Nevertheless, the central idea is the application of Information and Communication Technologies (ICT) in urban development to foster opportunities for harmonious progress and enhance resource management, service provision, and the standard of living (Ishkineeva, Ishkineeva and Akhmetova, 2015; Carter, 2017). Despite the ambiguities, the integration of ICT remains a pivotal element in shaping the future of urban environments and their adaptability to emerging societal challenges (Shah, 2023).

Smart cities are envisioned as urban environments that utilise ICT, innovation, and democratic principles to foster sustainable development, economic growth, and improved quality of life by integrating technology, government institutions, and the diverse, creative knowledge of individuals to enhance democratic governance and equity (Batty *et al.*, 2012; Ballas, 2013; Gil-Garcia, Helbig and Ojo, 2014; Yin *et al.*, 2015; Anthopoulos and Reddick, 2016; Castelnovo, Misuraca and Savoldelli, 2016). Smart city definitions converge on three core elements: technological infrastructures, institutional governance, and the human capital comprising creativity, diversity, and education (Caragliu, del Bo and Nijkamp, 2011; Nam and Pardo, 2011).

Recent urban studies emphasise the interplay of these components as essential for smart city development, highlighting not just the technological foundations but also the crucial role of human aspects in making cities smarter (de Oliveira, Campolargo and Martins, 2015). This role includes fostering connections among people and urban infrastructures, as well as promoting innovation, creativity, and entrepreneurship to drive economic and governance advances in smart cities (Kitchin, 2014; Kogan and Lee, 2014; Sepasgozar *et al.*, 2019; Soomro *et al.*, 2019). As such, the human dimension and technological advancements are increasingly recognised as fundamental to smart cities' sustainable and inclusive development (Zhou, Loiacono and Kordzadeh, 2023; Parappallil Mathew and Bangwal, 2024).

Smart cities require smart governance, characterised by transparency, accountability, and participation, encompassing formal institutions and informal networks essential for managing states, organisations, or collectives (Lopes, 2017). Governance within the smart city framework necessitates the implementation of intelligent, flexible management and decision-making processes, often facilitated by digital technology and data analytics to enhance information processing and decision-making capabilities (Scholl and Alawadhi, 2016). The incorporation of ICT into government services, an essential aspect of smart governance, marks a transformative shift towards enhancing organisational performance and governance effectiveness (Dai *et al.*, 2024), with the government playing a crucial role in shaping the necessary administrative structures and processes for smart city governance effectiveness (Alawadhi and Scholl, 2016). Effective governance creates a conducive environment through proper legal frameworks and mechanisms (Bokhari and Seunghwan, 2024), ensuring government responsiveness to citizens' needs and leading smart city initiatives (UN-Habitat, 2002; UN-Habitat, 2004).

2.1.2 The roles of E-government in smart city governance

The concept of leveraging ICT to support government operations and service delivery, known as electronic government (e-government), plays a vital role in smart city governance by transforming public institutions' efficiency and service quality (Anderson *et al.*, 2015; Anthopoulos and Reddick, 2016; Vrabie and Tirziu, 2017). Since the early 2000s, e-government has been pivotal in modernising public sector services, boosting administrative efficiency, performance, and citizen-centricity (Siddiquee and Mohamed, 2015). Governments can foster smart cities by emphasising public service efficiency and transparency, using ICT in smart governance to improve decision-making and collaboration (Rodríguez Bolívar, 2016; Pereira *et al.*, 2018). The strategic application of technology by governments to enhance the efficiency and quality of urban services and strengthen the bond between governments and their citizens underscores the critical role of governance in advancing smart city development, facilitating a more integrated, responsive, and sustainable urban future (Hollands, 2008; Lee and Lee, 2014; Gracia and García, 2018).

The move towards smart governance has led to a shift in government management, with e-government as a crucial foundation and support for transitioning to a service-oriented government (Wenhua and Jian, 2010). In smart cities, effective governance depends on the strategic use of ICT by public servants to enhance decision-making and service delivery, showcasing the essential role of e-government in enabling streamlined, transparent processes (Nam and Pardo, 2011; Pereira *et al.*, 2018). This crucial smart governance approach utilises intelligent ICT frameworks to bolster decision-making and align closely with e-government principles, ensuring governance is open, accountable, collaborative, and participatory (Lopes, 2017; Pereira *et al.*, 2018). The restructuring of administrative systems towards smart governance, incorporating innovative technologies and strategies, is crucial for enhancing public services and decision-making, embodying e-government principles essential for the success of smart city initiatives (Gil-Garcia, Helbig and Ojo, 2014; Alawadhi and Scholl, 2016; Lopes, 2017; Pereira *et al.*, 2018).

2.1.3 ICT and government in developing countries

The governance of smart cities in developing countries is deeply intertwined with technological challenges and opportunities. While these nations face financial constraints that often limit their ability to invest in advanced technologies (Khan, Shah and Rizwan, 2021), the role of technology in smart city initiatives is crucial (Shah, 2023). Digital infrastructure, including IoT, sensors, and big data analytics, can address urban challenges and improve the quality of life for city residents (Shamkuwar, More and Patil, 2023). E-governance platforms can further enhance governance efficiency and transparency, though their effectiveness is often influenced by political and cultural factors (Yang *et al.*, 2022).

From a technological standpoint, the successful implementation of smart city and e-government initiatives hinges on several critical factors. Performance expectancy, effort expectancy, and system quality are key determinants in adopting e-government services, shaping how users perceive and interact with these technologies (Sabani, Thai and Hossain, 2023; Almufti, Sellami and Belguith, 2024). Social influence and facilitating conditions also play a significant role, either promoting or hindering the use of these services (Almufti, Sellami and Belguith, 2024). These factors and a supportive social and infrastructural environment ensure the widespread adoption and long-term success of smart city and e-government initiatives (Puron-Cid and Gil-Garcia, 2022; Sugandha, Freestone and Favaro, 2022).

In developing countries, the lack of essential infrastructure, such as reliable internet access and sufficient technological devices, poses a significant barrier to the widespread adoption of e-government services (Bregni, 2018; Ruffini *et al.*, 2019). This infrastructure gap exacerbates the digital divide between urban and rural areas, making it difficult to scale and implement effective e-government solutions (Tamilarasi *et al.*, 2024). Furthermore, issues such as data security, privacy concerns, and the need for adherence to regulatory frameworks complicate the deployment of cloud-based e-government platforms (Tamilarasi *et al.*, 2024). Addressing these challenges requires coordinated efforts to improve infrastructure, bridge the digital divide (Singh and Chobotaru, 2022; Alfiani *et al.*, 2024), and ensure robust security and regulatory compliance to sustain e-government services in developing countries (Ranchordas, 2020).

The Unified Theory of Acceptance and Use of Technology (UTAUT), detailed in the section 2.4.5, provides a comprehensive framework for understanding the technological adoption process in these contexts (Venkatesh *et al.*, 2003). By integrating external factors, UTAUT helps address the challenges that influence user adoption of e-government services, particularly in developing countries where ICT skills, financial resources, leadership, and government support are critical (Sihotang *et al.*, 2023). Thus, the UTAUT framework offers valuable insights for policymakers and practitioners, helping them tailor e-government strategies that account for users' unique challenges and needs in developing countries (Fuad and Hsu, 2018; Bayaga and du Plessis, 2024).

Despite these challenges, the technological advantages of e-government are substantial. Improved efficiency, enhanced data protection, and better service delivery are among the benefits of successfully implementing e-government technologies (Madaki, Ahmad and Singh, 2024). Developing innovative frameworks, particularly those incorporating UTAUT, can effectively address the external factors impacting user adoption, leading to more successful and widespread use of e-government services (Almufti, Sellami and Belguith, 2024). Although UTAUT models are robust, their complexity and need for context-specific adaptations present limitations, which can be addressed by combining them with other technology acceptance models for a more comprehensive understanding of technology adoption (Obienu and Amadin, 2021; Abdekhoda, Dehnad and Zarei, 2022).

Ultimately, the technological dimension is pivotal in the governance of smart cities and the adoption of e-government in developing countries. By addressing infrastructure deficits, ensuring data security, and leveraging comprehensive frameworks like UTAUT, these regions can overcome technological barriers and fully realise the benefits of smart city and e-government initiatives. Policymakers and practitioners must prioritise technological advancements, strengthen ICT capabilities, and foster environments that support robust management and trust to maximise the impact of these technologies in improving governance and service delivery.

2.2 Data and decision making in governments

Data is highly valued across various sectors, including government, where its conversion into actionable knowledge is crucial for improving decision-making and enabling the leverage of information (Gates and Matthews, 2014; OECD/ITF, 2016; IRTAD, 2019; Choi *et al.*, 2021). Data utilisation can drive greater government efficiency and create social and economic value (Jetzek, Avital and Bjorn-Andersen, 2014; Matheus, Janssen and Maheshwari, 2020). Rapid technological advances in data storage and processing have led stakeholders to increasingly base their decisions more on data and less on intuition (Silva, Junior and Lacerda, 2022). The rapid growth of ICT has changed how organisations, including governments, manage and communicate data and information across devices (Hanna, 2010; Martínez-López *et al.*, 2016).

The growth of ICT has also led governments to work closely with data in areas like communications, data management, and performance management (Gmach *et al.*, 2009; Papadomichelaki and Mentzas, 2012). Innovations in online data storage enable the processing of extensive datasets from diverse sources, prompting public sector managers and administrators to increasingly rely on data for decision-making due to enhanced data creation, collection, and storage capabilities (Jetzek, Avital and Bjorn-Andersen, 2014; Choi *et al.*, 2021; Silva, Junior and Lacerda, 2022). Integrating big data and AI technologies enables the systematic analysis of large datasets, facilitating more informed and accurate decisions (Provost and Fawcett, 2013; Kitchin, 2014; Brynjolfsson and McElheran, 2016). In addition, robust data governance frameworks are required to manage the volume and diversity of data, ensuring quality and facilitating decision-making (Sexton *et al.*, 2017).

Making decisions based on the analysis and interpretation of verifiable data rather than intuition or observation alone is called Data-Driven Decision-Making (DDDM) (Gilbert, 2023). This approach leverages data-related evidence and insights to guide decision-making and verify action plans before implementation (Brynjolfsson, Hitt and Kim, 2011; Provost and Fawcett, 2013). DDDM advocates for a decision-making style anchored in systematically analysed data, positing that such methods yield more reliable outcomes than those based purely on personal intuition (Kurilovas, 2020). Advancements in analytics, such as machine learning and data mining, facilitate extracting actionable insights (Provost and Fawcett, 2013). These developments support the shift of DDDM, integrating data analysis into traditional intuition-based methods (Mandinach, 2012).

While data are essential to inform decision-making, they should also be integrated with human intuition and experience. Integrating personal experiences, known as tacit or implicit knowledge, with data-driven insights can enhance decision-making (Chourabi *et al.*, 2012; Garcia Alonso and Lippez-De Castro, 2016; Lopes, 2017; Vrabie and Tirziu, 2017). Tacit knowledge was first defined by Polanyi (1962), and it refers to the aspect of human knowledge that is challenging to articulate and acquired through direct experience. It helps decision-makers interpret and contextualise data, leading to more informed and effective decisions (Guo *et al.*, 2017; Sanford, Schwartz and Khan, 2020). Practitioners generally possess a wealth of tacit knowledge about their tasks, work practices, the context in which they use data, their behaviour, and preferences (Smith, 2001; Bano and Zowghi, 2015; Manaf *et al.*, 2017). Tacit knowledge enriches data-driven decision-making by providing the practical know-how and contextual understanding necessary for interpreting data and making informed decisions (Richards, 2002).

However, there is hesitancy among public sector organisations to integrate tacit knowledge and data-driven decision-making because it cannot be easily quantified or captured in conventional knowledge management systems, which tend to focus on explicit, measurable knowledge (Garrick and Chan, 2017). The hesitancy also arises either from employees who value their expertise and experience or those who question the relevance of tacit knowledge in favour of data-driven methods

(Giunipero, Dawley and Anthony, 1999; Brockmann and Anthony, 2002; Naziz, 2021). Public sector organisations can address the divide between tacit knowledge and data-driven decision-making by promoting collaboration and open communication (Bennett, 1998; Brockmann and Anthony, 2002), fostering a culture of information sharing (De Neys, 2010), and providing training on integrating knowledge with data (Arduin, Rosenthal-Sabroux and Grundstein, 2012), thereby enabling rational, collective decision-making that reconciles intuitions and norms.

While tacit knowledge is valuable, it may occasionally result in heuristics when making decisions (Maqsood, Finegan and Walker, 2004; Meng, 2017). Heuristics are cognitive shortcuts to make decisions more efficiently by focusing on the most relevant information while ignoring less critical details, which can lead to decisions that are "good enough" rather than optimal (Gigerenzer and Gaissmaier, 2011; Hjeij and Vilks, 2023). While trading accuracy for efficiency, heuristics are beneficial for making decisions when formal reasoning is impractical due to missing data (Pohl *et al.*, 2013; McLaughlin, Eva and Norman, 2014). Tacit knowledge should include domain-specific knowledge and leadership expertise to balance heuristic decision-making (Hanif, Ahsan and Wise, 2020).

Despite the obstacles, tacit knowledge is essential to improving strategic decision-making (Brockmann and Anthony, 2002), managing success (Matoskova *et al.*, 2013), problem-solving circumstances (St.Germain and Quinn, 2006) and enhancing decision quality through experience-based insights crucial for achieving organisational goals (Ganguly, Talukdar and Chatterjee, 2019; Sial *et al.*, 2023). Tacit knowledge is essential in decision-making across various domains because it can provide nuanced, context-specific insights not captured by explicit knowledge alone. Integrating tacit knowledge into formal decision-making processes can enhance strategic decisions, as seen in using decision support systems to explore and utilise tacit knowledge effectively (Al Ghazzawi, Al Subayi and Yaghi, 2018).

2.2.1 Benefits

DDDM benefits smart governance by providing comprehensive and efficient decision-making processes (Provost and Fawcett, 2013; Shyr and Spisic, 2014). DDDM revolutionises policy formation and decision-making processes within governments, facilitated by improved data collection (Brynjolfsson, Hitt and Kim, 2011), processing (Ganapati, 2011), storage (Van Der Geest and Velleman, 2014), and retrieval (Reddick, Chatfield and Jaramillo, 2015; Al-Harthei *et al.*, 2017). DDDM benefits from recent advances in data availability and analytic technologies by providing new insights with less uncertainty (Choi *et al.*, 2021). The DDDM's ability to provide accurate information has increased ICT usage and positively impacts user experience (Laugwitz, Held and Schrepp, 2008; Díaz-oreiro *et al.*, 2019; Hossin *et al.*, 2023).

DDDM also offers numerous benefits to the public sector. Data-driven approaches can significantly improve productivity and performance, with public administrations experiencing gains like those in the private sector. Brynjolfsson, Hitt and Kim (2011) found that data-driven firms are more productive and achieve higher returns on assets and market value. In the public sector, data-driven decision-making enhances transparency (Kitchin, 2014), accountability, and public trust (Matheus, Janssen and Maheshwari, 2020). Moreover, analysing and visualising data help public managers make more informed decisions, ultimately improving public service delivery (Kitchin and McArdle, 2016; Silva, Junior and Lacerda, 2022).

DDDM represents a transformative approach in public administration, driven by technological advancements and the push for greater transparency through accessible government data initiatives. While significant progress has been made, ongoing research and development are essential to address the challenges and maximise the potential of data-driven governance. By investing in skills development, infrastructure, ethical standards, and empirical research, the public sector can fully realise the benefits of DDDM and enhance its decision-making capabilities (Matheus, Janssen and Maheshwari, 2020; Silva, Junior and Lacerda, 2022).

2.2.2 Challenges and gaps

Despite the benefits, challenges are associated with implementing DDDM in the public sector. Integrating data analytics into decision-making frameworks requires significant organisational changes and adaptations (Silva, Junior and Lacerda, 2022). The public sector needs various skills, including statistical analysis, policy understanding, and knowledge of public values, to effectively use data for decision-making (Matheus, Janssen and Maheshwari, 2020). This multidisciplinary skill set is crucial for interpreting data within the context of public administration and ensuring decisions are both informed and aligned with public interests (Choi *et al.*, 2021). It is also crucial to ensure all government agencies have the necessary infrastructure and resources to implement data-driven practices consistently, including investing in technology and human resources to create a solid foundation for DDDM, as adequate infrastructure and trained personnel are essential for successfully integrating data analytics into public administration (Silva, Junior and Lacerda, 2022).

There is also a notable disparity in resources and expertise across different government agencies. Some agencies may lack the necessary infrastructure and trained personnel, creating inconsistencies in applying data-driven practices (Silva, Junior and Lacerda, 2022). These disparities can lead to uneven adoption of DDDM, with some agencies advancing faster than others (Choi *et al.*, 2021). In addition, using big data and AI in public administration raises significant ethical and privacy concerns. Ensuring that data-driven decision-making practices comply with legal and ethical standards is crucial for maintaining public trust and preventing data misuse (Gurstein, 2011; Marda, 2018). Addressing these concerns requires robust ethical guidelines and legal frameworks that protect individuals' privacy while enabling the benefits of data analytics (Silva, Junior and Lacerda, 2022).

There are also noted gaps in empirical evidence supporting the practical application of DDDM theories. While scholarly discourse suggests significant potential for organisational change, DDDM in the public sector received less attention than in the private sector (Dingelstad, Borst and Meijer, 2022). The disparity between the public and private sectors in adopting data-driven decision-making (DDDM) can be explained by their contrasting organisational environments and goals. Public organisations, often linked to bureaucratic structures and focusing on non-materialistic managerial values, encounter several obstacles in adopting business-oriented practices like DDDM (Boyne, 2002; Morris and Farrell, 2007). The public sector’s emphasis on producing "public goods" and addressing complex public issues, such as road traffic crashes, crime, and poverty, complicates the implementation of DDDM, which often requires straightforward solutions (Caudle, Gorr and Newcomer, 1991; Lopes and Farias, 2022). Moreover, the public sector's reluctance to embrace change further slows the adoption of new practices. The transfer of management techniques from the private to the public sector presents significant challenges, often facing resistance and requiring adaptation to suit the public sector's unique context (Krasnykov, 2023).

While DDDM offers transformative potential for governments through enhanced decision-making and efficiency, it also raises considerable ethical challenges. For example, algorithms and data analytics used in DDDM may inadvertently introduce or reinforce biases present in historical data, leading to discriminatory outcomes (Hadjimatheou and Nathan, 2022). This is particularly concerning in contexts like predictive policing, where data models have been shown to disproportionately target marginalised communities, further entrenching systemic inequalities (Browning and Arrigo, 2021; Alikhademi *et al.*, 2022; Purves, 2022; Montana *et al.*, 2023).

Furthermore, the reliance on automated decision-making tools often lacks transparency, creating challenges in accountability. The "black-box" nature of algorithms can obscure the rationale behind decisions, making it difficult for affected stakeholders to redress or challenge outcomes (de Bruijn, Warnier and Janssen, 2022; Brożek *et al.*, 2024). These ethical considerations highlight the importance of robust governance frameworks and ethical oversight to ensure that DDDM delivers efficiency and aligns with fairness, inclusivity, and social justice principles (Economou-Zavlanos *et al.*, 2024; Kyriakou and Otterbacher, 2024). Integrating ethical principles into governance structures can help mitigate DDDM biases and ensure equitable outcomes (Seger, 2022; Zhu, Zhang and Xu, 2024).

These factors contribute to the lack of attention given to DDDM in the public sector, underscoring the need for tailored strategies to overcome the specific challenges encountered. Therefore, future research should explore how DDDM is carried out in government organisations, focusing on the practical steps and challenges civil servants face when using data in their work (Dingelstad, Borst and Meijer, 2022) while also examining the use of various data types and analytics tools in decision-making processes to provide insights into which tools function best in certain situations (Brynjolfsson and McElheran, 2016), thereby complementing theoretical propositions and informing practitioners to improve DDDM implementations (Silva, Junior and Lacerda, 2022). Empirical research and systematic studies are encouraged to explore the benefits and limitations of DDDM in various public sector contexts, including examining the integration of computational models and predictive analytics in decision-making processes, as this empirical research will provide the evidence needed to refine DDDM theories and practices (Hino, Benami and Brooks, 2018; Silva, Junior and Lacerda, 2022).

2.2.3 DDDM for urban road safety

In urban road safety, DDDM has offered valuable insights for designing safer roads and evaluating the effectiveness of safety interventions (Xu *et al.*, 2019). City stakeholders have used data to address safety concerns by considering various scenarios in urban traffic and evaluating safety properties (Wegman *et al.*, 2015; Behnood *et al.*, 2017; Guo *et al.*, 2019). Developing decisions based on data can assist policymakers in assessing road safety planning strategies and prioritising investments in safety measures (Chang, Vavrova and Mahnaz, 2022). Data-driven approaches can also improve road infrastructure maintenance planning, pavement management, and distress detection methods for safer and more comfortable roads (Ragnoli, De Blasiis and Di Benedetto, 2018).

The WHO advocates for traffic crash data collection and utilisation to enable targeted research and policy recommendations (Ganapati, 2009; IRTAD, 2019; Shuey, Mooren and King, 2020; Department for Transport UK, 2021). These data help develop a holistic road safety strategy to reduce traffic-related deaths and injuries (Dell'Acqua, De Luca and Mauro, 2011) and to realise safer road users, vehicles, infrastructure, and post-crash measures (Shrivastava, Shrivastava and Ramasamy, 2014; United Nations, 2018b). Many countries have supported the WHO by maintaining traffic crash record systems to inform road policies and regulations (e.g., Indonesian National Police, 2018; NCSA, 2018; Department for Transport UK, 2021).

Studies have highlighted the potential of traffic crash data for DDDM in urban traffic crash management. For example, traffic crash data can be analysed using data mining techniques like Random Forest to predict crash occurrences and severities and identify influential factors (Ramya *et al.*, 2019; Atumo, Fang and

Jiang, 2022). Analytics of traffic crash data can reveal crash trends and take appropriate mitigation measures on urban roads (Shikhar *et al.*, 2016; Kolisnyk *et al.*, 2022). Data-driven approaches can also be used for traffic management and crash hotspot identification (Mesquitela *et al.*, 2022; Dmitrieva *et al.*, 2024). Big data analytics are also beneficial in analysing and extracting relevant information from traffic crash data (Abberley *et al.*, 2017; El Abdallaoui *et al.*, 2018).

Data-driven decision-making (DDDM) in traffic safety has provided valuable insights for policymakers in developing countries, helping to reduce crashes and enhance road safety. For example, in Latin America, an analysis of over 10 billion observations revealed a non-linear relationship between traffic congestion and crashes, indicating that reducing traffic delays could significantly lower crash rates (Sánchez González, Bedoya-Maya and Calatayud, 2021). In Bangladesh, machine learning techniques were applied to traffic crash data to identify key factors influencing crash severity, such as driver characteristics, vehicle types, road conditions, and environmental factors. These findings have supported the development of targeted safety interventions (Bhuiyan *et al.*, 2022). In Rwanda and Sri Lanka, DDDM has pinpointed high-risk areas for road crashes (Staton *et al.*, 2015).

Overall, DDDM studies in developing countries underscore the importance of a multifaceted approach to road safety, combining infrastructure improvements, behavioural interventions, and targeted policies. By leveraging data, policymakers can better address the complexities of traffic crashes and enhance road safety across various contexts. In this way, DDDM becomes crucial for developing more effective, context-specific strategies to improve road safety and reduce traffic-related incidents in developing countries (Sohail *et al.*, 2023).

2.2.4 The roles of dashboards in DDDM

A dashboard is a software tool designed to integrate and visualise data across various applications, providing a concise representation that allows users to quickly understand the current situation and make informed, data-driven decisions (Beuschel, 2008; Kumar *et al.*, 2010; Wilbanks and Langford, 2014). Dashboard potentials have led to widespread adoption in public service delivery, driven by their ability to consolidate and visualise complex data, enabling decision-makers to track and analyse trends (Gleeson, Kitchin and McCarthy, 2022). This ability is crucial in the public sector, where dashboards can support the development of performance metrics and the monitoring of urban systems (Maheshwari and Janssen, 2014; Vila, Estevez and Fillottrani, 2018).

Dashboards are essential tools that help the government implement DDDM because they simplify and make complex data more accessible, which helps workers make decisions. They are a focal point for monitoring and assessing many urban systems, including transport, energy, and health, which is crucial for effective strategic planning and governance (Lock *et al.*, 2020; Dingelstad, Borst and Meijer, 2022). Data literacy, critical thinking, and data analytical abilities are necessary for effective DDDM, and they are supported by dashboards that make data interpretation and stakeholder participation easier (Stehle and Kitchin, 2019). They also help interpret data and lessen cognitive load (Lawson-Body, Lawson-Body and Illia, 2023). Additionally, dashboards can facilitate a more inclusive approach to governance by bridging the gap between data and decision-making by offering visualisations that correspond with the requirements of different stakeholders, including the general public and policymakers (Dasgupta and Kapadia, 2022).

Dashboards are essential tools in smart cities for monitoring public safety and urban performance by collecting, visualising, and analysing data to support decision-making (Jing *et al.*, 2019; Farmanbar and Rong, 2020). Dashboards can produce different visual outputs to meet development goals and improve smart city governance transparency and trustworthiness (Vinet and Zhedanov, 2011; Allio, 2012; Maheshwari and Janssen, 2013; Vila, Estevez and Fillottrani, 2018; Matheus, Janssen and Maheshwari, 2020; Gupta, 2021). Dashboards embody the transformative potential of ICT in urban contexts, provided their implementation is guided by ethical considerations (Kitchin and McArdle, 2016), participatory design (Cardullo and Kitchin, 2019), and a commitment to bridging the digital divide (Jing *et al.*, 2019), thus creating technologies that are effective and aligned with the broader public interest (Matheus, Janssen and Maheshwari, 2020; Gru, 2021).

The following section focuses on employee participation in developing a user-centred dashboard, highlighting its importance in the success of e-government ICT initiatives. Integrating technology in public administration is most effective when it includes active participation from public-sector employees. Their involvement ensures that ICT systems are aligned with practical needs, fostering ownership and improving adoption. Effective participation is key to bridging the gap between technology and real-world application, enhancing decision-making and service delivery.

2.3 Employee participation in government's ICT development: a user-centred dashboard

In smart cities and e-government initiatives, the role of public-sector employees in enhancing infrastructure, public services, and urban governance through ICT engagement is crucial (Nam and Pardo, 2011; Sepasgozar *et al.*, 2019). The smart city emphasises the need for a holistic approach that integrates technology, people, and processes in decision-making, highlighting that ICT alone is insufficient for effective governance (Lopes, 2017; Vrabie and Tirziu, 2017; Sanctis *et al.*, 2021). The ICT enhancement of public servants' decision-making capabilities should be complemented by the crucial need to balance technological focus with human aspects (Estevez and Janowski, 2013; Pereira *et al.*, 2018; Darioshi and Lahav, 2021). The personal experience of public servants, combined with data-driven insights, is crucial in leading smart governance initiatives in smart cities (Chourabi *et al.*, 2012; Castro, 2016; Lopes, 2017; Vrabie and Tirziu, 2017).

Involvement in project groups and information sharing are critical predictors of ICT acceptance among government employees (Rehouma, 2020). A lack of user engagement and participation, leading to user attrition, often marks an unsuccessful outcome, highlighting the importance of understanding the dynamics behind technology adoption and usage (Lyytinen and Hirschheim, 1988; Claussen, Kretschmer and Mayrhofer, 2013). Active participation in ICT development enhances the adoption and acceptance of e-government initiatives (Abdulkareem *et al.*, 2022). Responsive and transparent ICT development can build user trust and increase engagement, thereby improving the quality of e-government services (Dukić, Dukić and Bertović, 2017).

Public sector employees tend to resist IT adoption more than their private sector counterparts due to inadequate infrastructure and unsupportive policies, but these barriers can be mitigated through effective employee participation, leading to enhanced productivity and service delivery (Madaki, Ahmad and Singh, 2024). However, research on employee participation in public-sector IT projects is limited (Rehouma, 2017), while it has been argued as crucial for IT adoption in the public sector (Simonofski *et al.*, 2020). This gap is significant given the increasing reliance on ICT to improve public sector efficiency, service delivery, and citizen engagement (Rehouma, 2019; Martins and Nielsen, 2020). With their deep understanding of business processes, these employees are vital to digitalisation efforts (Kozanoglu and Abedin, 2021) and effective participation enhances their contributions (van der Voet, Groeneveld and Kuipers, 2014).

2.3.1 User participation

The concept of "participation" is significant across various disciplines, including social science, political science, economics, and business management (Barki and Hartwick, 1994). In employee engagement, participation refers to how individuals or groups are involved in decision-making processes, directly or through representatives (Heller *et al.*, 1998). Direct participation involves personal involvement in decisions, while indirect participation occurs through intermediaries such as lobbies or staff councils (Dachler and Wilpert, 1978). Participation involves mutual influence in decision-making, shaping future outcomes (Mumford, 1995).

Participation engages employees at all organisational levels through information sharing and consultation, covering tasks from minor to major strategic decisions (Wilkinson, 2010). Employee participation is categorised into downward communication, upward problem-solving, task-based participation, and teamwork and self-management, where downward communication, the weakest form, transmits information (Marchington and Wilkinson, 2005). Participation ranges from formal to informal and is based on power or legitimacy stemming from design values, goals, and specific organisational and social contexts (Dachler and Wilpert, 1978). It spans a spectrum from rejection to active approval, defined as voluntary acceptance (Stahlknecht and Hasenkamp, 2002). The levels of involvement range from merely providing information to having complete control (Marchington and Wilkinson, 2005).

User participation in designing and developing technological innovations is crucial for ensuring system success regarding acceptance, trust, usage, and overall quality (Abelein, Sharp and Paech, 2013). In system development, participation refers to user engagement in analysis activities (Zowghi, 2018). Terms like "involvement" or "empowerment" are often used synonymously with participation, emphasising active engagement in system development and success (Király and Miskolczi, 2019; Kim and Lee, 2023). Recognising user participation as multidimensional is crucial, acknowledging its dynamic nature and impact on system success (Lou *et al.*, 2021). User participation enhances ownership and satisfaction (Barki, Pare and Sicotte, 2008; Simonofski *et al.*, 2020). Effective participation management involves identifying the correct user, involving users early and often, maintaining quality relationships, and facilitating easy improvements (Symon and Clegg, 2005; Simonofski *et al.*, 2020). User responsibilities extend from the beginning to the end of the development process, including testing and evaluation (Kujala, 2003; Chen, Liu and Chen, 2011).

2.3.2 User participation in dashboard development: User-centred design (UCD) approach

Developing dashboards requires thoroughly understanding users' diverse information requirements and needs (Stehle and Kitchin, 2019; Vazquez-Ingelmo, Garcia-Penalvo and Theron, 2019; Lock *et al.*, 2020). Dashboards should feature easy navigation, precise data, consistent visual themes, relevant visualisations (Young and Kitchin, 2020), and "information at a glance" for effectiveness (Sarikaya *et al.*, 2019; Matheus, Janssen and Maheshwari, 2020). Young and Kitchin (2020) advocate combining current and historical data, focusing on intuitive design for user-friendly interfaces, and developing tailored communication strategies to enhance user understanding and interaction. Well-designed dashboards provide a simple interface that enables users to understand presented information easily and make decisions quickly (Sarikaya *et al.*, 2019; Pastushenko, Hynek and Hruška, 2021).

It is vital to address how users' perceptions and societal influences shape their data interaction, necessitating a consistent focus on user needs throughout the development process for optimal outcomes (Kintz, Kochanowski and Koetter, 2017; Kim, Reinecke and Hullman, 2018; Vazquez-Ingelmo, Garcia-Penalvo and Theron, 2019). Leveraging users' insights on tasks and preferences is crucial to enhancing adoption rates and ensuring the dashboard's success (Amoako-Gyampah, 2007; Chagas *et al.*, 2021). By prioritising designing with the user in mind and continuously incorporating user feedback, developers can significantly improve adoption rates and ensure the dashboard's effectiveness in meeting users' needs (Richter Lagha *et al.*, 2020; Young, Kitchin and Naji, 2021).

Understanding users' needs can be achieved with a User-Centred Design (UCD) approach (Dwivedi, Upadhyay and Tripathi, 2012; Kitamura, Hayashi and Yagi, 2018; Stehle and Kitchin, 2019). UCD customises technological solutions to user needs and preferences by incorporating cognitive aspects and comprehending user and task requirements (Young, Kitchin and Naji, 2021). The UCD approach enhances efficiency, user satisfaction, and adoption rates, proving particularly beneficial for public-sector urban dashboards (Baroudi, Olson and Ives, 1986; Abelein and Paech, 2012; Abelein, Sharp and Paech, 2013; Vila, Estevez and Fillottrani, 2018; Young, Kitchin and Naji, 2021). Emphasising user-centred design in developing e-government services requires involving public servants in the ICT development process (Madyatmadja and Prabowo, 2016; Meydani, 2017). Engaging users throughout system development provides valuable insights into their needs and preferences, which enhances user satisfaction and ease of use (Bano and Zowghi, 2015).

By applying UCD from the beginning of the software development process, a requirement elicitation or requirement gathering phase can lead to better software design and development outcomes (Neetu Kumari and Pillai, 2013; Mahmoud, 2015). This phase involves gathering and analysing the needs and expectations of stakeholders to ensure that the final product meets their requirements (Goguen and Linde, 1993; Zowghi and Coulin, 2005). This process utilises a range of techniques, including interviews, surveys, observations, and workshops, to identify and document the system's functional and non-functional requirements (Goguen and Linde, 1993; Zowghi and Coulin, 2005; Ribeiro *et al.*, 2014).

Among these methods, interviews, which can be unstructured, structured, or semi-structured, are particularly valuable for gaining in-depth stakeholder insights (Girardi *et al.*, 2020). Given the need to explore complex, context-specific information about government employees' decision-making in this study, semi-structured interviews were selected as the primary method for data collection, detailed in section 3.8.1. This approach allows for probing deeper into participants' experiences and perspectives, providing rich qualitative data that is not as easily captured through more rigid methods like questionnaires. This choice aligns with the literature, which underscores the effectiveness of interviews in understanding user needs and expectations in UCD (Neetu Kumari and Pillai, 2013). While questionnaires are cost-effective and can collect data from a large audience (Moore and Shipman, 2000), and techniques like Think-Aloud and focus groups offer other benefits (Nielsen, 1993; Avila-Garcia *et al.*, 2022), interviews were chosen for their ability to facilitate a more nuanced exploration of stakeholder needs, which is critical for the successful application of UCD in software development (Nielsen, 1993; Girardi *et al.*, 2020).

Once the users' requirements have been gathered, the next step is to create a preliminary system version through prototyping to allow for feedback from stakeholders and help validate design decisions (Snyder, 2003; Buxton, 2010). Prototyping bridges the gap between requirement elicitation and system design, providing a robust framework for developing clear, complete, and consistent requirements (Smith *et al.*, 2002). Prototypes come in different forms, such as low-fidelity paper sketches or high-fidelity interactive mock-ups. Low-fidelity prototypes like paper sketches are quick, cost-effective, and valuable for early design stages to explore ideas and gather initial feedback without detail complexity, enabling rapid iteration (Rettig, 1994; Snyder, 2003). In contrast, high-fidelity prototypes such as interactive mock-ups offer detailed, polished simulations of the final product, ideal for testing advanced features and conducting usability tests to identify issues in pre-production (Walker, Takayama and Landay, 2002; Dow *et al.*, 2011). Based on these advantages, this study will use a high-fidelity dashboard prototype, detailed in section 4.3.

UCD aligns with the broader goals of smart cities to elevate urban life quality through technological innovation, emphasising the crucial roles of human capital, creativity, and innovation (Shapiro, 2006; Hollands, 2008; Kitchin, 2014; Kogan and Lee, 2014). Smart cities should prioritise user-centred services for effectiveness through user participation, perspectives, and feedback (Fang and Shan, 2024). Integrating UCD into smart city technologies enhances user-friendliness, efficiency, and effectiveness, thereby contributing to the success of e-government initiatives (Young, Kitchin and Naji, 2021). Incorporating UCD into smart city systems not only improves usability and utility for diverse user groups (Delmastro, Arnaboldi and Conti, 2016) but also enhances decision-making processes, real-time monitoring, and user experiences (Santoso, Hadi Putra and Farras Hendra S, 2021).

2.4 Empirical studies on government employees' ICT adoption

Quantitative surveys are commonly used as the primary research methodology for studying government employees' ICT adoption (e.g., Hu, Clark and Ma, 2003; Hung *et al.*, 2009; Wirtz, Lütje and Schierz, 2009; Karavasilis, Zafiropoulos and Vrana, 2010; Reeves and Li, 2012; Yousef, 2017). Surveys are effective at identifying the various internal and external factors that contribute to the adoption of government ICT (Wang and Feeney, 2016). In addition, surveys can uncover the key factors contributing to the successful adoption of IT innovation in government sectors. These surveys provide valuable insights into the factors that positively or negatively impact ICT adoption (Kamal, 2006). The structured nature of quantitative surveys also provides an opportunity to analyse specific hypotheses within the context of government initiatives (Gupta, Dasgupta and Gupta, 2008).

While useful for standardised data collection, quantitative surveys also have several limitations. One issue is the potential misalignment between survey questions and respondents' understanding, especially in cross-cultural contexts, leading to inaccurate data (Scott *et al.*, 2019). Surveys also can fail to capture the complexity of human identities; for example, predefined demographic options may not fully represent diverse identities (Ghorbanian, Aiello and Staples, 2022). The rigidity of structured surveys can hinder rapport, affect the accuracy of responses, and introduce measurement errors that compromise validity (Bell, Fahmy and Gordon, 2016). Additionally, formalising these surveys can result in findings that lack external validity and fail to reflect real-world dynamics (Smith, 1988). Despite rigorous methodologies, quantitative surveys cannot entirely eliminate biases or establish causation, limiting their applicability to complex social issues (Walker, 2005; Clare *et al.*, 2014). Addressing these weaknesses requires integrating qualitative elements and considering cultural and identity diversity to improve the depth and relevance of findings. To mitigate these limitations, this study will incorporate interviews in developing survey hypotheses to capture more nuanced perspectives and ensure a deeper contextual understanding.

Most quantitative government ICT studies use behavioural intention as the primary dependent variable, followed by examining adoption, actual use, and attitudes towards use (Rehouma and Hofmann, 2018). Among these studies, the Technology Acceptance Model (TAM) is the most frequently applied theory (e.g., Hu, Clark and Ma, 2003; Melitski, Gavin and Gavin, 2010; Singh and Punia, 2011; Barua, 2012; Tarus, Gichoya and Muumbo, 2015; Muthu *et al.*, 2016; Deligiannis and Anagnostopoulos, 2017), followed by the Unified Theory of Acceptance and Use of Technology (UTAUT) (e.g., Gupta, Dasgupta and Gupta, 2008; Barua, 2012; Mosweu and Bwalya, 2018), The Theory of Planned Behaviour (TPB) (e.g., Azamela *et al.*, 2022), and the Diffusion of Innovations (DOI) (Rogers, 1962).

The following section explores key theories of technology acceptance and behaviour, beginning with the Theory of Reasoned Action (TRA), which laid the groundwork for subsequent models, and extending to the Unified Theory of Acceptance and Use of Technology (UTAUT), which integrates and builds on these foundational theories to explain technology adoption in various contexts. These theories have been applied in public sector studies to understand the challenges in implementing e-government and smart cities.

2.4.1 Theory of Reasoned Action (TRA)

In 1975, a seminal article entitled Theory of Reasoned Action (TRA) was published by Fishbein and Ajzen, laying the foundation for acceptance studies. The article described the connections between attitudes and actions, and according to this idea, both the attitude toward carrying out the activity and the subjective norm influence the intentions, which in turn influence the behaviour (Fishbein and Ajzen, 1975; Wang, 2016). This theory is considered one of the most imperative and influential in measuring human behaviour (Fishbein, 1979; Venkatesh *et al.*, 2003; Wang, 2016). The key concepts in this theory are: ‘subjective norm’, which is people’s normative beliefs about behaviours’ acceptability; ‘attitude’ is the people’s feeling about a particular behaviour; ‘behavioural intention’ is the normative component which consists of attitudes and subjective norm; and finally, ‘behaviour’ is the outcome measurement of the model, precisely the performed behaviour (Figure 2.1) (Fishbein and Ajzen, 1975; Fishbein, 1979).

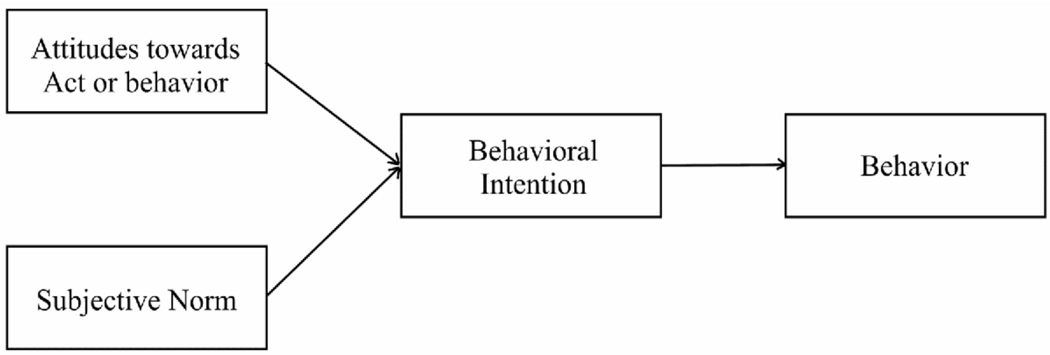


Figure 2.1 Theory of Reasoned Action (Fishbein and Ajzen, 1975)

TRA aimed to explain the associations between behaviours and attitudes in human action and hypothesised that behavioural intentions, the imminent preceding of behaviour, are the function of subjective norms and attitude factors. The researchers argued that the likelihood of the person performing the behaviour results from stronger behavioural intentions that lead to increased effort to perform the behaviour (Fishbein and Ajzen, 1975; Fishbein, 1979).

2.4.2 Theory of Planned Behaviour (TPB)

The TRA was later refined and expanded by Ajzen (1991) to the theory of planned behaviour (TPB) to overcome discrepancies between behaviour and attitude. TPB is also called the extended TRA. Ajzen added the perceived behavioural control factor as a component that influences the behavioural intention and the (performed) behaviour. Perceived behavioural control is defined as people’s perceptions of their control after observing the opportunities, resources, and ease of a particular task (Ajzen, 1991). TPB posits that perceived behaviour control has associations with attitude, subjective norm, and intention (Figure 2.2). It also envisages a direct relationship with intention and an indirect relationship with the performed behaviour (Ajzen, 1991).

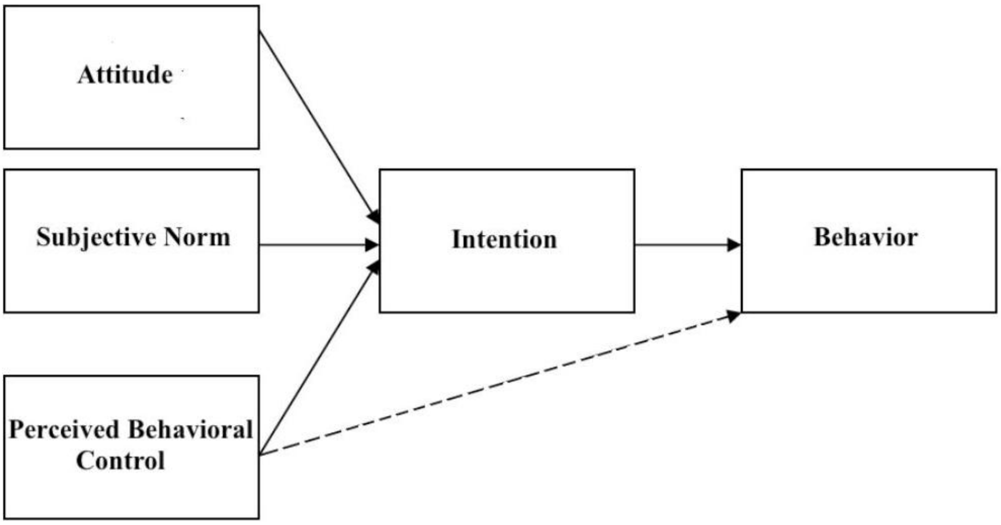


Figure 2.2 Theory of Planned Behaviour (Ajzen, 1991)

2.4.3 Technology Acceptance Model (TAM)

TRA inspired the technology acceptance model (TAM) (Davis, 1986). TRA posits that attitudes and subjective norms influence an individual's behavioural intentions, providing a foundational framework for understanding how beliefs affect behaviour. Building on this foundation, TAM was designed to explain and predict user acceptance of information technology (Davis, 1989). TAM introduces two constructs: “Perceived Usefulness”, i.e. the individual’s perception of how helpful the technology is, and “Perceived Ease of Use”, i.e. the individual’s perception of how easy it is to use technology (Davis, 1986). PU and PEOU are intended to replace and simplify previous constructs of the attitude of TPB (Figure 2.3). This amendment was intended to make it easier to predict acceptance.

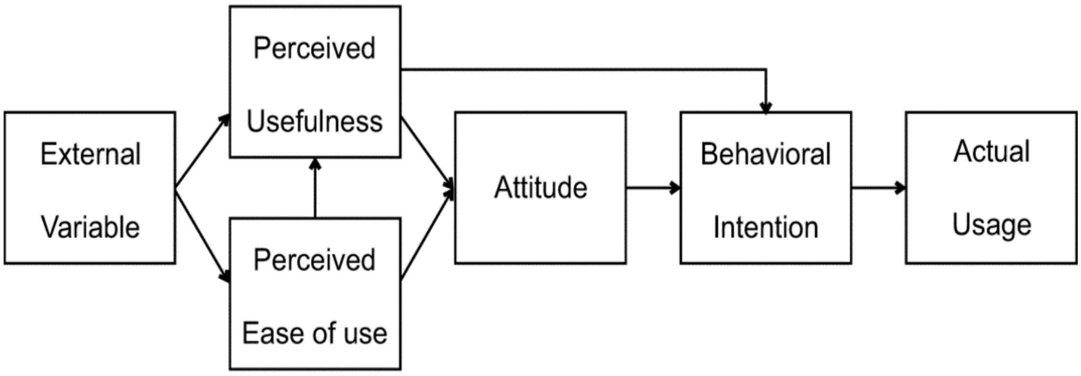


Figure 2.3 Technology Acceptance Model (Davis, 1986)

By focusing on these constructs, TAM offers a robust and parsimonious model for assessing user acceptance and has been extensively applied and validated across various technological contexts (Davis and Venkatesh, 1996; Venkatesh *et al.*, 2003). The evolution from TRA to TAM marked a significant advancement in technology adoption research, providing a more tailored approach to understanding the determinants of technology acceptance in organizational settings. Since its introduction, TAM has gradually gained popularity among IS adoption studies. From 1990 to 2021, TAM had around 280,000 citations and was considered a native theory (Gupta, Abbas and Srivastava, 2022).

2.4.4 Innovation Diffusion Theory (IDT)

Another prominent theory that investigates the acceptance of technology is the innovation diffusion theory (IDT), which was first introduced in 1962 in the book “Diffusion of Innovation” by Everett Rogers (Rogers, 1962). Rogers examined more than five hundred diffusion studies and unified them to describe at what rate, how, and why the new technology ideas diffuse among people and organisations. The word diffusion can be defined as people’s social process as a response when learning about innovation. Furthermore, diffusion involves progressively communicating the innovation through some channels (Dearing and Cox, 2018).

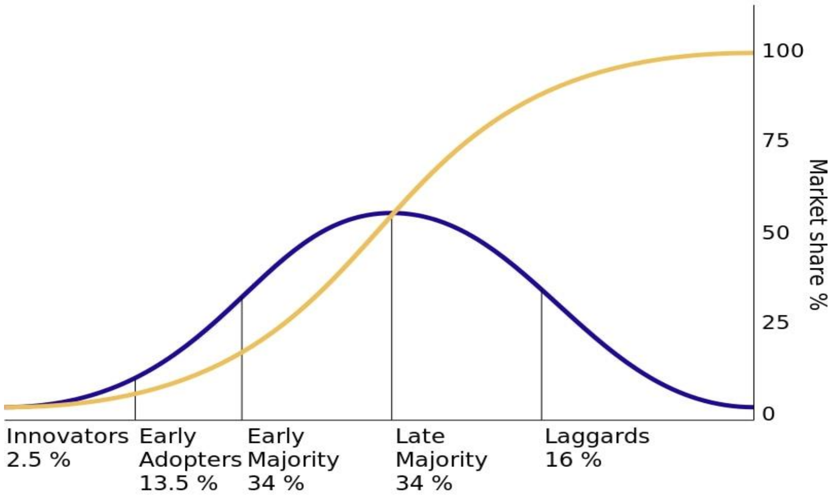


Figure 2.4 Innovation Diffusion Theory (Rogers, 1962)

IDT classifies people who adopt the innovation as innovators, early adaptors, early majority, late majority, and laggards. These adopter groups are identified as IDT's key elements. (Rogers, 1962). The author provided the diagram (Figure 2.4) to explain categories in IDT, where the blue line shows the adopter categories while the yellow line symbolises the market share of the innovation, which ultimately reaches saturation at 100 per cent.

2.4.5 Unified Theory of Acceptance and Use of Technology (UTAUT)

One of the most widely used technology acceptance models is the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh *et al.*, 2003; Venkatesh, Thong and Xu, 2012; Anas, Othman and Fathey, 2018; Shachak, Kuziemsky and Petersen, 2019). UTAUT focuses on individual behaviour in utilising specific technologies, emphasising the technology's ease of use and perceived utility. This model is versatile as it applies to mandatory and voluntary use of technologies (Venkatesh *et al.*, 2003; Venkatesh, Thong and Xu, 2012). The UTAUT was proposed by Venkatesh et al. (2003) to unify existing technology acceptance theories, aiming to achieve more comprehensive measurement results by incorporating a broader range of attitude and behaviour factors. This unified model integrates elements from several prior models, including the social cognitive theory, innovation diffusion theory, model of PC utilization, theory of planned behaviour, theory of reasoned action, and technology acceptance model.

In their seminal study, Venkatesh et al. (2003) employed structural equation modelling (SEM) to compare the correlations between technology acceptance variables across different theories. SEM is a statistical technique that combines factor analysis and multiple regression to analyse the relationships among observed and latent variables, allowing researchers to test complex theoretical models (Kline, 2023). Venkatesh et al. (2003) classified variables from past technology acceptance theories into four key factors: facilitating conditions, social influence, effort expectancy, and performance expectancy. The sophisticated design of SEM allowed the researchers to incorporate several moderating variables into their analysis. They found these moderators, such as gender, age, experience, and voluntariness of use, to be statistically significant in influencing the relationships among the primary factors. By consolidating these diverse theoretical perspectives (Figure 2.5), UTAUT provides a robust framework for understanding the determinants of technology acceptance and use. Its comprehensive approach makes it an invaluable tool for researchers and practitioners aiming to predict and enhance user engagement with new technologies.

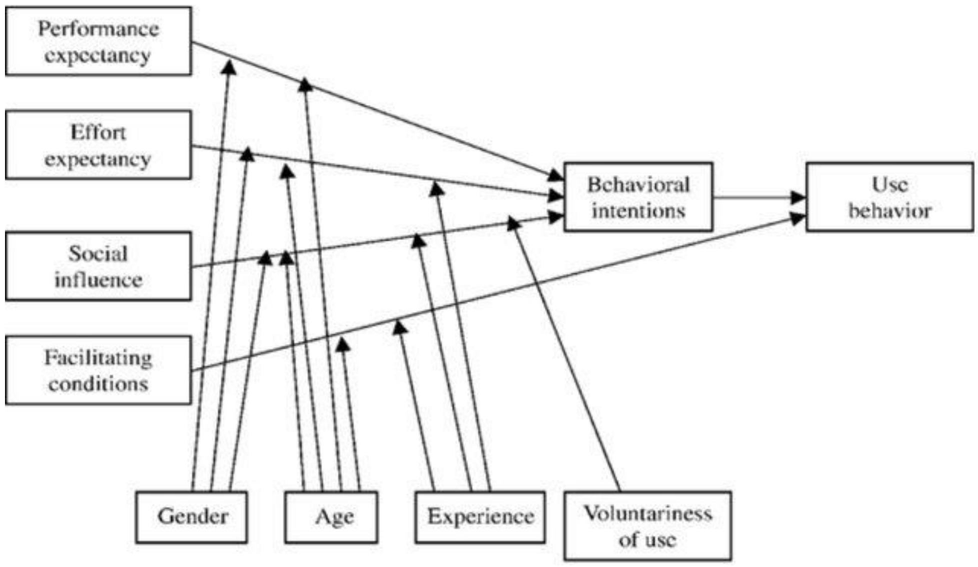


Figure 2.5 UTAUT Model (Venkatesh *et al.*, 2003)

No	Theory/ Framework	Original constructs	UTAUT Constructs
1	Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1975)	1. Attitude. 2. Subjective Norm.	Social Influence.
2	Theory of Planned Behaviour (TPB) (Ajzen, 1985)	1. Attitude. 2. Subjective Norm. 3. Perceived behavioural control.	1. Social Influence. 2. Facilitating Conditions.
3	Technology Acceptance Model (TAM) (Davis, 1986)	1. Perceived Usefulness. 2. Perceived Ease of Use.	1. Performance Expectancy. 2. Effort Expectancy.
4	Technology Acceptance Model2 (TAM2) (Venkatesh & Davis, 2000)	1. Perceived Usefulness. 2. Perceived Ease of Use. 3. Subjective Norm. 4. Image. 5. Job Relevance. 6. Output Quality. 7. Result Demonstrability.	1. Performance Expectancy. 2. Effort Expectancy. 3. Social Influence.
5	Innovation Diffusion Theory (IDT) (Rogers, 1995)	1. Relative Advantage. 2. Complexity. 3. Image. 4. Compatibility. 5. Voluntariness Use.	1. Performance Expectancy. 2. Effort Expectancy. 3. Social Influence. 4. Facilitating Conditions.
6	Combined TAM-TPB (C-TMA-TPB) (Taylor & Todd, 1995)	1. Perceived Usefulness. 2. Subjective Norm. 3. Perceived behavioural control. 4. Attitude.	1. Performance Expectancy. 2. Social Influence. 3. Facilitating Conditions.

Table 2.1 Theories that the UTAUT unifies

Table 2.1 provides the predecessor theories on which the UTAUT has unified. Many studies have utilised UTAUT to examine users' acceptance behaviour of governments' technologies, such as how they employ the internet for their duties (Isaac and Mutahar, 2017; Isaac *et al.*, 2019), how they use their electronic document management (Stainson, 2018), how police officers use their electronic traffic enforcement application (Yumami, Budiyanto and Suyoto, 2018), and how the police use their body-worn cameras (Obasi, 2018; Stainson, 2018). These studies found that the UTAUT could assess the behavioural factors affecting users' use of the technologies. This existing body of research underscores the relevance of UTAUT in understanding technology adoption in government-to-employee (G2E) contexts, which is closely related to the focus of this thesis. The following section addresses existing G2E adoption literature to provide this study's theoretical foundation and contextual relevance.

2.4.6 Factors influencing G2E ICT adoption

G2E technology acceptance studies used existing ICT adoption and acceptance theories and extended them to suit their specific contexts. The factors utilised span various dimensions: technological, individual, managerial, organisational, environmental, trust, and demographic. This section provides an overview of factors that shape ICT adoption among government employees, drawing on examples from empirical G2E studies.

2.4.6.1 Technological

Technological factors play a crucial role in shaping employees' behavioural intentions. Key factors include perceived usefulness (or performance expectancy in the UTAUT model) and perceived ease of use (or effort expectancy). Research has shown that system quality (Hu, Clark and Ma, 2003; Bhattacherjee and Sanford, 2006; Gupta, Dasgupta and Gupta, 2008; Seo and Myeong, 2021), compatibility (Barua, 2012; Shin, 2012; Mohammed *et al.*, 2017), data security (Hung *et al.*, 2009; Karavasilis, Zafiropoulos and Vrana, 2010; Muthu *et al.*, 2016), system integration (Singh and Punia, 2011; Stefanovic *et al.*, 2016), infrastructure support (Deligiannis and Anagnostopoulos, 2017; Mosweu, Bwalya and Mutshewa, 2017), and technical support (Chimtengo, Hanif and Mvonye, 2016) positively influence IT adoption.

Perceived usefulness is frequently emphasised as influencing employees' intentions to use IT (Hu, Clark and Ma, 2003; Antón, Camarero and San José, 2014; Lai, 2017). Likewise, the level of performance expectancy plays a crucial role in influencing one's intention to adopt a system (Barua, 2012; Mosweu, Bwalya and Mutshewa, 2017). Enhancing IT adoption can be facilitated by involving users in the design and requirements-gathering process, which improves perceived usefulness and ease of use (Deligiannis and Anagnostopoulos, 2017). System quality is also a critical measure of the success of e-government systems (Stefanovic *et al.*, 2016).

2.4.6.2 Individual

Research on factors influencing IT adoption in the public sector highlights various individual variables that play a crucial role in shaping adoption behaviour. These include technological skills (Hu, Clark and Ma, 2003), self-efficacy (Bhattacherjee and Sanford, 2006), and subjective norms (Chimtengo, Hanif and Mvonye, 2016), which have been identified as significant predictors of IT usage. Interpersonal influence and internal barriers, such as technical know-how and risk-oriented attitudes, also affect individuals' ability and willingness to adopt new technologies (Hung *et al.*, 2009; Mosweu, Bwalya and Mutshewa, 2017). Furthermore, factors such as training (Nichols and Maner, 2008), user expertise (Wirtz, Lütje and Schierz, 2009), and attitude toward technology (Nurdin, Stockdale and Scheepers, 2010) impact the adoption process, along with perceived risks, including privacy and security concerns (Anjum and Ismail, 2022).

Additional influences include technology anxiety, computer attitude, and resistance to change, all of which can hinder IT adoption (Hu, Clark and Ma, 2003; Reeves and Li, 2012; Kaushik and Mishra, 2019). User satisfaction, job relevance, and job satisfaction have also been shown to affect adoption behaviour (Bhattacherjee and Sanford, 2006; Nichols and Maner, 2008; Tarus, Gichoya and Muumbo, 2015; Stefanovic *et al.*, 2016), while factors such as net benefits, relative advantages, and knowledge of these benefits shape perceptions of IT use (Muthu *et al.*, 2016; Mosweu and Bwalya, 2018). Personal characteristics, including innovativeness, responsibility, staff motivation, and interest in the technology, further contribute to the overall likelihood of successful IT adoption (Nichols and Maner, 2008; Muthu *et al.*, 2016; Mosweu and Bwalya, 2018).

Interpersonal influence and self-efficacy are particularly significant predictors of IT adoption, with IT staff more likely to engage with new technologies due to their inherent skills and confidence (Nichols and Maner, 2008; Shin, 2012). Computer self-efficacy and technical expertise have positively impacted intentions to use IT systems (Hu, Clark and Ma, 2003; Hung *et al.*, 2009; Singh and Punia, 2011). However, public sector employees often face barriers such as qualifications deficits and risk-averse attitudes, which can impede adoption efforts (Wirtz, Lütje and Schierz, 2009; Wirtz *et al.*, 2016). Engaging employees early in the process can help reduce resistance to new technology, although resistance remains a persistent challenge (Chimtengo, Hanif and Mvonye, 2016).

Other factors, such as attitudes towards computers and computer anxiety, influence adoption, with personal innovativeness and perceived relative advantage indirectly shaping intentions and attitudes (Muthu *et al.*, 2016; Mosweu, Bwalya and Mutshewa, 2017). Motivation and interest in technology are also crucial, with concerns about job loss due to IT implementation affecting overall engagement (Hung *et al.*, 2009; Tarus, Gichoya and Muumbo, 2015; Chimtengo, Hanif and Mvonye, 2016).

2.4.6.3 Managerial

Research on public managers reveals that their perceptions of technology, attitudes towards public service, and organisational power positively influence their IT usage (Melitski, Gavin and Gavin, 2010; Shin, 2012). Managers committed to public service show higher IT usage, with decision-making authority and IT capabilities being significant factors (Melitski, Gavin and Gavin, 2010; Camarena and Fusi, 2022). It is recommended that training programs be organised to boost employees' computer self-efficacy, thus promoting IT adoption (Compeau and Higgins, 1995; Hung *et al.*, 2009; Singh and Punia, 2011).

Managerial characteristics, including age, tenure, education, gender, pro-innovation stance, and political orientation, are also important (Damanpour and Schneider, 2006, 2009). These studies indicate that the personal traits of managers play a more critical role in innovation adoption than demographic factors. Enhancing education and competency development is crucial for managing IT adoption processes in the public sector (Damanpour and Schneider, 2006, 2009).

2.4.6.4 Organisational

Organisational roles are examined through culture, climate, and internal barriers, such as hierarchical structures and bureaucracy. Research indicates a strong relationship between an individual's willingness to adopt technology and their perceptions of organisational dynamics, including work environment (Wirtz, Lütje and Schierz, 2009), communication flow (Melitski, Gavin and Gavin, 2010), decision-making practices, and coordination (Krutova *et al.*, 2022).

Organisational factors like financial resources (Veit, Parasie and Huntgeburth, 2011), political commitment, centralisation, and the experience of peer organisations (Horani *et al.*, 2023) are significant determinants of IT adoption. Organisations with robust economic health are more inclined to invest in innovation, underscoring the crucial role of financial resources in supporting innovation initiatives (Damanpour and Schneider, 2006; Horani *et al.*, 2023).

2.4.6.5 Environmental (social and external characteristics)

Environmental factors influencing IT adoption are divided into social and external categories. Social factors, including social influence (Nurdin, Stockdale and Scheepers, 2010), image (Barua, 2012), and visibility/observability (Tarus, Gichoya and Muumbo, 2015; Mosweu, Bwalya and Mutshewa, 2017), play a significant role in shaping employees' intentions to use IT. External factors such as urbanisation, community wealth, and population growth positively impact innovation adoption (Damanpour and Schneider, 2006; Craig, Hoang and Kohlhase, 2023). Additionally, trade unions and legal frameworks are critical external elements affecting public organisations' adoption process (Veit, Parasie and Huntgeburth, 2011; Neumann, Guirguis and Steiner, 2024). These factors could be linked to the public sector's Environmental, Social, and Governance (ESG) policies, as ESG considerations often intersect with IT adoption decisions, especially in the context of social and environmental impacts (Baldini *et al.*, 2018; Zioło *et al.*, 2022).

2.4.6.6 Trust

Trust factors, including information quality, argument quality, source credibility, and adaptability, are crucial for the transparency and trustworthiness of systems used in government organisations (Venkatesh *et al.*, 2016; Almuqrin *et al.*, 2022). These factors indirectly support the organisation's role in adopting, implementing, and using IT. Trust in data is especially significant in influencing user intentions (Barua, 2012; Kumar and Saha, 2017).

2.4.6.7 Demographic

Often utilised as control variables, demographic factors influence ICT adoption in the public sector. These factors include gender, age, education, organisational complexity, and size. While some research identifies gender differences in attitudes toward IT (Damanpour and Schneider, 2006), others do not find significant variations (Rana, D Williams and Kumar Dwivedi, 2012; Rana, Dwivedi and Williams, 2013). Organisational complexity and size positively correlate with innovation adoption in public organisations (Damanpour and Schneider, 2006). Additionally, education is a critical factor in the adoption process (Damanpour and Schneider, 2006; Chung, Lee and Kuo, 2016).

2.4.7 Gaps in G2E ICT adoption studies

Most research studies in G2E ICT adoption are quantitative surveys that used established theories, which were overviewed in section 2.4.6. Meanwhile, the fast-paced development of IT in organisations often challenges research, as existing theories and findings may not adequately explain certain phenomena of interest (Venkatesh, Brown and Bala, 2013). This current study will adopt a mixed-methods approach, as a quantitative-only approach might fail to capture nuanced user experiences and contextual factors (Venkatesh, Brown and Bala, 2013). The reliance on models like TAM, UTAUT, and TPB can lead to oversimplified findings that do not fully address real-world complexities (Venkatesh, Brown and Bala, 2013; Rehouma, 2020; Graeber *et al.*, 2023). Technology acceptance studies have also extended the hypotheses to be tailored to specific contexts, as seen in the G2E field and other contexts (Sukackė, 2019), as described in section 2.4.6.

There is a notable scarcity of qualitative approaches, which can provide rich, context-specific insights often missed by quantitative methods (Venkatesh, Brown and Bala, 2013; Rehouma and Hofmann, 2018; Rehouma, 2020). Employing qualitative methods, such as interviews and case studies, can uncover context-specific insights and develop novel theoretical perspectives in technology acceptance research (Gil-Garcia and Pardo, 2006; Venkatesh, Bala and Sykes, 2010; Venkatesh, Brown and Bala, 2013; Bano and Zowghi, 2015; Barile *et al.*, 2018; Rehouma and Hofmann, 2018). This study will incorporate qualitative approaches to develop constructs and hypotheses that better reflect the lived experiences of government employees' ICT adoption, as the current literature recommends (Barile *et al.*, 2018; Rehouma and Hofmann, 2018).

In addition, it has been suggested that empirical quantitative studies should consider a parsimonious approach, favouring simplicity and minimal assumptions to prevent speculative theories and reduce the complexity of questionnaires, which are linked to higher response rates (Whetten, 1989; Wacker, 1998; Weger, 2019; Burgard, Bošnjak and Wedderhoff, 2020; Wu, Zhao and Fils-Aime, 2022). Parsimony, or the principle of simplicity, is often advocated because it can enhance explanatory power and reduce the risk of overfitting, making models more generalisable and robust (Vanderburgh, 2014; Falk and Muthukrishna, 2023). For instance, in structural equation modelling, a commonly used method in examining ICT adoption, parsimony helps in selecting models that are not only simpler but also more likely to be valid across different datasets (Sansom *et al.*, 2018; Oeberst and Imhoff, 2023).

Finally, section 2.4 has established the theoretical foundations and contextual factors that influence technology adoption in public organisations, setting the stage for the next section's focus on road traffic crashes and police patrolling allocations. The upcoming section will specifically review studies related to these topics, providing an overview of this study's research scope in the context of traffic patrolling allocation and road traffic crashes.

2.5 The scope of the study: overviews of studies on traffic patrolling allocations and road traffic crashes

2.5.1 Traffic patrolling allocation studies

This section presents examples of patrolling allocation studies that, in alignment with the approach of this research, involve police officers in the research process to understand urban government employees' data-driven decision-making. Engaging police in the research process is crucial for translating academic insights into practical policing strategies, bridging the gap between research and practice, and enhancing the real-world impact of these studies (Hartmann *et al.*, 2018; Fyfe, 2019; Boulton *et al.*, 2021). Patrolling allocation topic was chosen given the well-documented positive influence of police presence on traffic behaviour and road safety through both manned and unmanned vehicles (Armour, 1984; Kaplan *et al.*, 2000; Rosenfeld, Maksimov and Kraus, 2017; Ravani and Wang, 2018). The mere sight of a police car alone can symbolise law enforcement, significantly impacting high-speed areas such as motorways (Armour, 1984; Kaplan *et al.*, 2000; Ravani and Wang, 2018). Stationary police cars and traffic controllers notably reduce traffic speed (Shinar and Stiebel, 1986), and activated flashing lights increase driver awareness of police presence (Nakano *et al.*, 2019).

Larson and Stevenson (1972, 1974, 1975) conducted pioneering research on hypercube queuing models and dynamic programming algorithms to optimise police patrolling in New York City. Their work involved close collaboration with police departments, gathering data and validating models to minimise response times and enhance patrol efficiency. Building on this, Olson and Wright (1975) employed Monte Carlo simulations to maximise police visibility in high-crime areas of Chicago. This study was conducted with significant input from local police over 21 days to test the effectiveness of visibility strategies. Similarly, Chelst (1978) used resource allocation models in Syracuse, NY, where the collaboration with police officers improved crime interdiction rates through increased police visibility.

Further studies focused on response times and workload balancing, with direct involvement from police in each case. Chaiken and Dormont (1978) developed the PCAM model to reduce response times, while Green and Kolesar (1984) used queuing models to assess high-priority call delays in NYC. Both studies relied on collaboration with police, which was critical for enhancing response efficiency through accurate data collection and model validation. Kwak and Leavitt (1984) tackled workload balancing in St. Louis County, MO, by allocating beats across different watch times in close coordination with police departments, thereby improving operational efficiency. Bliss *et al.* (1999) in New Zealand demonstrated effective resource allocation to reduce crash costs, with police involvement ensuring that the models were practically applicable and led to enhanced road safety through optimised police presence.

Studies have also integrated advanced models and GIS technology to further refine police patrolling strategies, with police involvement playing a crucial role in each study. Curtin, Hayslett-McCall and Qiu (2010) used GIS and location models to optimise patrol areas in NYC, working directly with police to address operational challenges and ensure the models met real-world needs. In Greece and China, Geroliminis, Karlaftis and Skabardonis (2009) and Chen, Cheng and Ye (2019) developed sophisticated algorithms for emergency response unit deployment and district design, respectively, with continuous collaboration from police departments to ensure the effectiveness and practicality of these algorithms. Similarly, Kennedy, Caplan and Piza's (2011) risk terrain model in New Jersey and Kuo, Lord and Walden's (2013) patrol route optimisation in Texas involved police throughout the research process, ensuring that GIS-based models were accurate and effective in enhancing patrol efficiency.

Several international studies also underscore the importance of police involvement in the research process. Chen, Cheng and Wise (2017) developed an online cooperative patrol routing strategy in London and Chicago, demonstrating enhanced patrol coordination and reduced response times, with police participation being integral to validating the model. Adler *et al.* (2014) optimised traffic patrols in Israel through close collaboration with the Israeli Traffic Police, while Mukhopadhyay *et al.* (2016) used bi-level stochastic programming in Nashville to minimise response times, with detailed input from police officers ensuring the model's accuracy and applicability. Chandra, Silalahi and Guritman (2023) in Indonesia addressed the Vehicle Routing Problem with Time Windows, optimising patrol routes to minimise operational costs and enhance efficiency, with the police actively involved in the research. Nurhumam and Mahmudy (2008) also, in Indonesia, improved patrol operations through heuristic and algorithmic approaches, with police collaboration ensuring the practical application of the models.

Collectively, these studies illustrate the evolution of police patrolling allocation research from foundational models to sophisticated algorithms and GIS integration. The continuous collaboration with police departments underscores these models' practical significance and applicability. This synthesis highlights the importance of optimised patrolling strategies to enhance police visibility, response times, and overall operational efficiency.

This review of police patrolling allocation studies suggests a potential lack of detailed information on police involvement in communicating the research findings within departments. The existing literature suggests that future research should address this gap by understanding how findings are disseminated within police organisations (Boulton *et al.*, 2021; Mowatt, 2023). Effective dissemination is crucial for translating academic insights into practical policing strategies (Fyfe, 2019; Boulton *et al.*, 2021), bridging the gap between research and practice, and enhancing the real-world impact of these policing studies (Hartmann *et al.*, 2018). More research is needed to examine how these innovations are integrated into police operations (Fyfe, 2019; Boulton *et al.*, 2021). Additionally, the involvement of police officers in research and the dissemination of findings within departments require further exploration to bridge the gap between academic research and practical application (Boulton *et al.*, 2021).

Although the reviewed studies demonstrate significant advancements in police patrolling allocation through various models and algorithms, there appears to be limited explicit discussion on developing or integrating dashboards specifically designed to support data-driven decision-making in police operations. To address this potential gap, the current study will develop a dashboard prototype aimed at enhancing police patrolling allocation by translating research findings into practical, user-friendly decision-making tools. Additionally, this study will examine how these research findings are communicated and applied within police organisations to improve the practical implementation of academic insights in real-world policing contexts.

2.5.2 Road traffic crash studies

The following section provides an overview of studies regarding data analyses related to road traffic crashes (RTC), which have utilised various analytical techniques to understand and reduce the frequency and severity of these incidents. Recording traffic crashes exemplifies the vital data collection and utilisation which is highly recommended by the WHO's Decade of Action for Road Safety 2011-2020 to enable targeted research and policy recommendations regarding road safety education, enforcement, and engineering (Ganapati, 2009; IRTAD, 2019; Shuey, 2019; Department for Transport UK, 2021). Traffic crash data collection enables authorities to monitor trends, identify hazardous road sections, and make decisions for targeted interventions to mitigate risks (Butsenko, 2022; Banerjee *et al.*, 2023). This overview provides several commonly used methods, such as statistical analyses, Geographic Information Systems, Machine Learning, and smart city technologies.

2.5.2.1 Statistical Analysis

Statistical analyses remain essential in RTC research (Lord and Mannering, 2010; Abdulhafedh, 2017). Traditional statistical methods like negative binomial regression, Poisson regression, and multinomial logistic regression are commonly used due to their reliability and ease of interpretation (Li *et al.*, 2020; P. Zhang *et al.*, 2022). Statistical analysis provides a robust framework for understanding the factors affecting crash frequencies (Mehdizadeh *et al.*, 2020). These statistical techniques are indispensable for trend analysis, which identifies increasing or decreasing crash rates across different regions, thereby informing targeted safety measures (Kumar and Toshniwal, 2016).

Statistical methods have been used to handle complex relationships in traffic crash analysis (Zhang *et al.*, 2023). A key approach involves using graphical models, such as Markov random fields (MRF), Bayesian networks, and graphical XGBoost, to uncover latent relationships between factors associated with traffic crashes. These models are beneficial in scenarios where observations are limited, as they can infer latent relationships that are not directly observable through traditional methods (Ulak and Ozguven, 2024). Bayesian networks, for instance, allow probabilistic modelling of variables and are particularly effective in modelling complex systems with high levels of uncertainty and unpredictability, such as traffic systems, by capturing the dependencies between various risk factors and outcomes (Hanea, Christophersen and Alday, 2022). Unobserved heterogeneity in crash data can also obscure variable relationships, but multiple heterogeneity-ordered probit models effectively capture these effects. Studies on suburban roads highlight how these models identify factors like nighttime indicators, providing insights for strategies to reduce crash severity (Khanal, Zahertar and Lavrenz, 2024).

Spatial statistical methods such as Empirical Bayes and spatial autocorrelation have been used to identify crash locations that pose a risk of injury or death, allowing for the implementation of safety measures and the reduction of future crash incidences through targeted interventions (Ma, Kockelman and Damien, 2008; Sipos, Afework Mekonnen and Szabó, 2021). Techniques such as kernel density estimation and spatial-temporal modelling are extensively used in this category (Anderson, 2009; Cheng *et al.*, 2018; Feizizadeh *et al.*, 2022). Kernel density estimation helps identify crash hotspots without assuming a specific data distribution (Zhang *et al.*, 2023). These methodological advancements contribute to a more nuanced and comprehensive understanding of traffic crash dynamics, paving the way for improved safety measures and policy decisions (Kumar and Toshniwal, 2016; Yang *et al.*, 2017).

2.5.2.2 Geographic Information Systems

Geographical Information Systems (GIS)-based analysis systems have also been proven effective in identifying accurate spatial patterns of crashes and blackspots (Ye *et al.*, 2010; Cafiso and Di Silvestro, 2011; Al-Harthei *et al.*, 2017; Zhu, Zhou and Chen, 2020; Wan, He and Zhou, 2021). However, to enable practical GIS analysis to locate crash sites, it is crucial to ensure the reliability of crash data (Amiri *et al.*, 2021) and reduce the possibility of geocoding mistakes (Sarasua, Ogle and Geoghegan, 2008; Qin *et al.*, 2013). Web-based software can provide accurate and complete crash data (Elise Carreker and Bachman, 2000; Yahya *et al.*, 2013; Montella *et al.*, 2017).

Geographic Information Systems (GIS) significantly enhance road traffic crash analysis by providing robust spatial and temporal data integration, visualisation, and analysis tools. GIS allows for identifying crash hotspots through methods like Hot Spot Analysis, which helps visualise the spatial distribution of crashes and identify high-risk areas (Anderson, 2009; Cheng *et al.*, 2018; Feizizadeh *et al.*, 2022). GIS-based methods allow researchers to visualise and analyse the geographical distribution of crashes, identifying hotspots and spatial patterns critical for targeted interventions (Pu *et al.*, 2011).

Studies have highlighted the effectiveness of GIS in providing detailed spatial analyses of road crashes, such as mapping crash locations, identifying high-risk areas, and analysing the impact of environmental and infrastructural factors on crash occurrences (Yunus and Abdulkarim, 2022; Mohammed *et al.*, 2023). GIS-based analyses are crucial for urban planners and policymakers in designing safer road networks and implementing effective traffic management strategies (Pu *et* *al.*, 2011). The ability of GIS to integrate various types of data, such as traffic volume, road conditions, and environmental factors, allows for comprehensive spatial analyses that can uncover hidden patterns and relationships (Wang *et al.*, 2012). This integration is crucial for developing targeted interventions that address specific local conditions, thereby enhancing the effectiveness of road safety measures (Castro and De Santos-Berbel, 2015; Mekonnen, Sipos and Krizsik, 2023).

2.5.2.3 Machine Learning

Machine Learning (ML), a subset of artificial intelligence that enables computers to learn from data and improve their performance on tasks without being explicitly programmed (Mitchell and Mitchell, 1997), has contributed significantly to RTC analysis with its ability to process vast amounts of data and discover hidden patterns without predefined assumptions (Huang and Abdel-Aty, 2010). ML includes a range of techniques, from traditional classification models to advanced deep learning methods (Savolainen *et al.*, 2011). ML models are particularly effective at detecting complex, non-linear relationships, making them suitable for predictive analytics in road safety (Huang and Abdel-Aty, 2010). Techniques such as random forest, deep learning, convolutional neural networks (CNN), and transfer learning have shown exceptional performance in predictive tasks, like forecasting crash occurrences and severities based on historical data (Savolainen *et al.*, 2011; Santos *et al.*, 2021).

Despite their strengths, ML models often face criticism for their "black box" nature, making them difficult to interpret (Huang and Abdel-Aty, 2010). Some studies have attempted to address this nature by incorporating explainable artificial intelligence (XAI), which refers to artificial intelligence systems designed to provide clear and understandable explanations of their decisions and actions (Samek, Wiegand and Müller, 2017) to make ML models more transparent and understandable to policymakers and stakeholders (Savolainen *et al.*, 2011; S. Ahmed *et al.*, 2023). For instance, explainable ML methods such as Shapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) methods can provide accurate predictions and increased trust among end-users and domain experts (Madushani *et al.*, 2023).

In addition to predictive accuracy, ML methods offer considerable flexibility in handling various data types, such as real-time traffic data, weather conditions, and social media feeds, to predict crash hotspots and severity (Cheng *et al.*, 2018). The ability of ML algorithms to integrate these diverse data sources allows for a more holistic approach to traffic safety management, potentially reducing the incidence of RTCs through proactive measures (Wen *et al.*, 2021). This integrative capability represents a significant advancement in traffic safety analysis.

For example, The Geographically Weighted Neural Network (GWNN) model integrates neural networks with geographically weighted modelling to address spatial heterogeneity in speeding-related crashes, enabling targeted safety interventions by analysing local factors such as driver condition and weather (Zhang *et al.*, 2024). Similarly, the Sparse Spatio-Temporal Dynamic Hypergraph Learning (SST-DHL) framework combines hypergraph and self-supervised learning to enhance the interpretability of spatio-temporal dependencies in traffic crash data, which is crucial for accurate predictions (Cui *et al.*, 2024). Machine learning (ML) models, such as deep neural networks, have also been used effectively in traffic simulations, outperforming traditional models in accuracy and scalability (Hao and Ruan, 2024). Additionally, algorithms like XGBoost, CatBoost, and LightGBM have accurately identified crash risk factors, highlighting ML's transformative role in traffic safety (Alshehri *et al.*, 2024). Integrating connected vehicle data with ML models further enhances real-time crash prediction, enabling proactive safety measures (Mussah and Adu-Gyamfi, 2022).

2.5.2.4 Smart cities

Smart city technologies investigate RTC using advanced technologies to improve urban traffic management and safety (Lilhore *et al.*, 2022). This category leverages advancements in ICT, such as the Internet of Things (IoT) and big data, to create intelligent and responsive transportation systems (Al-Sultan *et al.*, 2014; Anedda *et al.*, 2023). These technologies enable real-time data collection and communication between vehicles and infrastructure, proactively managing traffic and potential hazards (Zeadally *et al.*, 2012; Musa *et al.*, 2023).

Studies have demonstrated the practical applications of these technologies in reducing RTCs. Integrating these technologies into urban infrastructure enhances traffic efficiency and improves road safety (Alahi *et al.*, 2023). For example, utilising IoT tools in urban planning supports the ongoing modification of transport and communication systems, ensuring that they meet the evolving needs of city inhabitants (Lilhore *et al.*, 2022). Integrating IoT and Intelligent Transportation Systems (ITS) enables real-time traffic management and decision-making, which helps predict traffic outcomes and minimize congestion, reducing the likelihood of crashes (Musa *et al.*, 2023). Moreover, big data management systems like cyber-physical systems can leverage real-time traffic data to construct weighted city graphs. These graphs help make intelligent decisions regarding traffic flow and safety, reducing the likelihood of crashes (Rathore *et al.*, 2021). Similarly, a big data analytics platform was used to develop an intelligent transportation model that significantly improved safety prediction accuracy and congestion management (Liu, Zhang and Lv, 2022).

Additionally, advanced road surveillance systems using deep learning methods for license plate detection and crash alert systems installed on smart roads further enhance safety by providing timely alerts and reducing multiple-vehicle collisions (Nawaratne *et al.*, 2021; Lilhore *et al.*, 2022). Deploying autonomous vehicles and advanced driver-assistance systems (ADAS) also represents a significant step in smart city traffic management (Louati *et al.*, 2024). These technologies aim to improve safety and enhance the overall driving experience.

Smart city technologies hold significant promise for improving urban traffic management and safety but face several challenges. One major issue is the integration of advanced technologies like IoT, big data analytics, and AI with existing transportation systems, which requires a co-evolution to ensure seamless operation and efficiency (Mitieka *et al.*, 2023). The complexity and heterogeneity of traffic in smart cities, involving human-driven and connected automated vehicles, make sustainable traffic management difficult, necessitating robust frameworks that can handle real-time data and decision-making processes (Musa *et al.*, 2023). Intelligent Traffic Management and Control (ITMC) systems, while effective in forecasting traffic states and controlling intersection signals, often lack robustness in unusual scenarios, such as oversaturated conditions, which can compromise their reliability (Reza *et al.*, 2021). Additionally, the rapid increase in vehicle numbers without a corresponding increase in road capacity exacerbates congestion, leading to higher crash rates and economic losses, which current traffic management systems struggle to mitigate effectively (Naveed *et al.*, 2022).

2.6 Summary of Chapter

This chapter has reviewed the literature on data-driven decision-making (DDDM), ICT adoption in the public sector, and government employees' participation in ICT development. The review highlights that while DDDM can improve operational efficiency and service delivery, existing studies have primarily focused on theoretical discussions rather than empirical evidence of implementation in governance contexts. A critical gap exists in understanding the practical challenges that government employees face in applying analytical tools for decision-making, particularly in urban governance settings.

Research on employee participation in ICT development also identified a noticeable gap. While studies acknowledge the importance of involving end users in system design, they often lack detailed insights into how participation influences system usability and adoption. Given that user engagement can enhance the effectiveness of ICT tools, this study examines the role of government employees in co-developing an ICT tool and its impact on adoption outcomes.

Existing ICT adoption studies in government settings oftenly rely on quantitative approaches using established models such as TAM, TPB, and UTAUT. While these models provide structured frameworks, they may not fully capture the context-specific factors that influence adoption decisions among government employees. Meanwhile, qualitative insights are essential for understanding the contextual factors influencing ICT adoption, complementing the study’s quantitative analysis of adoption intentions.

Finally, the literature reveals a gap in research on the role of dashboard tools in public sector decision-making. While dashboards are widely used for data visualisation, their practical application in real-time decision-making, particularly in traffic policing, remains underexplored. This study contributes to this area by developing and evaluating a dashboard tailored to Jakarta’s traffic police, offering empirical evidence on its usability and impact on decision-making efficiency.

By identifying these research gaps, this chapter provides a foundation for the study, highlighting its contributions to DDDM, ICT adoption, and user-centred technology development in government settings. The next chapter outlines the research methodology used to investigate these issues, detailing the data collection and analysis approach in both the requirement elicitation and adoption intention examination phases.

Chapter 3 Methodology and requirement elicitation phase's methods

3.1 Introduction

This chapter describes the overarching research methodology and the methods for the first requirement elicitation phase, a dashboard prototype development involving traffic police. This phase aims to explore the decision-making processes and participation of traffic police in developing a dashboard intended to inform their patrolling allocations. By involving the police in the development process, the study seeks to identify the necessary contents and expected features for the dashboard to ensure it meets their needs.

In the subsequent adoption intention examination phase, quantitative hypotheses will be developed by exploring the factors the traffic police perceive would motivate them to use ICT for decision-making. These hypotheses will be used to examine the police's behavioural intention to adopt the dashboard. Therefore, the methods for the examination chapter will be presented after the results chapter of the requirement elicitation phase.

A research design was depicted to guide the entire study, as seen in Figure 3.1

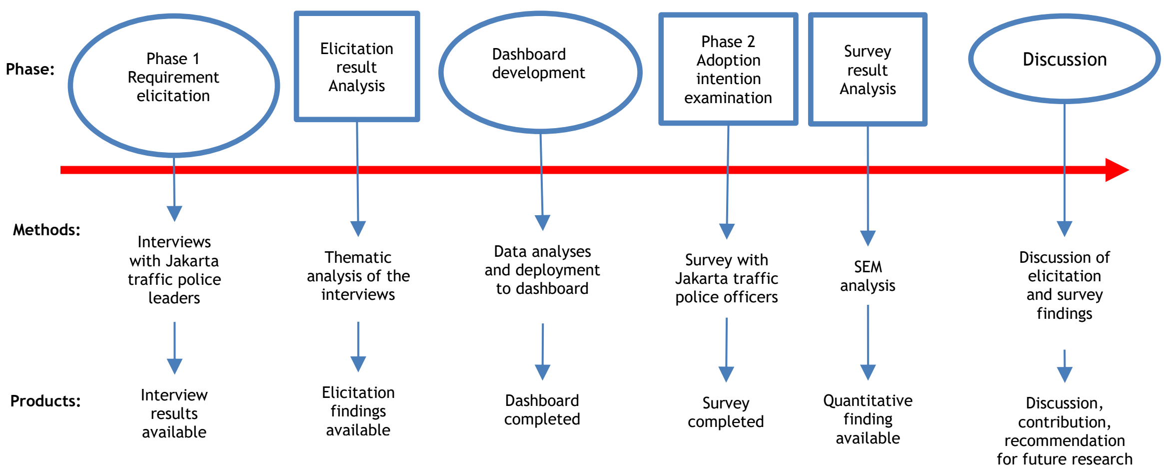


Figure 3.1 Research design

3.2 Research approach and paradigm: mixed methods, ontology, and epistemology

This study, which will be conducted in two phases, adopted a mixed methods approach due to its ability to blend the detailed data of qualitative research with the generalisable findings of quantitative research to provide a comprehensive view (Creswell and Tashakkori, 2007; Denzin, 2010). A mixed methods approach offers dual advantages: it balances research biases and supports inductive and deductive reasoning, allowing various methods to address research questions (Ivankova and Wingo, 2018). The approach is also adopted to capture the contextual factors described previously in the literature review in section **Error! Reference source not found.** to contribute to the gap in the public sector's technology acceptance studies.

Based on the purpose of this research, an exploratory sequential mixed-methods design was chosen. This approach begins with collecting qualitative data to gain a deep understanding of the research topic, which then informs the development of quantitative measures. The subsequent quantitative data collection is used to assess the generalisability of the qualitative findings, providing a comprehensive analysis (Sahin *et al.*, 2019). Researchers use this design to explore a phenomenon through qualitative data and then use this understanding to inform or validate quantitative measures or theories (Onwuegbuzie *et al.*, 2009).

This study takes a pragmatic approach to epistemology by using practical philosophical and methodological approaches for specific research problems (Tashakkori and Teddlie, 1998; Clark *et al.*, 2007; Creswell and Tashakkori, 2007), prioritising research outcomes over specific methods (Maxcy, 2003; Johnson and Onwuegbuzie, 2004; Biesta, 2010; Denzin, 2010; McNabb, 2018). Pragmatism advocates using multiple methodologies, encompassing qualitative and quantitative approaches (Feilzer *et al.*, 2010; Sahin *et al.*, 2019).

Due to this study's pragmatic epistemology, both constructivist and positivist perspectives are adopted. Constructivism focuses on individual experiences within specific contexts (Glasersfeld, 1989; Cooperstein and Kocevar-Weidinger, 2004; Creswell, 2009; Lincoln, Lynham and Guba, 2011). Constructivism is adopted to explore government employees' decision-making, dashboard feature preferences, and perceived motivation factors for ICT usage. Constructivism helps to understand how personal experiences and contextual factors influence government employees' engagement with data-driven decision-making (DDDM) and shape their preferences for dashboard features while providing valuable insights into the subjective meanings shaping their behaviour and attitudes towards ICT usage. The adoption intention examination phase utilises a survey and statistical analysis, which aligns with the positivist research paradigm. It is based on the principle that truth and reality are not influenced by the viewer or observer (Aliyu *et al.*, 2014). Positivism emphasises an independent and objective truth by focusing on hypothesis testing, measurement, and alignment with empirical evidence and observable facts (Park, Konge and Artino, 2020). The study's adoption intention examination phase is structured and focuses on empirical testing and validation of theories about ICT adoption intention among government employees. This approach allows for developing generalisable findings that can contribute to a broader understanding of the factors influencing ICT adoption in public sector organisations.

3.3 Research setting: Jakarta traffic police and IRSMS crash database

This study focuses on traffic issues in developing countries, with Jakarta selected as the study location. As the capital of Indonesia, Jakarta is one of the most populous megacities globally and the largest city in Southeast Asia (Martinez and Masron, 2020; World Bank, 2024). Like many cities in developing nations, Jakarta faces significant challenges due to limited space, leading to overcrowding (Jedwab, Loungani and Yezer, 2021). However, it stands out due to its rapid urbanisation and motorisation, resulting in one of the most severe congestion problems and a high number of traffic collisions globally (Soehodho, 2017; Rukmana, 2018; TomTom, 2023).

Socioeconomic factors, such as the high use of motorcycles and inadequate enforcement of traffic laws, also contribute to the high fatality rates in Jakarta. This pattern is typical in other Southeast Asian countries, where motorcycles are a primary mode of transport, increasing the likelihood of traffic crashes (Kitamura, Hayashi and Yagi, 2018). Weak enforcement of regulations, such as helmet and seatbelt use, further worsens the severity of injuries in collisions. This is a widespread issue in developing countries, including Indonesia, where public awareness and education on road safety are limited (Satria *et al.*, 2020). Jakarta's geographical layout and environmental conditions further complicate its traffic challenges. The road network is frequently congested, and traffic incidents vary significantly based on factors such as road type, traffic volume, and weather conditions (Zhang *et al.*, 2024).

Southeast Asian capitals like Manila and Bangkok face similar challenges, but their efforts in urban planning, public transportation, and intelligent transport systems are more advanced, which helps mitigate traffic incidents (Huang and Loo, 2022; Bando *et al.*, 2023). While cities like Bangkok and Manila also face traffic challenges, Jakarta's collision statistics, particularly regarding fatalities and serious injuries, surpass those of its regional counterparts, highlighting a more critical situation (WHO, 2018; TomTom, 2023). In 2022, Jakarta experienced 332,019 collisions, resulting in 26,948 fatalities and 29,297 serious injuries, underscoring the urgent need for sustainable measures to address this problem (Patriot, 2023). The lack of an efficient public transportation system has exacerbated the reliance on private vehicles, contributing to higher traffic volumes and crash rates (Nadi and Murad, 2019).

Human behaviour plays a significant role, particularly among Indonesian motorcyclists, who account for many road fatalities. Young motorcyclists often violate traffic rules due to peer pressure and a lack of awareness, while drowsy driving is a persistent problem (Joewono and Susilo, 2017; Rahmadiyani and Widyanti, 2023). Human error remains a leading cause of crashes, including distracted driving (Puspasari *et al.*, 2023), fatigue, sleepiness (Achmad, Suryadhi and Subur, 2023), and aggressive driving (Sitorus, Melisa and Herninda, 2023). This highlights the potential benefit of increased police intervention in enforcing traffic laws, improving driver behaviour, and enhancing traffic data management to help reduce crashes and fatalities.

These factors make Jakarta an ideal use case for exploring effective traffic patrolling and management strategies in developing nations. Given the focus of this study on decision-making in traffic patrol allocations, as discussed in section 1.4.1, the Jakarta traffic police were selected as the use case. They are the primary government authority responsible for managing traffic and ensuring public safety (Indonesian Government, 2002, 2009; Indonesian National Police, 2011). The Jakarta traffic police are part of the Indonesian National Traffic Police Corps (INTPC), whose responsibilities are outlined in Law 22 of 2009 on Road Traffic and Transportation. These responsibilities include road policing, traffic management, crash investigation, reporting, and analysis (Indonesian Government, 2009; Yahya *et al.*, 2013).

One of the primary duties of the Jakarta traffic police is to patrol the roads to maintain traffic order (Indonesian National Police, 2011). Jakarta has seven highway police stations that patrol most of the busiest roads. The stations have between 100 and 200 officers and cover various roads, the shortest being ten kilometres to the longest of seventy-nine (Korlantas Polri, 2022). Each station has a chief and three patrol unit leaders who directly lead the patrolling activities in their jurisdictions (Figure 3.2).

Figure 3.2 The organisation structure of the Jakarta highway patrol police station

They are the decision-makers who ensure optimal patrolling allocations (Indonesian National Police, 2011). In their daily operations, before starting their patrol beats, the leaders hold a briefing roll call with the on-duty officers to discuss the patrol plan (Korlantas Polri, 2018). This briefing ensures that all officers align with the day’s objectives. The officers are also empowered to issue traffic warnings or tickets to road users if necessary (Indonesian Government, 2009).

The Jakarta traffic police maintain the Indonesian Road Safety Management System (IRSMS) traffic crash database, which contains detailed records for

Indonesia and will be used to discuss their decision-making in patrolling allocations in this study's requirement elicitation phase. IRSMS was first developed by the INTPC and Consia Denmark in 2012 with funding from the World Bank IBRD Loan 4834 (Yahya *et al.*, 2013; Indonesian National Police, 2018; Consia Consultants, 2021). The IRSMS has a spreadsheet structure that resembles other countries' traffic crash databases, such as the UK's STATS19 and the US's NHTSA record (Department for Transport UK, 2021; NHTSA, 2021). All Indonesian traffic police stations that deal with traffic crashes, including Jakarta traffic police, are required to report all collected investigation information to the system to keep the IRSMS database up to date. The variables recorded in the IRSMS are provided in Table 3.1.

No	Variable	Description
1	No	Sequential number for the record.
2	Crash No.	Unique identifier for each crash incident.
3	Police Department	The police department responsible for the area where the crash occurred.
4	Date of Incident	The date when the crash took place.
5	Crash Severity	The crash's severity level (e.g., minor, serious, fatal).
6	Number of Fatalities	The number of people who died because of the crash.
7	Number of Serious Injuries	The number of people who sustained severe injuries in the crash.
8	Number of Minor Injuries	The number of people who sustained minor injuries in the crash.
9	GPS Coordinate - Latitude	The latitude coordinate of the crash location.
10	GPS Coordinate - Longitude	The longitude coordinate of the crash location.
11	Reference Point	A landmark or notable point near the crash location.
12	Distance to Crash Location	The distance from the reference point to the crash site.
13	Direction from Reference Point to Crash Location	The direction from the reference point to the crash site.
14	Special Information	Additional or noteworthy details related to the crash.
15	Crash Type	The type of crash includes a collision, rollover, or single-vehicle crash.
16	Lighting Conditions	The lighting conditions at the time of the crash (e.g., daylight, night, dusk).
17	Weather	The weather conditions during the crash (e.g., clear, rainy, foggy).

No	Variable	Description
18	Prominent Crash	Indicates whether the crash was particularly significant or involved high-profile circumstances.
19	Road Number	The official number assigned to the road where the crash occurred.
20	Road Name	The name of the road where the crash occurred.
21	Road Point	A specific point or marker on the road related to the crash location.
22	Road Function	The primary function of the road (e.g., residential, arterial, highway).
23	Road Class	The classification of the road based on traffic volume and importance (e.g., major, minor).
24	Road Type	Road type based on the number of lanes, directions, and the existence of a road separator.
25	Geometric Shape	The geometric shape of the road at the crash location (e.g., straight, curved, intersection).
26	Road Surface Condition	The road surface condition at the time of the crash (e.g., dry, wet).
27	Speed Limit at Location	The posted speed limit at the crash location.
28	Road Slope	The gradient or slope of the road at the crash location.
29	Road Status	The operational status of the road (e.g., open, under construction, closed).
30	Estimated Non-Vehicle Material Loss	The estimated value of material losses excluding vehicles.
31	Total Vehicle Material Loss	The total estimated material loss related to vehicles involved in the crash.
32	Loss Description	A description of the types of losses incurred because of the crash.

Table 3.1 IRSMS variables

3.4 The requirement elicitation phase's purpose and questions

This study's first phase aims to provide several contributions. First, it will involve the Jakarta traffic police in developing a dashboard to inform their patrolling allocations. Engaging police officers throughout the development process is intended to ensure the dashboard meets their needs, making complex data accessible to non-technical users (Zowghi and Coulin, 2005; Abelein, Sharp and Paech, 2013; Jing *et al.*, 2019; Farmanbar and Rong, 2020). By exploring the police's decision-making practices for patrolling allocations and their preferences for dashboard features, the study seeks to gain empirical insights into how public sector data-driven decision-making (DDDM) is implemented, including the analytical tools used, the impacts, and the challenges faced (Brynjolfsson and McElheran, 2016; Hino, Benami and Brooks, 2018; Dingelstad, Borst and Meijer, 2022).

The police involvement in this process also aims to contribute to the understanding of employee participation in public sector ICT development, particularly in identifying strategies for effective engagement in such projects, considering the unique dynamics of the public sector (Abdulkareem *et al.*, 2022; Dingelstad, Borst and Meijer, 2022). Moreover, this phase addresses the call for studies that involve police in the research process (Mowatt, 2023) and examines how research findings can be effectively disseminated within departments (Boulton *et al.*, 2021). This is crucial for translating academic insights into practical policing strategies (Fyfe, 2019; Boulton *et al.*, 2021), bridging the gap between research and practice, and enhancing the real-world impact of policing studies (Hartmann *et al.*, 2018).

Ultimately, this phase's purpose is to understand government employees' decision-making processes and participation in ICT development, using the Jakarta traffic police's patrolling allocation as a use case and the dashboard as an ICT example. The insights gained will inform the subsequent phases of dashboard development and contribute to broader discussions on public sector ICT adoption and employee involvement in technology-driven initiatives.

The following research questions will be addressed in this first phase:

RQ1: How do government employees conduct decision-making within the data-driven decision-making framework?

RQ2: "What features do government employees prefer in an ICT for decision-making, and how does their participatory involvement in its development provide insights into user-centred design practices?"

3.5 The adoption intention examination phase’s purpose and questions

The second phase examines the Jakarta traffic police’s behavioural intention to adopt the developed dashboard. This study takes an approach that capitalises on the researcher’s deep familiarity with the study environment (Appendix F) to gain meaningful insights into the factors influencing government employees' behavioural intention to adopt the developed ICT tool. In this phase, qualitative semi-structured interviews are conducted to explore employees' perceptions, followed by a quantitative survey analysed using Structural Equation Modelling (SEM) to validate the identified factors. This approach balances qualitative insights with quantitative methods to better understand ICT adoption in the public sector (Graeber *et al.*, 2023).

The researcher’s professional background, established relationships with key personnel, and extensive understanding of operational processes provided unique advantages in obtaining contextually rich data and fostering trust and openness during data collection (Appendix F). This familiarity enabled a thorough exploration of ICT adoption challenges and ensured the relevance of the findings to public sector settings to enrich the understanding of contextual factors that enhance the applicability of existing technology acceptance theories (Venkatesh, Brown and Bala, 2013; Bano and Zowghi, 2015; Rehouma, 2017; Barile *et al.*, 2018).

The following research questions will be addressed in this second phase of the research:

RQ3: What factors are perceived as motivating government employees' adoption of ICT tools, and how can these insights inform the understanding of technology acceptance in the public sector?

RQ4: "What are the relationships between identified motivational factors and the behavioural intention of government employees to adopt ICT, and how do these findings contribute to the refinement of ICT adoption theories in public sector settings?"

3.6 Ethical considerations: power relationships and participant autonomy

Ethical considerations were central to both phases of this research, particularly given the hierarchical structure of the Indonesian National Traffic Police (INTP). The researcher, holding the rank of police commissioner, conducted research with participants of similar or lower ranks, necessitating careful attention to power dynamics and voluntary participation (further discussed in section 3.8.2.1). While rank disparities may appear minimal, it was acknowledged that implicit power relationships could influence participants' willingness to participate and the authenticity of their responses. Therefore, multiple measures were implemented to ensure voluntary participation, protect confidentiality, and uphold ethical standards.

Ethical approval was obtained from the University of Glasgow's College of Social Sciences Research Ethics Committee for the first phase, which focused on requirement elicitation through qualitative interviews. The research followed ethical guidelines outlined in the approved ethics documents (Appendix A.1). Participants were provided with a comprehensive participant information sheet and privacy notice detailing the study's objectives, procedures, and data handling practices. Written informed consent was acquired via email before the interviews, and participants were reminded of their rights to withdraw without explanation. To ensure transparency, the researcher re-explained the study's purpose, interview scope, and pseudonymisation practices at the start of each session. Participants were informed that while every effort was made to anonymise their responses, complete anonymity could not be guaranteed due to the limited number of leadership positions within the organisation.

In the second phase, which examined the adoption intention of the dashboard through an online survey, ethical approval was also obtained from the same ethics committee (Appendix A.2). Participants were invited to participate in the survey independently, with consent obtained electronically to ensure their privacy and autonomy. They were assured of their right to decline participation or withdraw at any stage without consequences. Confidentiality measures were reinforced by anonymising responses and ensuring no personally identifiable information was collected.

Throughout both phases, specific measures were taken to address power dynamics and ensure participants could realistically decline participation without feeling pressured. All communications stressed the voluntary nature of participation, and no incentives or coercive measures were involved. Independent communication channels were provided to facilitate consent and withdrawal, and efforts were made to ensure that the study was conducted independently of senior management's influence. The researcher maintained a neutral stance during the interviews, with questions designed to encourage open and candid responses. Follow-up discussions were conducted only after participants had provided their initial responses to avoid leading their answers.

Participants were reassured that their involvement in the study would not impact their professional standing or relationships with the researcher. To further reduce potential pressure to participate, survey invitations were distributed through administrative channels without direct involvement from senior officers. Moreover, the researcher remained mindful of their positionality and deliberately cultivated a supportive and neutral research environment.

By implementing these ethical measures, the study sought to foster an environment where participants felt comfortable and confident in sharing their perspectives without apprehension about potential professional implications. This ethical framework was designed to uphold the principles of autonomy, confidentiality, and voluntary participation to enhance the credibility and authenticity of the collected data.

3.7 Requirement elicitation phase's methods

This requirement elicitation phase aims to understand government employees' decision-making processes and participation in ICT development, using the Jakarta traffic police's patrolling allocation as a decision-making use case and a dashboard development as an ICT participation example. The dashboard development follows a User-Centred Design (UCD) approach, gathering and integrating the police's requirements. This approach is adopted because designing dashboards for users with unknown or varying degrees of visual and analytical literacy requires developers to avoid assuming set designs for specific audiences (Sarikaya *et al.*, 2019).

In this phase, Jakarta traffic police are involved in developing a dashboard intended to inform their patrolling allocations. The study aims to understand how the police make decisions regarding their patrolling allocations and determine the necessary dashboard contents. Additionally, the police will be asked about the features they expect in the dashboard. The results from this exploration will inform the subsequent dashboard development, which will be the focus of the adoption intention examination phase.

The objectives for this phase are:

O1: To explore how government employees conduct decision-making within the data-driven decision-making framework through qualitative semi-structured interviews analysed using thematic analysis.

O2: To identify the features government employees prefer for an ICT for decision-making through thematic analysis of interview data and participatory ICT development to provide insights into user-centred design practices.

The findings from this phase will guide the next stage of ICT development, which will be the research focus in Phase Two.

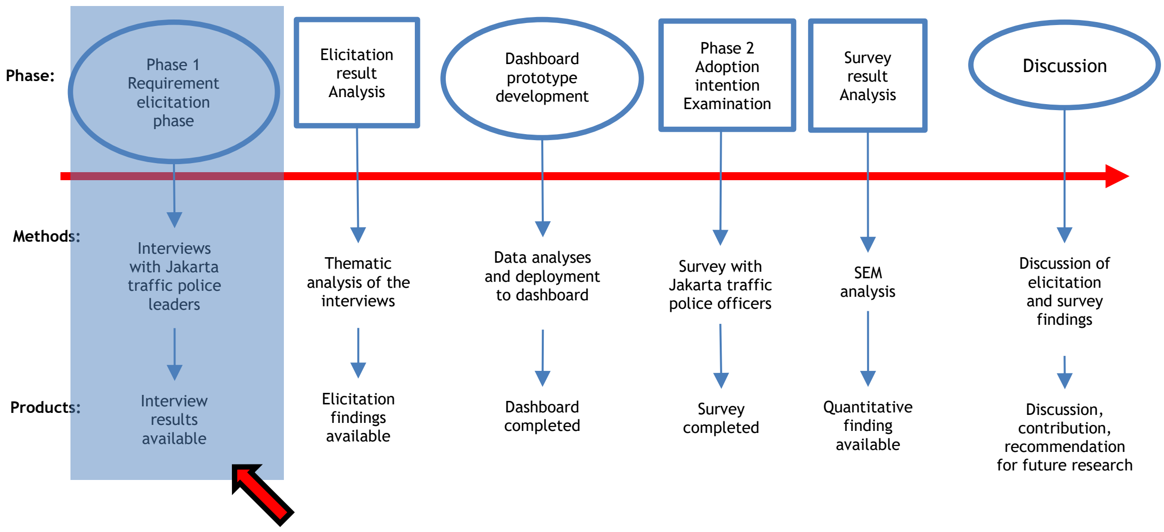


Figure 3.3 Phase 1 Requirement Elicitation

The requirement elicitation phase is depicted in Figure 3.3, and the following section provides details of the data collection method for this study phase.

3.8 Data collection

This section outlines the data collection process. Subsection 3.8.1 details the semi-structured interview approach, while Subsection 3.8.2 discusses the measures taken to ensure research rigour. Subsection 3.8.3 outlines the specific interview topics, and Subsection 3.8.4 explains the process of transcript translation. Subsection 3.8.5 presents the thematic analysis method used. Following this, Subsection 3.9 provides an overview of the data collection procedures, and finally, Subsection 3.10 offers a summary of the chapter.

3.8.1 Semi-structured key informant interviews for exploring decision-making to elicit dashboard requirements

This study focuses on the allocation of police patrols in Jakarta, where the patrol leaders, due to their extensive knowledge and experience, are identified as the key informants within their organisation, making them particularly relevant to this research topic. In this context, key informants are individuals with specific roles in policy and decision-making processes whose insights can provide valuable research contributions (Farmer, 2017; Mason-Bish, 2019; Farmer, Miller and Kennedy, 2024). The police leaders, as high-level practitioners, can help bridge the gap between research and practice by ensuring that the requirements gathered are relevant and practical (Franch *et al.*, 2022). Having senior practitioners involved can enhance the elicited requirements' acceptability, as their endorsement adds credibility to the elicitation process (Hanea, Hemming and Nane, 2022).

Interviews were conducted to gather requirements for a dashboard supporting traffic patrolling allocation among Jakarta traffic police leaders. As a valuable method for understanding user needs, interviews facilitate meaningful discussions and provide qualitative data essential for comprehending the domain and meeting stakeholder requirements (Neetu Kumari and Pillai, 2013; Debnath and Subramanian, 2022). They also offer insights into the informal internal dynamics and nuanced experiences of public sector operations, aiding in understanding police decision-making for patrolling allocations (Stevens *et al.*, 2011; Jiwani and Krawchenko, 2014).

Interviews are particularly effective for engaging key informant participants and understanding their operational, strategic, and tactical needs (McClure and McNaughtan, 2021; Grant *et al.*, 2024). This method allows flexibility to address complex topics, fosters trust and open communication, and encourages candid insights vital for strategic decision-making systems (Von Soest, 2022). Furthermore, real-time clarification during interviews helps reduce ambiguities, ensuring a clear understanding of the dashboard's functionalities and design (Kvale, 2011). By tailoring the interview process to the specific environment of the Jakarta traffic police, the design of the dashboard can incorporate unique insights from these key participants, aligning with the importance of context-sensitive research methods (Myers and Lampropoulou, 2013).

The chosen interview type is semi-structured due to their ability to facilitate discussions and uncover stakeholders' needs, which is essential for developing a system that meets user expectations (Debnath and Subramanian, 2022). Semi-structured interviews help mitigate communication ambiguity, a significant obstacle in requirement elicitation, by allowing for follow-up questions and clarifications, ensuring a clear understanding of the requirements by both the analyst and the stakeholder (Spoletini *et al.*, 2016). In addition, since the purpose of this phase was to understand how Jakarta traffic police conduct decision-making and their dashboard feature preferences, semi-structured interviews are helpful because their flexible structure allows the researcher to ask follow-up questions for needed clarifications (Adeoye-Olatunde and Olenik, 2021).

3.8.2 Research rigour: reflexivity and trustworthiness

3.8.2.1 Reflexivity

Reflexivity is commonly defined as a continuous internal conversation and critical self-evaluation of the researcher's positionality, as well as active awareness and explicit understanding that this position may alter the research process and output (Pillow, 2003; Guillemin and Gillam, 2004; Bradbury-Jones, 2007; Stronach *et al.*, 2007). Reflexivity, recognised as crucial for knowledge generation in qualitative research (Gerstl-Pepin and Patrizio, 2009; Ahmed, Hundt and Blackburn, 2011; Rahman, 2020), is commonly used to acknowledge the impact of interpersonal dynamics on data collection and interpretation (Walker, Read and Priest, 2013).

Researchers have also devoted considerable attention to the complexity of positionality based on ethnic origin, religion, class, sexual orientation, gender, age, handicap, or personality (Kobayashi, 2003; Korstjens and Moser, 2018). In this study's requirement elicitation phase, the researcher acknowledges that their dual identity as a researcher affiliated with a UK institution and an officer in the Indonesian National Traffic Police (INTP) may have shaped the research process. Conducting research within their organisation in their native language (Indonesian) while producing a thesis in English presents unique challenges in balancing cultural and institutional expectations.

The researcher is an officer in the INTP headquarters, specifically in the traffic security and safety directorate. The hierarchical structure of the INTP introduces important reflexive considerations regarding power relationships and interpersonal connections. The researcher's rank as a police commissioner is similar to that of most participants or slightly higher than that of some (police captains). While the rank disparities can be considered minimal, they are acknowledged as potentially influencing the participants' responses.

Additionally, the researcher is familiar with many individuals directly because the headquarters and the regional police frequently work together, especially when the headquarters are piloting a new policy. The study occurred in Jakarta, the jurisdiction of a regional police station that deals with practical duties. While the researcher works in the headquarters, which can give regional police forces advice and commands, regional stations have room for discretion, especially in their daily practices. The researcher's pre-existing professional relationships with participants, cultivated through joint initiatives between INTP headquarters and regional police forces, may have facilitated rapport but also introduced potential biases.

A critical reflexive consideration concerns the potential influence of senior management and institutional culture on data authenticity (Mauthner and Doucet, 2003; Mao *et al.*, 2016). In a hierarchical organisation such as the police force, participants may tailor their responses to align with institutional expectations or perceived organisational goals rather than expressing their candid views (Oberwittler and Roché, 2022; Keddie, 2023). Commanders' or senior management' narratives on data-driven innovation, particularly the push for digital transformation and performance-based evaluations, may inadvertently shape how participants perceive and discuss their decision-making processes. The researcher remained mindful of this potential influence by designing interview questions to encourage open, unbiased discussions and providing assurances of confidentiality to mitigate response bias.

The researcher acknowledges that participants may disclose several decision-making ideas that the researcher has never encountered. Each city has its traffic characteristics primarily due to the nature of Indonesia as an archipelagic country consisting of thousands of islands (Cribb and Ford, 2009). Even in neighbouring cities, the allocation decisions might differ. This condition should exist in Jakarta as well. As the decision-makers in their jurisdictions, the participants might have different approaches in prioritising how, where, and when to deploy their patrol resources. The researcher attempted to as far as possible ensure that participants did not just accept the researcher’s perspective without expressing their own. This was realised through the research design and the tone and content of the questions posed to minimise subjectivity, where, as an example, follow-up discussions only occurred after the participant had provided the initial answer to the question posed.

Being a police officer since graduating from the Indonesian police academy in 2006, the researcher has worked in different Indonesian cities and has considerable experience in the force, including understanding the terms often used in the police force. Reflexive measures were implemented by clarifying any specific terminology used by participants to ensure accurate interpretation and by customising terminology to align with participants' lived experiences and operational context (Few, Stephens and Rouse-Arnett, 2004). Moreover, the researcher actively sought to minimise subjectivity by ensuring that participants did not merely conform to pre-existing perspectives. This was attempted through a research design prioritising open-ended questioning and careful phrasing to encourage authentic responses. For instance, follow-up discussions were only conducted after participants had provided their initial answers to avoid leading their responses.

Finally, the researcher acknowledges that while personal experience within the police force provided valuable contextual insights, it also necessitated a conscious effort to maintain an objective stance throughout the data collection and analysis phases. Reflexivity was maintained by continuously reflecting on positionality, recognising its impact, and striving for transparency in interpreting findings.

3.8.2.2 Trustworthiness

Trustworthiness in qualitative studies can be interpreted as confidence in the data, interpretation, and methodologies used to guarantee the quality (Lincoln and Guba, 1982, 1986; Mathison, 2005; Polit and Beck, 2010). One of the criteria for trustworthiness is credibility, which examines whether the study accurately translates the participants' initial viewpoints into study conclusions (Lincoln and Guba, 1982, 1986). This study reviewed and refined the interview questions in consultation with the police administrative officers to ensure their appropriateness and relevance to the operational context.

Another criterion of trustworthiness is confirmability (Lincoln and Guba, 1982, 1986). One way to ensure this criterion is by exclusively establishing research findings based on research data (Lincoln and Guba, 1982, 1986) to ascertain the researcher's comprehension of data (Lincoln and Guba, 1986). To make this efficient and stay aligned with this phase's objective, the researcher developed a dashboard to realise the information and feature requirements and then presented the prototype to the participants. The participants were then asked to give feedback on whether the dashboard prototype met their requirements. This feedback process will be described in the dashboard development section in Appendix B.

3.8.3 Interview topics: decision-making processes and dashboard development

The interviews were designed to gather insights into the decision-making processes and dashboard feature preferences of traffic patrol officers in Jakarta. The interviews began by confirming the ethical requirements established in section **Error! Reference source not found.**. This initial segment was an i ntroduction, allowing the researcher to introduce himself, verify the participants' identities, and establish rapport. Participants were also asked to share their experiences and the duration of their current positions.

The discussion then explores the decision-making processes for traffic patrolling allocations. Participants discussed the types of information they rely on when planning patrol activities and the reasons why these pieces of information are considered critical—this part of the interview aimed to uncover the underlying factors influencing their strategic traffic management decisions. As part of this exploration, The interview also focused on participants' awareness and use of the IRSMS crash data to understand how this tool supports operational decisions for their patrolling allocations.

The discussion also covered the development of a dashboard tailored to the Jakarta police's needs. Participants shared their preferences for dashboard features, offering insights into what functionalities would most effectively support their work. This topic was critical in understanding how the dashboard prototype could be optimised to support their traffic management and patrolling efficiency.

Finally, participants were asked about their willingness to provide ongoing feedback on the dashboard prototype. The researcher planned follow-up sessions to gather input on the prototype's performance and any necessary adjustments, further described in Appendix B. This iterative feedback process was designed to ensure that the final tool met the participants' requirements to support their operational capabilities.

Through these interviews, the researcher aimed to build a comprehensive understanding of the practical needs and challenges faced by traffic patrol officers in Jakarta. This methodological approach allowed for a nuanced exploration of the topics, providing valuable insights that would inform the development of a tailored traffic allocation dashboard.

3.8.4 Transcript translation

The data collection was conducted in Indonesian. The next step would be converting the transcript into English before data analysis. However, this would be a lengthy procedure and may pose additional caveats. For instance, throughout the translation process, researchers may add their subjective interpretations and explanations to the original meaning of the interview data (Twinn, 1997). These additions may influence how relevant codes and themes are developed throughout the data analysis.

Additionally, researchers frequently encounter challenges when finding accurate English terms that effectively convey the intended meaning, which can result in misrepresentation and a loss of data richness (Twinn, 1997; Turhan and Bernard, 2022; Qun and Carey, 2024). Therefore, this study attempted to avoid these risks by analysing the interview data in Indonesian, the original language of the collected data. After defining the codes and mapping them into themes, the researcher translated all codes, themes, and excerpts into English to discuss and present the results (Grimshaw *et al.*, 2012).

3.8.5 Thematic analysis

The transcript analysis adopted a Thematic Analysis (TA) approach, a widely recognised qualitative data analysis technique known for its fundamental approach to identifying, organising, analysing, and reporting patterns or themes within textual data or transcripts (Braun and Clarke, 2006, 2013; King and Brooks, 2018; Vaismoradi and Snelgrove, 2019; Shayan *et al.*, 2020; Sharifi *et al.*, 2021). The process of TA involves a sequence of data familiarisation, coding, theme creation, and modification (King and Horrocks, 2010). These themes are essentially codes that represent recurring patterns in the participants' narratives. TA aims to simplify and clarify the data as much as possible (Braun and Clarke, 2013). TA's versatility allows it to be applied in various research contexts, including interviews (Braun and Clarke, 2013, 2019).

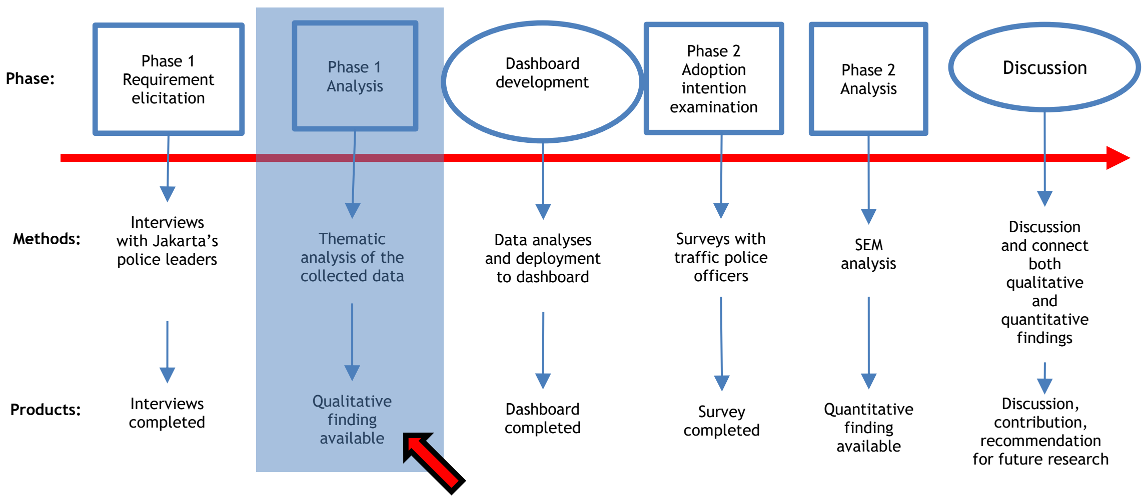


Figure 3.4 Phase 1 data analysis

The transcripts were analysed to understand information and feature requirements for a dashboard for patrolling allocation and ICT usage motivation factors of Jakarta police (Figure 3.4). The TA's six stages to analyse the data are (Braun and Clarke, 2006, 2019):

1. Familiarising with the data: transcribing, repetitively reading the transcript, writing initial ideas,

2. Generating initial codes: systematically coding relevant data features and collating data to each code,

3. Searching for themes: gathering codes into potentially relevant themes,

4. Reviewing themes: checking if the themes work with the coded extracts and the entire dataset,

5. Defining and naming themes: conducting continual analysis to improve the themes' specifications and the whole analysis's story, creating names and definitions for all themes, linking the analysis to the literature and research questions to produce the analysis report,

6. Producing the report: Selecting compelling and clear evidence, final analysis for chosen extracts, and writing analysis report.

An inductive approach was used to enhance the rigour of the thematic analysis, allowing themes to emerge directly from the participants' experiences and perspectives rather than being predefined (Naeem *et al.*, 2023). This data-driven method ensured that the themes closely reflected participants' perspectives (Braun *et al.*, 2024). Specific examples of codes contributing to each theme were provided to illustrate the analytical process. Additionally, steps were taken to maintain reflexivity, including regular self-assessment during coding to minimise bias. These improvements strengthen the link between the findings and the research questions while ensuring transparency and trustworthiness in the analysis.

3.9 Data collection process overview

The data was collected from November to December 2021 during the COVID-19 pandemic, when the Indonesian government was enforcing health restrictions and protocols, including limiting social gatherings (The Jakarta Post, 2021). The participants, Jakarta's police officers, are public servants and considered essential workers. Due to these conditions, the data collection was online instead of in person to comply with the regulations. Several digital platforms, such as Zoom, Skype, and Microsoft Teams, are available nowadays, providing alternatives to researchers where face-to-face data collection is impossible or not preferable. These platforms allow people to communicate remotely in a synchronous way that can be used to collect data. In addition, the ability of the video conference to provide the FTF aspects, such as visual and audio contact, even if it took place in separate countries, made the whole conversation appear more intimate and natural (Nehls, Smith and Schneider, 2014). Therefore, online data collection should be viewed as a viable choice for researchers rather than an alternate or secondary choice when face-to-face interviews cannot be accomplished (Deakin and Wakefield, 2014).

The police patrol chiefs and unit leaders were invited as participants via email through their stations' administrative office, including a consent form, participant information sheet, and privacy notice. The Jakarta police's administrative office informed that fifteen police from five stations (one chief and two leaders each) agreed to participate online using the Zoom application at times selected by the participants. The stations were pseudonymously designated as A, B, C, D, and E in an arbitrary sequence. Additionally, the pseudonyms of the participants were assigned to the numerals (1,2,3) in no particular order.

During the research invitation correspondence, participants from different stations expressed different preferences regarding the data collection methods. As a result, one-to-one interviews were conducted with nine participants (stations A, D, and E), while six participants from stations B and C opted to be interviewed with their colleagues from the same station. Despite their preferences, the sessions were treated and conducted in an interview format rather than focus groups due to the research objective, which was to elicit individual responses rather than to encourage group discussion or interaction, which is a defining characteristic of focus groups, where the emphasis is typically on facilitating group dialogue and interaction (Morgan, 1997; Krueger, 2014).

The police's different preferences potentially provide benefits to the requirement elicitation phase. Joint interviews, when utilised alongside other qualitative methods, such as individual interviews, can help to triangulate data and enhance validity (Boateng and William, 2018; Davis *et al.*, 2019). Conducting group interviews, particularly in situations where participants feel more comfortable or find it logistically easier, is recognised as a legitimate qualitative method, provided the emphasis remains on gathering individual perspectives (Langford, 2012). Throughout these sessions, the researcher attempted to guide the conversation to ensure that individual perspectives are not lost, which is suggested to allow each participant to share their views independently to maintain the integrity of the data collection process (Almutrafi, 2019).

This approach was taken to align with the semi-structured interview methodology, which values adaptability and responsiveness to participant needs while focusing on the research objectives (Longhurst, 2003; Kvale, 2011). Even within a group setting, the sessions attempted to retain the characteristics of interviews, concentrating on capturing individual perspectives. Therefore, the participants' individual and group interview preferences can be accommodated while maintaining the purpose of this research phase. Each session lasted approximately one hour, with participants providing written consent for the sessions to be audio-video recorded via Zoom. The researcher communicated entirely in Indonesian throughout these interactions.

3.10 Summary of chapter

This chapter described the overarching methodology adopted by this study, including the purposes and the research questions of the requirement elicitation and the subsequent quantitative study phases. In addition, details of the methods for the requirement elicitation were provided, including data collection, rigour, and analysis. The next chapter will provide the results of the elicitation requirement phase.

Chapter 4 Requirement elicitation results

This chapter provides the results of the requirement elicitation sessions (Figure 4.1) with Jakarta traffic police leaders regarding their decision-making in patrolling allocations and dashboard feature preferences (Table 4.1), which will be described in the following sections. In addition, a dashboard prototype overview section is also provided to demonstrate how the themes guided its content and features.

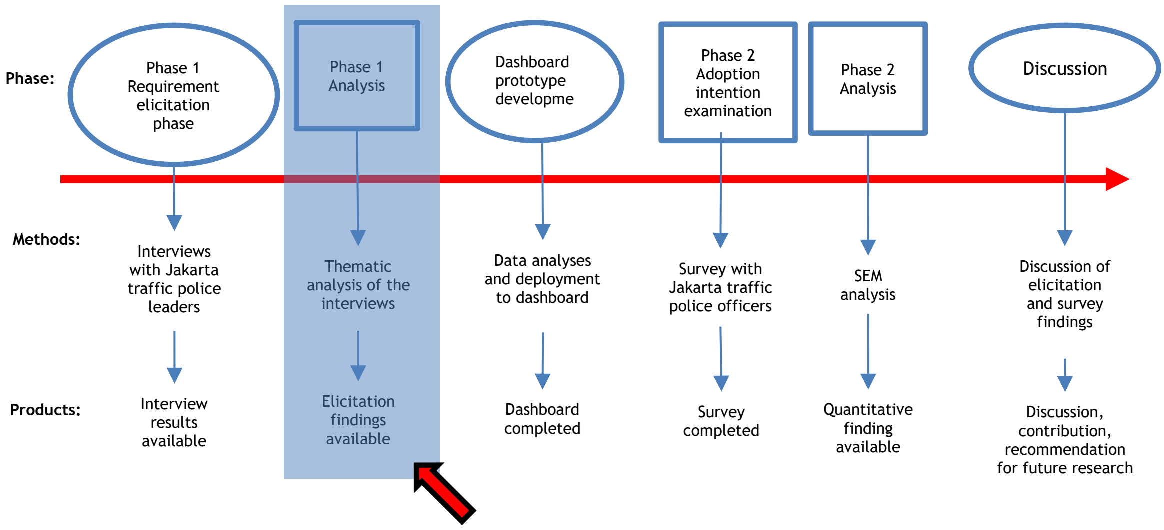


Figure 4.1 Research phase 1 analysis

No	Topic area	Theme
1	Decision-making for patrolling allocation	1. Proactive traffic crash prevention 2. Visual data for strategic patrol allocation 3. Data summarisation and predictive analytics 4. Role of tacit knowledge 5. Area coverage 6. Protocol adherence
2	Dashboard feature preferences	1. Data-driven information 2. Notice board functionality 3. Device compatibility 4. Simple interface 5. User guidance

Table 4.1 Topic area and themes

4.1 Decision-making for patrolling allocation

The interview findings on patrolling allocation practices among traffic police officers reveal prominent contradictions rooted in the officers' discretionary power, influenced by both data-driven approaches and personal judgement. These contradictions, discussed in detail in the following sections, are evident in officers' proactive traffic crash prevention methods, use of crash data, real-time traffic monitoring, and balancing data with their tacit knowledge.

The Jakarta traffic police administrative office stated that while police headquarters require recording traffic crashes and their entry into the IRSMS traffic crash database, they do not mandate its use in daily operations, including patrol allocation. Instead, patrol chiefs and leaders can allocate officers and vehicles based on their judgment. This discretionary authority, intended to serve the public interest, is rooted in their mandate to ensure traffic security, safety, order, and smooth flow (Indonesian Government, 2002, 2009). Consequently, interviews revealed varied and sometimes contradictory statements reflecting how this discretion is exercised.

First, although all officers emphasised proactive traffic crash prevention, their strategies varied significantly. Some officers advocate for systematically using IRSMS crash data to guide patrol allocations, emphasising an evidence-based approach that identifies high-risk areas for targeted interventions. This method, rooted in historical crash data analysis, aims to enhance road safety by preemptively addressing potential hazards.

In contrast, other officers rely more on personal experience and intuition for patrol decisions. One officer highlighted the importance of tacit knowledge gained from years of road experience in identifying crash-prone areas. While valuable, this subjective approach can lead to deviations from strict data-driven protocols, revealing a tension between empirical evidence and individual discretion. The role of tacit knowledge and its implications will be further explored in the subsequent sections.

Second, contradictions also emerged in using real-time traffic monitoring tools and predictive analytics. Some officers strongly support modern tools like Google

Maps and Waze, which provide real-time traffic data crucial for responding to traffic conditions and preventing crashes. These officers aim to enhance their response agility and flexibility by integrating real-time data into patrol strategies.

However, other officers expressed concerns about the complexity of the current data systems, such as the IRSMS database, which they find too detailed for efficient decision-making. These officers prefer simplified data summaries that facilitate quick decisions and resource allocation. This preference underscores a practical challenge: while detailed data is invaluable, its complexity can hinder usability, prompting some officers to seek more straightforward solutions.

Finally, perspectives differed on the use of predictive tools for anticipating crashes. Some officers are keen on developing predictive analytics to forecast potential crashes, reflecting a proactive vision for traffic safety. In contrast, others focus more on immediate, observable trends, highlighting a gap between current IRSMS capabilities and some officers' forward-looking needs.

The contradictions identified in the interviews illustrate the complex interplay between data-driven approaches and subjective judgement in traffic patrol operations. Despite a shared goal of enhancing road safety, the diversity in strategies and the discretion exercised by individual officers present challenges in standardising patrol practices. This complexity underscores the need for a balanced approach integrating empirical data with invaluable insights from officers' on-the-ground experiences.

Further details on the interview findings, grouped into six main themes, will be discussed in the subsequent sections. The first four themes focus on data usage in patrol allocations: proactive traffic crash prevention, visual data for strategic patrol allocation, data summarisation and predictive analytics, and the role of tacit knowledge. The remaining two themes—area coverage and strict protocol adherence—explore other considerations in allocating traffic patrolling resources.

4.1.1 Theme 1: Proactive traffic crash prevention

Proactive traffic crash prevention emerged as a critical focus for the participants, who reported using data and knowledge to inform their patrol strategies. Rather than reacting solely to incidents, they described a forward-thinking approach by regularly analysing crash data to anticipate and mitigate risks. According to the participants, this proactive mindset reflects a shift towards preventative measures to enhance road safety. They believed that the data-driven nature of their efforts ensures that patrol decisions are based on evidence, allowing them to identify high-risk areas, adjust their presence accordingly, and continuously improve the effectiveness of their interventions. By focusing on preventing crashes before they occur, participants conveyed a commitment to protecting public safety through informed, strategic action rather than just responding to them. Additionally, they suggested that using advanced technological tools and real-time monitoring supports this proactive approach, enabling them to stay ahead of emerging risks and allocate resources more efficiently.

4.1.1.1 Use of crash data for prevention

Participants emphasised the importance of using the IRSMS data to prevent future crashes, ensuring their strategies are evidence-based and contextually relevant. A1 shared,

> *"Preventing traffic crashes is a top priority for us. We look at the number of crashes to evaluate how well we are doing. By regularly checking the number of crashes and victims, we can see if our strategies are effective or if we need to make adjustments to improve safety."*

A1's statement highlights a systematic and quantitative approach to evaluating the effectiveness of patrol allocations. Regularly evaluating crash data enables officers to identify trends and adjust strategies accordingly, ensuring continuous improvement in their efforts.

B1 stressed the importance of traffic monitoring, noting,

> *"We make sure our patrol cars regularly monitor areas where past crashes happened. This way, we keep a close eye on spots that have been problematic in the past, hoping to prevent further incidents."*

This practice aims to increase police presence in high-risk areas based on historical crash data, reflecting a targeted approach to risk management. By focusing on known hotspots, officers can pre-emptively address potential hazards.

D1 also pointed out his commitment to continuous improvement and proactive measures, reflecting a dedication to public safety that extends beyond reactive responses,

> *"As a patrol leader, I always focus on preventing crashes. I think about where crashes have happened before and what we can do to stop them from happening again. It is about being proactive and staying ahead of the issues."*

E1 explained that when he conducted his responsibility to report the crashes that occurred in his station to the IRSMS portal, he also used the information to allocate the patrol officers,

> *"We look at the times and locations of recent crashes, which we report to the IRSMS portal when deciding where to allocate patrols. By knowing where and when crashes possibly happen, we can send our officers to those areas at the right times to prevent more crashes."*

E1's statement illustrates data integration into their operations, ensuring patrol decisions are responsive to the latest information. The officers believe that using crash data allows them to prioritise their efforts in areas where crashes are most likely to occur, enhancing the efficiency and effectiveness of their patrols.

4.1.1.2 Real-time traffic monitoring

Real-time traffic monitoring tools and communication systems play a crucial role in Jakarta traffic police's traffic crash prevention, allowing officers to respond promptly to emerging risks and adjust their patrol strategies accordingly. E2 valued the use of technological tools in patrol operations, noting that modern technology provides officers with up-to-date information, allowing them to anticipate and prevent potential crashes:

> *"I think systems like Google Maps and Waze that monitor real-time traffic conditions are helpful in monitoring traffic flows. These tools show us where congestion is building up so we can act before it becomes a bigger problem. It helps us keep the roads safer for everyone."*

Integrating these tools into their strategies enhances their ability to manage traffic and prevent crashes.

B2 highlighted the preparedness aspect, adding,

> *"By monitoring real-time traffic conditions in-person and also using online traffic information such as on Google Maps, we aim to be ready to respond if a traffic problem such as a traffic jam or crash happens. Our goal is to get to the scene as quickly as possible to provide help and manage the situation. The patrol officers are on the roads during their shift and stay alert and prepared for emergencies."*

This statement indicates that B2 believes in a state of preparedness facilitated by real-time data, such as traffic information from Google Maps. The on-duty officers stay on the roads during their shifts and monitor the traffic using in-person and online approaches. This readiness ensures a rapid response to incidents, mitigating the severity of crashes. Being always ready to respond highlights the importance of agility and flexibility in patrol operations.

Additionally, the leaders oversee patrolling activities using several approaches involving radio communication, WhatsApp[1] messenger group chat, and in-person inspections. They believe this method allows them to address emergent circumstances and promptly manage their resources. C1 explained this approach, saying,

> *"Combining radio updates with direct inspections helps us stay on top of any issues that arise. It ensures we have real-time information and can respond immediately. We also use WhatsApp group chat, but mainly for sharing photos and videos of the current traffic."*

Each patrol unit regularly reports the traffic status of their designated patrol routes to the monitoring centre of the station at intervals of no longer than thirty minutes. This frequent reporting ensures that the monitoring centre is constantly updated on traffic conditions, allowing for timely interventions when necessary. D1 emphasised the importance of this system, stating,

> *"Regular updates from our patrol units keep us informed about current conditions, allowing us to make swift decisions and deploy resources where they are most needed."*

D1 stressed the significance of regular updates from patrol units, noting that timely information allows for quick decision-making. This ensures that resources

[1] WhatsApp is a messaging app that enables text, voice, video calls, and media sharing over the internet (WhatsApp LLC, 2024).

are deployed efficiently to areas most urgently required, enhancing responsiveness to current conditions.

4.1.1.3 Public awareness campaigns

Using data for public awareness campaigns was another strategy discussed by participants. These campaigns aim to influence driver behaviour by providing visible reminders of crash statistics. A1 explained this strategy, stating,

> *"We put up billboards with traffic crash data to remind road users to drive safely. Seeing the number of crashes and victims makes them think twice about their driving habits. We believe encouraging drivers to be more cautious and responsible is important."*

This approach leverages data to foster a culture of safety among road users. The visibility of crash data is intended to serve as a deterrent and encourage safer driving practices. Officers aim to raise awareness and promote responsible driving by making crash data publicly available. B3 added,

> *"By sharing statistics on crashes through public displays, we hope to reach a broader audience and instil a sense of accountability among drivers. Seeing the real impact of traffic crashes can be a good motivator for safer driving behaviour."*

The participant expressed a desire to increase public awareness by displaying crash statistics, aiming to influence safer driving behaviours. B1 believes that making the consequences of traffic crashes visible can encourage a greater sense of responsibility among drivers. The approach seems intended to engage a wider audience and foster accountability on the roads.

4.1.2 Theme 2: Visual data for strategic patrol allocation

The participants perceived visual data representations as crucial for informing patrol allocations. According to their views, visualising crash data on maps enables them to identify high-risk areas better and make more strategic decisions about resource deployment. From the participants' perspective, this approach helps them better understand the spatial patterns of crashes, which they believe facilitates more informed and targeted decision-making. They expressed the opinion that using visual tools such as maps allows for more effective allocation of patrols to areas where their presence is most needed. In their view, this ensures that resources are used efficiently and interventions focus on preventing incidents in vulnerable locations. The participants believe this method enhances the effectiveness of patrol allocations and improves road safety. Their perspectives suggest that employing visual data aligns with their strategy of adopting evidence-based, proactive measures to prevent crashes before they occur.

4.1.2.1 Mapping Crash Locations

Participants highlighted the importance of mapping crash locations for strategic decision-making. C1 discussed the value of visual data,

> *"I want to see the information about crash hotspots on a map, maybe for the past few months, so we can easily identify the areas that need attention. Visualising these spots helps us quickly identify high-risk areas and allocate resources more effectively. It makes the data easier to understand and act upon."*

This visual representation helps identify high-risk zones, allowing for targeted interventions. Maps provide a clear and accessible way to understand spatial patterns in crash data. A2 stated,

> *"I need information about past crash locations plotted on a map so I can allocate my officers there. Seeing the crash data on a map gives us a better perspective on where incidents are happening, which helps us plan our patrol routes more effectively. It helps us focus our efforts where they are most needed."*

The use of maps enhances spatial awareness and helps officers prioritise their efforts. Officers believe they can focus their resources more effectively by knowing the exact locations of past crashes.

D2 underscored the need for historical crash data to be easily accessible and interpretable,

> *"I want to know where past crash locations are on a map to anticipate future crash risks. Having a visual representation of past incidents helps us anticipate potential problem areas and take preventive measures before crashes occur. It is about being proactive and staying ahead of problems."*

This accessibility enables officers to make informed decisions based on past trends. The ability to anticipate future risks based on historical data is crucial for proactive planning.

E2 also emphasised the benefit of visual data, explaining,

> *"There are past crash locations that I can consider when planning patrols if they are displayed on a map. Visualising this data helps in making quick decisions about where to deploy officers, ensuring that our patrols are data-driven and targeted at high-risk areas. It makes our work more efficient and effective."*

The participants believe integrating visual data into patrol planning can ensure that resources are effectively allocated to high-risk areas. Several officers also emphasised the importance of considering temporal trends in crash data. As one officer (A3) noted,

> *"It is not just about where the crashes happen but when they occur. Understanding peak times is crucial for deploying resources when they are most needed."*

This highlights the officers' awareness that timing is as critical as location in effective patrol deployment. Another officer (B3) underscored this approach, stating,

> *"Identifying the locations is essential, but if we are not present during the high-risk periods, we miss the opportunity to prevent incidents."*

This sentiment reflects a recognition that the effectiveness of patrols is contingent on aligning their timing with periods of heightened risk. Integrating spatial and temporal data is believed to be essential to optimising patrol strategies, ensuring resources are focused where and when they are most needed.

4.1.2.2 Pattern Recognition and Resource Allocation

Participants believe that visual data aids in recognising patterns and making informed decisions. A1 noted that this approach allows for a more nuanced understanding of crash hotspots and facilitates the deployment of patrols to areas with the highest risk:

> *"When we see data plotted on a map, it is easier to spot patterns and trends. We looked at the crash data for the past few months to observe if any spots had more crashes. This helps us identify which areas need more attention and allows us to allocate our resources more effectively."*

E1 also supported this view, saying that the ability to visualise patterns enhances strategic planning and ensures that interventions are data-driven and targeted:

> *"By looking at the visual data, we can see which areas have recurring issues. This helps us predict where problems might happen and allocate our patrols accordingly."*

E1 emphasised the importance of visualising data patterns for more effective strategic planning. They highlighted that visual data allows for identifying recurring problem areas, enabling better prediction of future issues and more informed, targeted patrol allocations.

4.1.3 Theme 3: Data summarisation and predictive analytics

Participants perceived that simplified data summaries and predictive tools are essential for effective patrol planning. They expressed a need for more accessible data formats and predictive capabilities to enhance their decision-making processes, believing these would improve the efficiency and responsiveness of their patrol strategies.

4.1.3.1 Simplified data summaries

Participants find the current IRSMS database too granular and prefer more accessible summaries. D1 explained,

> *"I want a simpler summary of crash data instead of the detailed structure of IRSMS to refer to when allocating patrol routes and times. Detailed data is important, but having a summarised version helps in quick decision-making and efficient planning. We need the big picture at a glance."*

Simplified summaries make it easier for officers to interpret and use the data in patrol planning. Simplified summaries enhance decision-making efficiency by providing concise and relevant information. Regarding the crash summary, E1 mentioned,

> *"I always look at last week's crash statistics that we reported to the IRSMS when deploying patrol officers. Regular summaries of IRSMS data help us stay updated on current trends and allocate resources accordingly. It saves time and helps us make better decisions."*

This statement indicates a reliance on recent data summaries to guide patrol decisions, ensuring the strategies are based on current information. By explicitly mentioning “last week’s crash statistics,” it appears that E1 assumed that recent data would provide an accurate reflection of the current conditions on the ground, allowing him to deploy resources more effectively.

Regularly reviewing recent data helps officers stay informed about the latest trends and risks. E2 also mentioned the advantages, stating,

> *"I considered the recent crash locations and times. Having a summarised view of recent incidents helps us understand immediate risks and plan our patrol routes to address these issues. It makes the process more straightforward and effective."*

Accessing and interpreting recent data is viewed as critical for responsive and effective patrol planning. Officers can adjust their strategies to address current risks by considering recent incidents. E3 also highlighted the importance:

> *" I think summaries of past crashes provide better analysis. Simplifying crash data into summaries helps identify trends and make more informed patrol strategies and resource allocation decisions. These summaries help us see the patterns and plan accordingly."*

The participants believe summarising past crashes can provide a clearer picture of trends and patterns to inform their allocation decisions. A comprehensive understanding of historical data is seen to support their proactive planning and risk management.

4.1.3.2 Predictive tools

Participants expressed a desire for predictive tools to foresee potential crashes. C3 expressed,

> *"If only there were a way to predict unpredictable traffic crashes using IRSMS data. Predictive analytics could significantly enhance our ability to prevent crashes by identifying potential risks before they occur. It would be so much better for traffic safety."*

This expression reflects a desire for advanced analytical tools to provide insights into future crash risks. Predictive analytics are seen to help officers anticipate where and when crashes will likely occur, allowing for pre-emptive measures. The desire for predictive tools represents a proactive vision in traffic safety management. D1 repeated this sentiment, explaining,

> *"If possible, I want to have some kind of traffic crash predictions from traffic crash data. Knowing where crashes are likely to happen would allow us to allocate resources more effectively and prevent incidents before they occur. It is about being proactive and staying ahead of the issues."*

This underscores the perceived need for predictive analytics to enhance proactive planning and resource allocation. However, it is essential to note that predicting future crashes based on historical data is inherently challenging due to the complexity and unpredictability of traffic patterns. Developing and implementing predictive tools could improve patrol strategies' effectiveness by enabling officers to focus on high-risk areas before incidents occur. While participants strongly desired these tools, their effectiveness would depend on the accuracy of the predictions, which could be limited by the factors mentioned above.

4.1.4 Theme 4: Role of tacit knowledge

Participants viewed personal experience and knowledge as crucial elements in their patrol allocation strategies, a concept known as tacit knowledge. This type of knowledge, derived from individual experiences, insights, and instincts, is challenging to articulate, formalise, or convey (Pang, 2023). Participants perceived tacit knowledge as an essential complement to data-driven approaches, believing it enhanced decision-making by providing context and insight that numbers alone could not. Although subjective and varying according to each officer’s experience level, participants felt that tacit knowledge offered a valuable layer of understanding, particularly in identifying risks and planning patrols. This theme aligns with the discussion in section 2.2, which explores how tacit knowledge, despite its informal nature, can significantly inform decision-making processes in public safety.

4.1.4.1 Experience in allocation decisions

A2 explained the importance of personal insight, stating,

> *"Based on my experience with past traffic crashes, I allocate my patrol officers to the locations of recent crashes. My experience helps me understand which areas are more prone to crashes and need more attention. It is something you learn over time by being out on the roads."*

This highlights the significance of tacit knowledge in decision-making. A2 believes their experience provides a nuanced understanding of crash hotspots, which might not be immediately apparent from data alone. This reliance on personal experience complements the data-driven approach, offering a deeper insight into the specific contexts and conditions that lead to traffic crashes. Tacit knowledge, gained through hands-on practice, allows officers to interpret situations intuitively and apply their judgment accordingly.

4.1.4.2 Tacit Knowledge in Public Service and Assistance

Participants also rely heavily on their tacit knowledge—personal experiences and intuitive insights—in their roles. This knowledge is essential for effective decision-making, particularly when data alone may not provide a complete picture. While previous discussions about patrolling allocation have focused primarily on crash locations, several officers also identify and prioritise other types of locations based on their experiences. B2 elaborated on the importance of experience, stating,

> *"Based on their experience, my subordinates usually know the places where road users frequently need police presence, for example, the road sections where drivers pull over on road shoulders to take a rest. The patrol officers will guide them to move to a safer location, like a designated rest area. These areas can become dangerous, especially when heavy traffic increases the risk of crashes. They understand these needs because they have seen it happen many times."*

This proactive assistance aims to reduce roadside hazards and reflects the importance of experience in identifying and addressing safety issues. Officers' familiarity with local conditions allows them to provide targeted assistance that enhances road safety. Tacit knowledge enables officers to understand and anticipate the needs of road users based on past interactions and observations.

B3 shared their insights, saying,

> *"From my experience, long-haul truck drivers park and sleep on roadsides. The officers will wake them in the morning when traffic builds up, reminding them that moving to a designated area is safer. This helps prevent crashes that could be caused by stationary vehicles during busy times."*

Based on the participants' experience, this intervention mitigates risks that may not be immediately evident from available data. Officers prevent traffic disruptions and crashes by waking drivers and encouraging them to move. Although officers recognise these types of locations—such as areas where drivers frequently pull over or where trucks park overnight—through their experiences, there is currently no formal system for categorising or recording them. This lack of systematic documentation may pose challenges in ensuring that these locations are consistently monitored or addressed across different patrol shifts or regions.

Moreover, while these locations are not traditionally considered crash sites, they can potentially serve as crash hazards. For example, vehicles parked on the roadside, especially in high-traffic areas or during peak times, could contribute to crashes as drivers navigate narrower lanes and unexpected obstacles (Kadkhodaei *et al.*, 2023). Stationary vehicles can obstruct traffic flow or create unexpected obstacles for other road users, thereby increasing the risk of collisions (Badshah *et al.*, 2022). Therefore, the officers' proactive efforts to manage these situations are crucial because they may directly or indirectly relate to crash occurrences.

B3 also highlighted the importance of observing traffic conditions, adding,

> *"We always keep an eye through physical observation and our radio on where congestion occurs, especially during morning and evening rush hour. Stop-and-go traffic often leads to crashes. Knowing the usual patterns allows us to anticipate problems and act before they escalate."*

This observation underscores the importance of real-time situational awareness in preventing traffic incidents. Understanding traffic flow dynamics helps officers anticipate and prevent crashes caused by congestion. This also highlights a gap in traditional crash datasets such as the IRSMS, which typically do not capture these preventative activities. Tacit knowledge here is crucial as it allows officers to quickly recognise patterns and respond effectively based on their previous experiences. E1 further illustrated this concept by explaining how real-time communication aids in traffic monitoring, *"We share information via our police radios when we see traffic building up. If we know a section of road is causing traffic jams, we will deploy officers there. Lane changes often make traffic jams worse and can cause crashes. By acting quickly, we can manage traffic flow and reduce the risk of crashes."*

This quote emphasises how experiential knowledge combined with real-time data enables officers to respond effectively to dynamic traffic situations.

These examples underscore the significant role that tacit knowledge plays in the daily operations of the officers. The ability to anticipate road users' needs, recognise patterns in traffic behaviour, and respond proactively to potential hazards is rooted in the officers' personal experiences and observations. The insights shared by participants demonstrate that, while formal data collection and analysis are essential, the nuanced understanding gained through on-the-ground experience is considered vital in ensuring road safety. The officers consider this experiential knowledge to effectively address safety issues that may not be immediately apparent in traditional crash data, further highlighting its importance in the field.

4.1.5 Theme 5: Area coverage

Ensuring area coverage of their stations' jurisdictions (described in section 3.8.1) is seen as crucial to the participants' patrolling practices. They perceived this as vital to maintaining public safety and effective patrol management, recognising that an even distribution of resources across their jurisdiction was necessary to prevent any area from being neglected. B1 explained the planning involved, stating the importance of careful planning in achieving adequate area coverage:

"I always plan my allocations meticulously to include specific routes and ensure that all areas within our jurisdiction are covered. This involves detailed planning and a clear understanding of the traffic patterns and potential risk areas. By knowing our jurisdiction well, we can ensure every area gets the attention it needs."

B2 added further details, stating the need to ensure that all areas receive attention, which is crucial for maintaining public safety:

"Our patrol officers always cruise their entire patrol routes during their shift. We make it a point to cover every kilometre of our jurisdiction,

ensuring no area is left unchecked. This continuous movement helps in maintaining a visible police presence and deterring potential traffic violations and incidents. It is important to be thorough and consistent in our patrols."

A1 noted the systematic approach to resource allocation based on the geographical area:

"We distribute our patrolling resources, which are patrol officers and vehicles, by the length of our road jurisdiction, ensuring each patrol unit has a defined area to cover. This systematic approach helps in efficient resource allocation and ensures that all areas are adequately monitored. By dividing our resources effectively, we can maximise our coverage and effectiveness."

A1 emphasised a systematic approach to resource allocation, distributing patrol officers and vehicles based on the length of road jurisdiction. This method ensures that each patrol unit covers a defined area, promoting efficient resource distribution.

4.1.6 Theme 6: Protocol adherence

Participants stressed following established protocols and procedures to ensure consistency and reliability in patrol operations. This adherence to routine enables officers to provide timely assistance and prevent crashes. A1 stressed the importance of performance evaluation, stating,

"We use the number of crashes as one of the indicators to evaluate our performance. We do this by periodically evaluating the number of crashes and victims. By regularly assessing our performance, we can identify areas for improvement and make necessary adjustments to enhance traffic safety. It is about staying accountable and striving for better results."

This systematic evaluation ensures that patrol strategies are continuously refined based on empirical evidence. By regularly assessing their performance, officers can identify areas for improvement and implement changes that enhance traffic safety.

The topic of discipline related to area coverage also emerged. Participant C3 highlighted the importance of familiarity and consistency, stating,

> *"To maintain discipline, I want all my subordinates to experience every route in our jurisdiction on each shift. By rotating routes, we ensure officers are familiar with the entire area and not just their usual patrol routes. This practice enhances their situational awareness of the jurisdiction and ensures consistent coverage across all areas. Discipline and consistency are key to effective patrolling."*

This statement underscores the importance of discipline in ensuring comprehensive area coverage and the effectiveness of patrol efforts. Maintaining discipline in patrol operations highlights the dedication of traffic police departments to upholding professionalism and ensuring that all areas within their jurisdiction are effectively monitored.

4.2 Dashboard feature preferences

The interview results on dashboard feature preferences among traffic police officers reveal a clear interest in key functionalities supporting patrol allocations. Participants were informed about a prototype dashboard and asked to share their expectations, which were categorised into five main themes: data-driven information, notice board functionality, device compatibility, a simple interface, and user guidance.

Officers strongly preferred data-driven information, emphasising the need for accurate, data-backed insights to enhance decision-making by aligning with their field experiences. Notice board functionality was also valued for centralising important updates that complement existing communication tools like radios and WhatsApp groups. Device compatibility was highlighted as essential, allowing access across computers and mobile devices to ensure officers stay informed in various settings.

A simple interface was consistently requested, reflecting the need for a user-friendly design that supports quick and efficient decision-making in the field. Lastly, user guidance was deemed crucial, with officers advocating for built-in instructions to ensure all users can effectively navigate and utilise the dashboard.

The following sections will explore these themes in more detail, discussing the specific preferences and expectations of the traffic police officers regarding the dashboard features and how they reflect their operational needs.

4.2.1 Theme 1: Data-driven information

A prominent theme that emerged is the desire for the dashboard to have data-driven information, which refers to information derived from data to extract insights and inform decision-making processes (Noshad *et al.*, 2021). This desire reflects participants' need for accuracy and reliability in decision-making processes. Participants articulated that data-backed information enhances their practical experiences and ensures informed decisions. Integrating data-driven information into the dashboard was seen as a crucial element to bridge the gap between field experiences and analytical insights. For example, Participant B1 suggested integrating practical knowledge and data:

> *"It would be great if the dashboard could show data-based information because it could match our field experience well. Combining real-world insights I experience with data could improve our decisions on the field."*

The statement of B1 seems in line with the other officers' quotes about tacit knowledge in section 4.1.4, where B1 appears to be drawing on his personal experience in the field to validate and interpret data. This statement suggests that B1 and possibly other officers rely on their tacit knowledge to make sense of and trust the data. B1's preference for data that aligns with "real-world insights" indicates that tacit knowledge is a factor in their decision-making process. B1 believes that integrating tacit knowledge with data is crucial for improving decision-making. He suggests that a system combining both could enhance the process by leveraging the strengths of each.

Similarly, Participant C1 highlighted the importance of accuracy:

> *"I think the dashboard should provide accurate, data-backed information so that our decisions are based on reliable facts. Precision is crucial in our work, and trustworthy data such as the IRSMS is essential for making good public safety decisions."*

This statement underscores that the IRSMS is trusted by C1 and is seen as enhancing the reliability and effectiveness of decision-making, reinforcing the participants' trust in ICT platforms. C1 further explained:

> *"When I say trustworthy, I mean data that aligns with our field observations*

and operational needs. If the crash database meets these criteria, we rely on it confidently for decision-making."

Participant A2 emphasised the value of valid databases:

"It would be helpful if the dashboard used information from trusted databases such as the IRSMS because the accuracy of the data would make it more useful. The credibility of the data source would make our confidence in our decisions."

Participant D3 underscored the necessity of accurate information:

"I believe the dashboard should provide accurate data-driven information to ensure our decisions are well-informed and effective. Inaccurate data can lead to poor decisions, which in our context can have negative consequences for the public."

Finally, Participant E2 reiterated the importance of trustworthy data:

"I would suggest that the dashboard include precise, reliable data because it would improve our decision-making process and build confidence in our decisions. Trust in the data source is crucial for our success and maintaining high standards in our field."

The consistent emphasis on the accuracy and validity of data across different participants highlights a collective understanding that data-driven insights are crucial for operational success. This theme also reflects a broader trend in various fields where data-driven decision-making is increasingly important for strategic and operational effectiveness.

4.2.2 Theme 2: Notice board functionality

Another identified theme is the preferences for a noticeboard within the dashboard. Participants indicated that a notice board would facilitate disseminating important information, complementing existing communication channels such as radios and WhatsApp groups. While WhatsApp groups are commonly used among officers, they are primarily for general communication, such as traffic information updates (section 4.1.1.2), rather than for distributing critical or sensitive information. The notice board was seen as a tool that could enhance coordination and information flow by providing a more formal and centralised platform for essential updates. Participant E1 suggested the potential utility of this functionality:

> *"It would be really helpful if the dashboard could have a message board to broadcast information, complementing our radios and WhatsApp group. Having all relevant information in one place would be very convenient."*

This quote emphasises the convenience of centralising all relevant information in one place. E1 believed a notice board could enhance communication efficiency by providing a single, accessible platform for essential updates.

Participant B3 pointed out the practical application:

> *"A feature that delivers important information would be handy for coordinating our efforts in the field. This would ensure everyone is on the same page and can respond promptly to critical situations."*

This perspective highlights the practical application of a notice board in coordinating efforts within the field. It underscores the importance of having a reliable tool to ensure everyone is aligned and can respond promptly to critical situations.

Finally, Participant C2 emphasised the efficiency benefits:

> *"By having a centralised notice board, we could reduce the time spent checking multiple communication platforms. It would streamline our workflow and allow us to quickly access the most current and relevant updates without missing crucial information."*

This quote focuses on the efficiency benefits of a centralised notice board. Reducing the time spent checking multiple communication platforms could streamline workflows and improve the speed at which critical information is accessed.

These results reveal a strong consensus among interviewees about the need for a notice board within the dashboard, with multiple quotes reflecting a similar recognition of its potential benefits. This response similarity suggests a shared understanding of the value of centralising communication, even though these quotes were drawn from individual interviews (section 3.9). This recurring theme across separate interviews highlights its perceived value, likely from shared operational experiences. While prior discussions within their stations may have influenced the idea, its consistent mention across different participants underscores its relevance and potential benefits.

4.2.3 Theme 3: Device compatibility

The need for device compatibility was also highlighted, reflecting the participants' desire for accessibility across various devices. This theme ensures that the dashboard can be used effectively on computers and mobile devices, adapting to different screen sizes and orientations. This theme was underscored by Participant D2, who highlighted the practical need for cross-device functionality in their work.

> *"Being able to use the dashboard on both a smartphone and a desktop is beneficial for our work. At the office, we have PCs with large screens, but a phone's portability is key in the field. Therefore, I think the dashboard should adapt well to different devices."*

Accessing the dashboard on various devices was seen as a critical factor in ensuring that officers could remain informed and effective regardless of their location. Participant B1 suggested this need succinctly:

> *"It would be helpful if the dashboard worked well with mobile devices so we can check it on the go and stay updated even when we are not at our desks. This kind of flexibility is crucial for our work."*

Participant B3 expressed a similar preference:

> *"If possible, it would be great if we could use the dashboard on our phones because it would make things easier and more accessible during field operations. Being able to access important information on a phone would help us respond faster."*

Participant A2 also noted the importance of accessibility:

> *"The dashboard should be easy to use on both computers and mobile devices, so we can get the information we need, no matter what device we have."*

Participant C2 emphasised the value of a seamless experience across devices:

> *"Having a design that works well on different devices would make the dashboard useful in many situations, whether in the office or out in the*

> *field. This would help make sure that all officers have the information they need, wherever they are."*

Participant E3 offered insight into the varied contexts in which the dashboard might be used, emphasising the importance of versatility in device compatibility:

> *"Sometimes we are in the office, and other times we are out in the field. Having a dashboard that's just as effective on a smartphone as on a desktop means we can always stay connected and make informed decisions, no matter where we are."*

This theme reveals the importance of flexibility in ICT applications, facilitating the use of the dashboard in diverse operational environments. The emphasis on mobile compatibility underscores the need for a seamless user experience that supports officers' mobility and on-the-go decision-making. This theme aligns with broader trends in ICT development, where user-centric design and cross-platform compatibility are increasingly prioritised to enhance usability and accessibility.

4.2.4 Theme 4: Simple interface

Participants consistently emphasised the need for a simple, user-friendly interface. This theme stems from the interviewees' recognition that patrol officers may not have advanced technological skills, necessitating a straightforward and intuitive design. The importance of a simple interface was linked to the need for efficiency and ease of use in high-pressure environments. Participant B1 suggested the need for simplicity in practical terms:

> *"It would be helpful if the dashboard provided straightforward and easily digestible. A complex interface could hinder the officers' ability to respond quickly and accurately."*

Participant B3 stated:

> *"The dashboard should be simple and easy to understand for patrol officers in the field so they can combine the information with their field experience. Simplicity is key to making sure the dashboard is a helpful tool and not an extra hassle."*

Participant C1 provided further clarity:

> *"I think it is important for the dashboard to have a simple interface because We are not used to complicated and cluttered visualisation. An intuitive and user-friendly design would make sure it is widely used and effective."*

Participant D1 wished for a straightforward solution:

> *"A simple, modest, and easy-to-understand version of the traffic crash database would be very helpful for our daily work. The focus should be on providing clear and concise information that can be quickly understood and used."*

Participant D2 echoed the sentiment, stressing the need for simplicity to enhance productivity:

> *"The simplest interface possible is what we need. It would help us focus on our main tasks without getting bogged down by unnecessary complexity, such as a dashboard with too many boxes containing too much information."*

Participant E2 pointed out the significance of a familiar and intuitive interface:

> *"A familiar and easy-to-understand dashboard is essential for usability. It would ensure officers can quickly learn and use the system without much training, minimising the learning curve and maximizing efficiency."*

This theme indicates that an accessible and easily navigable interface is critical for ensuring that all users can effectively utilise the dashboard, regardless of their technical proficiency. The repeated call for simplicity highlights a collective demand for practicality and ease of use in the dashboard interface design. This theme aligns with user-centred design principles, prioritising end users' needs and capabilities to create more effective and efficient ICT solutions.

4.2.5 Theme 5: User guidance

Finally, participants strongly preferred built-in user guidance to aid in the comprehension and use of the dashboard. This theme includes clear instructions integrated into the user interface to support all users, regardless of their familiarity with the system. The provision of user guidance was seen as essential for ensuring that all team members could use the dashboard effectively. Participant C1 suggested the inclusion of guidance:

> *"It would be helpful if the dashboard included built-in instructions, like simple guidance in a text box, to help our officers understand and use it efficiently. Providing clear and concise instructions would help users navigate the system easily and confidently."*

Participant C2 reiterated the importance of this theme:

> *"A dashboard with built-in guidance would be an excellent addition, ensuring everyone can easily navigate and use it, regardless of their technical skills. Clear user guidance can make a big difference in usability."*

Participant C3 emphasised the need for simplicity in instructional design:

> *"Including a plain, easy-to-read instruction box would guide users, ensuring the dashboard is usable for all officers and preventing confusion. Clear and straightforward instructions can help reduce errors and improve the overall user experience."*

Participant A2 also highlighted the value of user guidance:

> *"Having built-in user guidance is crucial for getting new users up to speed and making sure everyone, from tech-savvy people to those less familiar with digital tools, can effectively use the dashboard. This feature would greatly improve overall usability."*

Participant D3 supported the inclusion of instructional elements:

> *"A dashboard with built-in user guidance can make learning the system much faster and help officers become proficient quickly. Providing step-by-step instructions and tips can prevent common user mistakes and enhance efficiency."*

This theme highlights the necessity of instructional support to enhance usability and ensure that all team members can efficiently use the dashboard. The call for built-in guidance reflects a proactive approach to user support, aiming to minimise confusion and maximise efficiency in using the dashboard. This theme aligns with best practices in instructional design, which emphasise the importance of providing clear, accessible, and context-specific guidance to support users in effectively navigating and utilising new technologies.

4.3 Overview of the dashboard prototype

This section provides an overview of the dashboard prototype, while all the details of the development and all the software codes are provided in Appendix B. The findings regarding Jakarta traffic police's decision-making in their patrolling allocations (section 4.1), except the non-data related themes such as tacit knowledge (section 4.1.4) and adherence to protocol (section 4.1.6), were used to guide the dashboard's content provision. In addition, all the feature preferences that were identified from the interview results (section 4.2) were adopted in the dashboard prototype (Figure 4.2). In the subsequent phase, the Jakarta traffic police's behavioural intention to adopt this dashboard will be examined.

Figure 4.2 The dashboard prototype

The dashboard prototype provides traffic crash data from IRSMS to inform the police's proactive traffic crash prevention efforts, which was decided based on the findings in section 4.1.1. The locations of crashes were visualised on a map to show where they occurred to inform the police where they might allocate their patrolling resources, as discussed in section 4.1.2. Various summaries of crashes, such as casualty percentages, hourly crash percentages, road type distribution, monthly crash data, and daily crash data, are visualised appropriately with bar and line charts to support their patrolling allocation, as discussed in section 4.1.3. In addition, crash prediction is visualised using a line chart and created using a Random Forest prediction model due to its widespread use in urban road safety studies, providing insights into crash prevention strategies (Ramya *et al.*, 2019; Atumo, Fang and Jiang, 2022; Pourroostaei Ardakani *et al.*, 2023). Finally, because the police allocate their patrolling resources based on their jurisdiction area (section 4.1.5), the dashboard provides a sidebar picker for selecting the area, year, and day of the crash data.

Regarding the police's dashboard feature preferences, especially the desire to have a data-driven dashboard (section 4.2.1), the IRSMS crash data were integrated into the development process. A notice board feature (second preference in section 4.2.2) was added to the dashboard in the top right corner in the "tentang aplikasi/ about" box. The dashboard has a fluid interface that can automatically adjust to different screen sizes to facilitate the police's preferences, as described in section 4.2.3. The dashboard interface was designed to be as simple as possible during the development to facilitate the preferences in section 4.2.4. The preferences for user guidance were facilitated by a feature where an additional information pop-up appears if the user hovers a cursor (on a computer) or taps (on a mobile device) over any content box. Finally, the dashboard includes an optional location-tracking feature, which displays the user's current location on a map which can be turned off.

4.4 Summary of chapter

This chapter provides the results from the requirement elicitation sessions in this phase, focusing on Jakarta traffic police leaders' decision-making processes for patrolling allocations and their dashboard feature preferences. The analysis identifies key themes in decision-making for patrolling allocation. Proactive traffic crash prevention is a significant focus, with officers utilising crash data to inform strategies and enhance road safety. Real-time traffic monitoring tools like Google Maps and Waze help officers respond to hazards promptly. Public awareness campaigns use crash data to influence driver behaviour positively.

Visual data for strategic patrol allocation is essential. Officers desire to visualise crash data on maps to identify high-risk areas and deploy resources effectively. Simplified data summaries and predictive analytics enhance patrol planning by making data more accessible and actionable. Tacit knowledge, derived from officers' personal experiences and intuitive insights, complements data-driven approaches, enriching decision-making. Strict adherence to protocols ensures consistency and reliability in patrol operations, with regular performance evaluations based on empirical data.

Regarding dashboard feature preferences, officers strongly desire accurate, data-driven information to improve decision-making. A notice board within the dashboard would centralise communication, enhancing coordination. Device compatibility is crucial, allowing access to both computers and mobile devices. Considering the varying technological skills among officers, a simple, user-friendly interface is necessary. Built-in user guidance is also essential for navigation and effective dashboard use.

The dashboard prototype was developed based on these findings, excluding tacit knowledge and strict protocol adherence. It integrates IRSMS crash data to support proactive crash prevention and visualises crash data on maps for strategic resource deployment. Various crash data summaries and predictive analytics are provided. The dashboard includes a sidebar picker for selecting crash data by area, year, and day. Regarding identified feature preferences, the prototype incorporates data-driven information, a notice board, and compatibility with computers and mobile devices. The interface is simple and user-friendly, with built-in user guidance through pop-up information boxes. An optional location-tracking feature displays the user’s current location on a map.

This chapter concludes the requirement elicitation phase, except for the discussion section, which will be provided later in Chapter 7 to maintain the thesis flow. The findings shaped the development of a dashboard prototype tailored to

Jakarta traffic police leaders' needs. By focusing on proactive crash prevention, strategic patrol allocation, and data analytics, the dashboard aims to inform decision-making and operational efficiency. The next chapter transitions to the adoption intention examination phase, evaluating the behavioural intention of Jakarta traffic police officers to adopt the dashboard.

Chapter 5 Adoption intention examination methods

5.1 Introduction

This chapter describes the methods used in the adoption intention examination phase. This phase investigates Jakarta traffic police officers' behavioural intention to adopt a dashboard for their traffic patrol allocation. In this context, the dashboard is intended as an ICT example. A set of hypotheses is developed by exploring the police's perceived motivation factors for ICT usage. The current study phase is depicted in Figure 5.1.

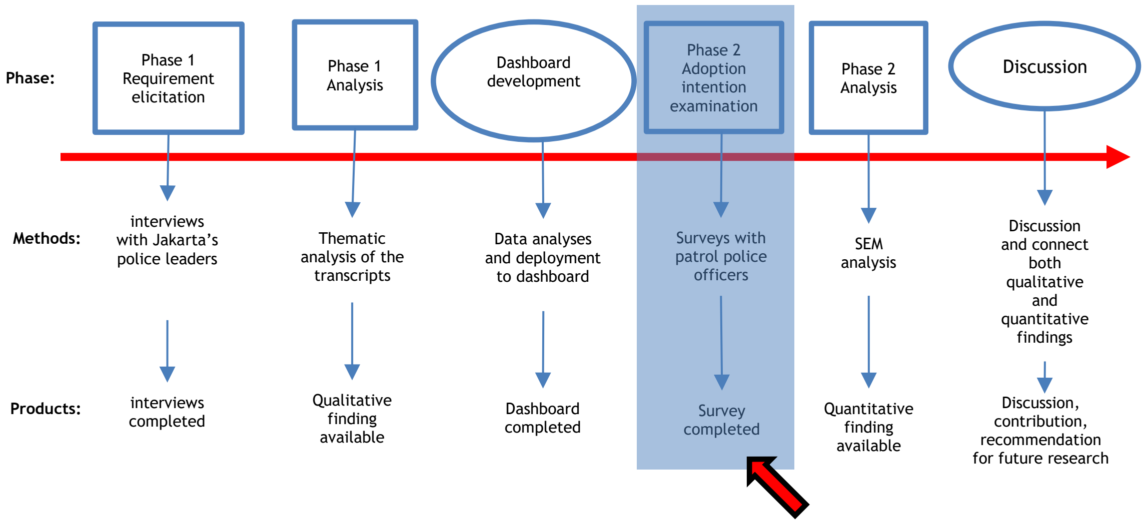


Figure 5.1 Current survey phase

Section 5.2 provides the research questions and objectives. Section 5.3 provides the hypothesis development. Section 5.4 provides the developed hypotheses. Section 5.5 outlines the data collection. Finally, section 5.6 provides the analytical methods to process the data obtained.

5.2 Research questions and objectives

RQ3: What factors are perceived as motivating government employees' adoption of ICT tools, and how can these insights inform the understanding of technology acceptance in the public sector?

RQ4: "What are the relationships between identified motivational factors and the behavioural intention of government employees to adopt ICT, and how do these findings contribute to the refinement of ICT adoption theories in public sector settings?"

The objectives for this phase are:

O1: To explore the factors perceived as motivating government employees' adoption of ICT tools through semi-structured interviews analysed using thematic analysis and to use these insights to inform the understanding of technology acceptance in the public sector.

O2: To examine the relationships between identified motivational factors and the behavioural intention of government employees to adopt ICT through a survey analysed using structural equation modelling (SEM) to refine ICT adoption theories in public sector settings.

This phase aims to provide empirical insights into the factors that promote or hinder ICT adoption in urban government settings, which is critical for improving public service delivery and operational efficiency. By exploring and examining the motivational factors and their relationship to employees' behavioural intentions, this research clarifies the key drivers and barriers to ICT adoption. These findings inform the refinement of ICT adoption theories for the public sector and help develop strategies that align with the specific needs of government employees, enhancing the likelihood of successful technology integration.

5.3 Hypothesis development

This study phase builds on the insights from qualitative interviews that explored key contextual factors influencing ICT adoption within the Jakarta Traffic Police. The qualitative findings informed the design of the quantitative survey by identifying relevant factors and refining the questionnaire items to reflect the operational realities faced by the participants. The quantitative phase subsequently examined the relationships between these identified factors and the intention to adopt the ICT tool using a structured survey approach. After the police leaders tried the dashboard prototype in the dashboard validation sessions, they were asked what factors they perceived would motivate them to use ICT, such as the dashboard. Their answers were then analysed and compared to the existing ICT adoption literature to identify possible similar factors that can be adopted for developing this phase's hypotheses. This multi-method approach was used to consider the distinct characteristics of public organisations and government employees when it comes to ICT adoption (Gil-Garcia and Pardo, 2006; Venkatesh, Brown and Bala, 2013; Bano and Zowghi, 2015; Barile *et al.*, 2018; Rehouma and Hofmann, 2018).

It is acknowledged that the survey participants might only access the dashboard prototype briefly before participating. Regarding this matter, technology acceptance theories such as TAM, UTAUT, and their extended versions, have been extensively used to understand the adoption and usage of various technologies across different contexts, including those that are used only once or for a short duration (Dwivedi *et al.*, 2019; Greener, 2022). In addition, these theories have been frequently employed to assess nascent technologies, such as those in the pre-deployment or prototype stages like the dashboard prototype of this study. To anticipate potential future user actions, researchers often modify survey questions by incorporating terms like "may" (e.g., *"Using augmented reality may enhance users' understanding of archaeological spaces"*), "will" (e.g., *"If the system is adopted, it will likely increase promotion opportunities"*), or "predict" (e.g., *"Users predict they would regularly employ the proximity tracing app if it were accessible"*) (Marto *et al.*, 2019; Trkman, Popovič and Trkman, 2021; Monteiro *et al.*, 2022).

Designing a questionnaire aligned with established theories or previous research is crucial for obtaining accurate data and increasing response rates, thereby thoroughly addressing the research questions (Robson, 2002; Saunders, Lewis and Thornhill, 2009; Saunders and Townsend, 2016). Questionnaire items from seminal and other relevant studies that utilised established models such as the Technology Acceptance Model (TAM), Innovation and Diffusion Theory (IDT), Unified Theory of Adoption and Use of Technology (UTAUT), and User Experience Questionnaire (UEQ) were incorporated and modified to the survey setting with minor linguistic adjustments. Modifying questionnaire items necessitates validation testing to guarantee the validity and reliability of the alterations, such as internal consistency and construct validity assessments (Parmenter and Wardle, 1999; Singh *et al.*, 2011; Kliemann *et al.*, 2016). The reliability and validity tests of the survey items were conducted in the subsequent data analysis, which will be discussed in section 5.6.5.

All the interview findings of this phase were used as variables in developing the hypotheses (sections 5.3.1 and 5.3.2) to evaluate the Jakarta traffic police's dashboard adoption intention comprehensively. In addition, no additional variables were included to ensure the hypotheses are contextual and also to adhere to the parsimony principle, favouring simplicity and minimal assumptions to prevent speculative theories and reduce the complexity of questionnaires, which are linked to higher response rates (Whetten, 1989; Weger, 2019; Burgard, Bošnjak and Wedderhoff, 2020; Wu, Zhao and Fils-Aime, 2022). This approach was particularly pertinent for this phase's online survey format, which is known for its lower participation rates than telephone or in-person methods (Cook, Heath and Thompson, 2000; Nulty, 2008). Considering the survey data will undergo quantitative analysis using Structural Equation Modelling (SEM), where adding variables diminishes statistical power, parsimony was essential (Cohen, 1977; Westland, 2010; Button *et al.*, 2013).

The following sections present the interview findings and related questionnaire items developed for the survey. Technology acceptance variables include four main factors: interoperability expectations, social incentives, social influence, and privacy concerns. Interoperability expectations highlight the need for seamless integration between different systems used by the police. Social incentives emphasise the role of recognition from peers and superiors in motivating technology adoption. Social influence shows that officers are more likely to use ICT if it is supported within their team. Privacy concerns focus on worries about continuous location tracking and data security. User experience variables cover preferences for innovative technology, leading-edge technology, speed, and supportive functionality. The survey will assess how these factors influence officers' behavioural intention to adopt the dashboard.

5.3.1 Technology acceptance variables

The following sections describe the interview analysis results and corresponding survey questionnaire items. Based on the interviews with the Jakarta traffic police, four factors were derived from the theories in the technology acceptance study field, namely interoperability expectations, social incentives, social influence, and privacy concerns. The survey will measure these factors using a 7-point Likert scale commonly used in technology acceptance studies (Rogers, 1962; Davis, 1986; Ajzen, 1991; Venkatesh *et al.*, 2003). The scale captures subtle differences in user perceptions and attitudes, which is crucial for understanding technology acceptance (Hayotte *et al.*, 2020). The 7-point Likert scale used in this study is defined as follows: 1 corresponds to 'Strongly Disagree,' 2 to 'Disagree,' 3 to 'Slightly Disagree,' 4 to 'Neutral,' 5 to 'Slightly Agree,' 6 to 'Agree,' and 7 to 'Strongly Agree'.

5.3.1.1 Interoperability expectations

Interoperability expectations emerged as a factor for ICT usage among Jakarta traffic police. Interoperability, as defined by Whitman, Santanu and Panetto (2006) and Handley (2013), refers to the seamless communication and data exchange between various systems, devices, or platforms. This capability is essential in complex operational environments like traffic management, where data from multiple sources must be integrated quickly and accurately to inform decision-making processes. Participants highlighted the importance of interoperability in their roles. For example, A1 noted,

> *"It would be a huge help if the traffic crash record system could talk directly with the driver's license database. This way, we would not waste time jumping between different databases."*

This comment highlights the inefficiencies caused by fragmented systems and the potential benefits of a more integrated approach. E3 reinforced this by pointing out,

> *"Right now, it is a hassle switching between systems just to piece together information on one incident,"*

emphasising the operational friction and potential for human error when dealing with disjointed data sources. Participant B4 expanded on this point, suggesting,

> *"If these systems could sync up, it would make our work much smoother,"*

indicating that integrated systems would enhance workflow efficiency and data reliability. Participants A2, B1, and B3 expressed a clear preference for interoperable applications over standalone ones. B3 explained in more detail,

> *"I prefer apps that can work together instead of standalone ones because they make my job much easier. Instead of juggling multiple platforms, I can focus more on important tasks like analysing traffic patterns and planning patrols."*

This preference for interoperability underscores the need for cohesive systems that facilitate their workflow. Participant C3 added,

> *"Switching between different apps to get related data is a pain. Integrated systems let us see everything in one place and make better decisions."*

These collective insights underscore the value of user-friendly, integrated systems in their daily operations, enhancing their ability to perform their duties more effectively.

Their expectations for such interoperable features can be linked to several technology acceptance theories, such as the UTAUT's facilitating conditions (FC) factor, which is the unification of the IDT's "compatibility" and TAM's "perceived usefulness" factor (Rogers, 1962; Davis, 1986; Venkatesh *et al.*, 2003). The FC factor was defined as the degree to which an individual perceives that the organisational and technical infrastructure exists to support the system's use (Venkatesh *et al.*, 2003) and is measured by items such as:

- *"The system is compatible with other systems I use"(Venkatesh et al., 2003),*
- *"DHIS2 is compatible with other systems that I use at work" (Karuri, Waiganjo and Orwa, 2014).*

Therefore, the survey items were designed to measure the interoperability expectations among Jakarta traffic police. The interview results underscored the operational challenges and preferences for interoperable systems, further justifying the focus on interoperability expectations. These insights highlighted the importance of interoperability in their daily operations, justifying its further investigation in the survey.

This approach assumes that user expectations are crucial in the initial acceptance of new technology, as outlined in the UTAUT's facilitating conditions (FC) (Venkatesh *et al.*, 2003). The FC factor within the UTAUT framework combines the concepts of compatibility from the Innovation Diffusion Theory (IDT) (Rogers, 1962) and perceived usefulness from the Technology Acceptance Model (TAM) (Davis, 1986). It specifically addresses the degree to which individuals believe the necessary organisational and technical infrastructure is in place to support the system's use. This is particularly relevant for the Jakarta traffic police, as their work relies heavily on integrating and compatibility with various systems to manage traffic effectively.

Although the dashboard's prototype state limited the ability to measure actual interoperability, the survey attempts to capture the perceived importance of this feature among Jakarta traffic police officers to provide insights into user needs and priorities. The expectations gathered through the survey could provide a foundational understanding of what users require for the system to be deemed valuable and compatible with their existing workflows. While the survey does not measure the impact of unmet expectations on long-term adoption, it could provide a foundational understanding of user requirements, which is critical in the early stages of technology implementation and iterative development processes. Based on this purpose, the adopted survey items were adjusted to measure user expectations by utilising two items:

1. The dashboard should be able to communicate with other technologies I use (coded as questionnaire item inter1)

2. The dashboard should be able to share data with other technologies I use (inter2)

Since significant modifications were made to the adopted survey items to capture the expectations of the Jakarta traffic police, these survey items will be first analysed through Exploratory Factor Analysis (EFA), which will be explained in section 5.6.2.1. EFA will help explore and identify these modified items' underlying structures without predefined assumptions (Henson and Roberts, 2006; Worthington and Whittaker, 2006). After establishing the new factor structure through EFA, Confirmatory Factor Analysis (CFA) (which will be explained in section 5.6.2.2), which can confirm and validate the structure (Brown, 2015), will be performed. This two-step approach ensures that the modified items accurately measure the intended constructs and provide reliable results for the study (Byrne, 2016; Kline, 2023).

5.3.1.2 Social incentives

The interview results highlighted the role of recognition and social incentives in motivating the use of ICT among Jakarta traffic police participants. As defined by Nguyen-Van, Stenger and Tiet (2021), social incentives motivate individuals to adopt particular behaviours in alignment with social norms or intrinsic/extrinsic motivations. These incentives range from peers and superiors' recognition, appreciation, and respect. Participant B1's statement illustrated the impact of social recognition:

> *"I think social factors influence whether officers use ICTs or not, especially when commanders show appreciation or give recognition. When we know our efforts are noticed, it makes us want to keep using these tools."*

This highlights the importance of social validation and its impact on ICT engagement, reflecting the broader organisational culture where recognition from leadership can drive behavioural change. Similarly, Participant C2 remarked on the effect of acknowledgement from supervisors, stating,

> *"Acknowledging usage can boost ICT adoption because officers want recognition from the office. When our supervisors see and appreciate our use of ICT, it encourages us to engage more with these systems."*

This suggests that feedback mechanisms can enhance ICT adoption by fostering a sense of accountability and appreciation. Additionally, Participant D3 emphasised the role of respect, saying,

> *"Officers are motivated to use ICTs effectively to earn respect, show discipline and obedience. Knowing that our usage of these tools is acknowledged and valued can really motivate us."*

These insights suggest that fostering a supportive environment where ICT usage is regularly recognised and rewarded can significantly enhance adoption rates. The findings align with broader theories of organisational behaviour, which posit that recognition and social incentives are powerful tools for driving technological adoption (Vallerand, 2000; Venkatesh and Bala, 2008). The participants articulated how recognition and appreciation from their colleagues and superiors influenced their intention to use ICT tools. This finding underlines the role of social incentives in driving ICT usage within the Jakarta traffic police force.

Past studies have identified incentives as influential factors for the intention and usage of ICTs (Leonard-Barton and Deschamps, 1988; Compeau and Higgins, 1995; Compeau, Higgins and Huff, 1999; Taherdoost, 2018). These studies used questions such as:

- *If I use the system, I will increase my chances of being promoted*
- *If I use the system, I will increase my chances of getting a raise*

Therefore, the survey used two items to measure the social incentive factor:

1. If I use the dashboard, I will increase my chances of being appreciated (this survey question was coded as questionnaire item incen1)

2. If I use the dashboard, I will increase my chances of being recognised (incen2)

5.3.1.3 Social influence

Social influence was another factor identified in the participants' responses. Social influence theory, as articulated by Cialdini and Goldstein (2004), posits that individuals often conform to the behaviours and attitudes of their peers to gain acceptance and maintain social harmony. In the context of the Jakarta traffic police, this dynamic is particularly evident. Participant B3 provided an illustrative example, mentioning,

> *"I am more likely to use an ICT if my coworkers use it too because it makes me feel like part of the team. It is important for me to stay in sync with my team, and using the same tools helps us work better together."*

This reflects how peer usage of ICTs creates a normative environment encouraging others to adopt similar practices. Participant C1's statement further underscored this point, noting,

> *"If the organisation starts using ICT for our work, I think using it shows that we are disciplined and cooperative with the organisation. It shows that we are all on the same page and committed to our duties."*

This highlights the role of collective compliance in fostering a disciplined and cohesive work environment, indicating that social influence is not only about conformity but also about demonstrating collective responsibility and commitment to organisational goals.

These observations align with theories that posit social influence is a critical determinant of ICT adoption (Venkatesh *et al.*, 2003; Crawford *et al.*, 2020). The social dynamics within the Jakarta traffic police suggest that creating a culture of collective ICT usage can enhance overall adoption rates and improve the effectiveness of these technologies.

Despite limited interaction with the prototype, the survey's decision to measure social influence is grounded in the specific characteristics of the participants and supported by the technology adoption literature. Interviews with the Jakarta police revealed a tendency to align with their peers' use of ICTs, which fosters team cohesion and organisational discipline. This underscores the importance of social factors in their work environment, making assessing social influence crucial. According to the Technology Acceptance Model (TAM) and its extended version (TAM2), as discussed by Davis (1989) and Venkatesh and Davis (2000), perceived usefulness, ease of use, and subjective norms can be measured even from brief interactions. Similarly, Rogers' Diffusion of Innovations theory (1962) and Moore and Benbasat (1991) emphasise that early adopter opinions, even with limited use, are crucial to understanding adoption behaviours.

Social influence in technology acceptance often comes from perceptions and subjective opinions rather than fully established experiences. Studies such as

Ajzen's Theory of Planned Behaviour (Ajzen, 1991) show that subjective norms and perceived social pressures can be assessed in early stages or hypothetical scenarios (Venkatesh *et al.*, 2003; Venkatesh, Thong and Xu, 2012). Even with limited exposure, initial perceptions play a significant role in shaping adoption intentions, and the survey aimed to capture these early impressions, acknowledging that they may evolve. The literature supports the view that brief prototype interactions provide valuable insights into social influence, as early perceptions strongly predict future technology adoption behaviours (Venkatesh *et al.*, 2003; Cialdini and Goldstein, 2004; Venkatesh, Thong and Xu, 2012).

Past studies used survey items to measure social influence (Venkatesh *et al.*, 2003), such as:

- *People who are important to me think that I should use the system.*
- *People who influence my behaviour think that I should use the system.*
- *In general, my organisation will support the use of the system.*

Based on the literature, the survey utilised three items to measure the social influence factor:

1. People who are important to me think that I should use the dashboard (this survey question was coded as questionnaire item influ1)
2. People who influence my behaviour think that I should use the dashboard (influ2)
3. In general, my organisation will support the use of the dashboard (influ3)

5.3.1.4 Privacy concerns

The next factor relates to privacy concerns. Privacy concerns reflect users' worries about the privacy of their information and pertain to data protection against unauthorised access and breaches (Dinev, Hart and Mullen, 2008). These concerns can significantly influence users' trust in ICT systems and willingness to share data (Joinson *et al.*, 2010). Privacy is crucial in the public sector, where sensitive information is frequently handled. Some participants noted that continuous location tracking can make them feel uneasy and watched. Participant A1 explained this concern, stating,

> *"I worry about privacy when using applications if I know they have continuous location trackers that cannot be turned off. It feels like I am constantly being watched, which is pretty uncomfortable."*

This highlights the discomfort and lack of privacy control felt by the participants. A2 shared a similar sentiment, describing,

> *"GPS location tracking on devices makes me feel like I am being monitored, especially when it cannot be switched off. I get why it is needed sometimes, but it is not always necessary and can feel invasive."*

This statement underscores the importance of having control over privacy settings and the need for transparency regarding data usage. Some participants indicated they would use an application only if they were confident their privacy would be protected. Participant E3 emphasised,

> *"I would only use an application if I knew my privacy was guaranteed. Trusting that my personal information and location data are secure is essential for me to feel comfortable using these tools regularly."*

This highlights the need for robust privacy protections to ensure user confidence and willingness to adopt new technologies. Ensuring privacy and data security can significantly influence the acceptance and usage of ICT systems among the officers, emphasising that privacy is a fundamental concern that needs to be addressed by developers and implementers of these technologies.

It is worth noting that location tracking within the dashboard can also be seen as a positive feature for officer safety. Continuous tracking could provide effective monitoring and rapid response, especially in dangerous or remote situations (Ho, Silvers and Stainton, 2014), enhancing overall safety and support for traffic police. While privacy concerns are valid and must be addressed, the security benefits of location tracking may be valuable for officers, particularly in high-risk scenarios.

Despite these considerations, it was decided to include privacy concerns in the survey. This decision was made to examine its potential relationship with the behavioural intention to adopt the dashboard. Understanding how privacy concerns influence adoption behaviour will provide valuable insights into whether the discomfort associated with potential privacy invasions outweighs the benefits of safety and monitoring.

Several technology acceptance studies have identified the influence of privacy concerns on intention to use ICT (e.g., Zhou, 2011; Dhagarra, Goswami and Kumar, 2020; Trkman, Popovič and Trkman, 2021, 2023). These studies used questions such as:

- *I am concerned that unauthorised people may access my personal information; I am concerned that health centres may collect too much personal information (Dhagarra, Goswami and Kumar, 2020).*

- *I am concerned that the information I submit through the proximity tracing app could be misused; I am concerned that the developers or the proximity tracing application provider can find private information about me through the app (Trkman, Popovič and Trkman, 2023).*

- *It is risky to provide personal information to the system (Zhou, 2011).*

Based on the literature, two survey items were created to measure privacy concerns:

1. I am concerned that the dashboard may constantly track my location (this survey question was coded as questionnaire item priv1).

2. I am concerned that the dashboard may not guarantee my privacy (priv2).

5.3.1.5 Demographic

The questionnaire also requested demographic information from participants, namely age, working experience, and educational background, since they have been utilised in most technology adoption studies as control variables and can provide insights about the survey participants (Damanpour and Schneider, 2006; Rana, D Williams and Kumar Dwivedi, 2012; Rana, Dwivedi and Williams, 2013; Rehouma and Hofmann, 2018). Since Jakarta patrol police officers are all male. The Jakarta traffic police’s administrative office informed that this gender demographic is expected in the Indonesian police on duties that require night shifts unless they have a limited number of male officers. Therefore, the survey did not incorporate a gender variable in the questionnaire.

5.3.2 User-experience variables

The interview results revealed that several factors that the police perceive would motivate them to use ICT, such as the dashboard, are related to user experience. It has been suggested that technology acceptance theories, which primarily focus on the relationship between information systems and user performance, are inadequate for capturing contextual factors and user experiences influencing technology adoption (Mosweu and Bwalya, 2018; Rehouma and Hofmann, 2018; Graeber *et al.*, 2023). Integrating user experience perspectives can provide a more comprehensive understanding of factors affecting technology acceptance and user experience (Hornbæk and Hertzum, 2017; Graeber *et al.*, 2023).

Recent studies also suggest including user experience (UX) factors to measure satisfaction with ICT, as UX has been found to positively influence technology adoption (Hornbæk and Hertzum, 2017; Mlekus *et al.*, 2020; Pallot *et al.*, 2020). UX evaluation models, such as the Modular Evaluation of Key Components of User Experience (meCUE), Attractive Differential (AttrakDiff) perceived attractiveness measurement, and the User Experience Questionnaire (UEQ), have been used in human-technology interaction studies to assess user experience in government ICT applications (Lallemand and Koenig, 2017; Forster *et al.*, 2018; Baumgartner, Sonderegger and Sauer, 2019; Díaz-oreiro *et al.*, 2019; Diáz-Oreiro *et al.*, 2021). While traditional technology acceptance models focus on usability, efficiency, and effectiveness (Davis, 1986; Hassenzahl, Burmester and Koller, 2003; Venkatesh *et al.*, 2003; Venkatesh, Thong and Xu, 2012), UX looks at the whole user experience to identify elements that contribute to positive interaction (Hassenzahl, Diefenbach and Göritz, 2010). Considering both perspectives provides a complete understanding of the factors influencing technology acceptance and user satisfaction (Hornbæk and Hertzum, 2017; Mlekus *et al.*, 2020).

The following sections describe the interview analysis results and their corresponding survey questionnaire items regarding UX factors such as Innovative technology, Leading-edge technology, Speed, and Supportive functionality. However, while most technology acceptance studies use advanced statistical methods such as Structural Equation Modelling (SEM) (Rehouma and Hofmann, 2018; Alwabel and Zeng, 2021), most UX theories use summary statistics to obtain simple and immediate results of user experience (Laugwitz, Held and Schrepp, 2008; Forster *et al.*, 2018; Díaz-oreiro *et al.*, 2019; Schrepp, 2019), such as an interface's overall satisfaction, appeal, or perceived quality (Hassenzahl and Tractinsky, 2006). A few studies incorporating UX factors to examine ICT adoption have also shown different outcomes (e.g., Deng *et al.*, 2010; Mlekus *et al.*, 2020; Idkhan and Idris, 2023). Therefore, this inconsistency in the literature necessitates an additional exploratory factor analysis before the UX variables are included in this study's adoption intention examination, which will be described in section 5.6.2.1 to ensure robustness. Finally, all the UX variables will be measured using a 7-point semantic differential scale, which is the commonly used measurement in user experience studies (Schrepp, 2019; User Interface Design GmbH, 2022).

5.3.2.1 Innovative technology

Innovative technology, which refers to the intentional introduction and application of new ideas, processes, products, or procedures designed to benefit individuals, groups, or society significantly (Oberender *et al.*, 1999), emerged as a motivating factor for ICT usage among participants. The appeal and impact of adopting ICT tools and applications that offer novel features and capabilities can significantly improve operational efficiency and effectiveness (Wells *et al.*, 2010; Bibri and Krogstie, 2017b). Participant B1 expressed his personal preference for innovative technologies, stating,

> *"I am always interested in trying out innovative ICTs. For instance, today's virtual and augmented reality technologies keep me engaged. These technologies offer new ways to visualise data and interact with information, which can be very exciting and useful in our work."*

This enthusiasm for new technologies indicates a proactive approach to embracing tools that can potentially enhance their operational effectiveness. C2 echoed this sentiment, adding,

> *"In my opinion, innovation is a sign of good ICT. It shows that the developer is creative and trying to provide better solutions. Innovative tools often have features that solve problems more effectively and make our tasks easier."*

This statement underscores the practical benefits of innovative ICTs, suggesting that officers appreciate technologies that introduce novelty and improve task efficiency and problem-solving capabilities.

These findings suggest that promoting innovative technologies within the police force can drive greater ICT adoption. Encouraging officers to experiment with and provide feedback on new technologies can foster a more engaged and forward-thinking workforce. Innovative technology can be related to the UEQ's novelty factor, which encompasses innovation, leading edge, and several other dimensions (Laugwitz, Held and Schrepp, 2007). The survey adopted a UEQ question to investigate innovativeness using seven-point semantic differential scales. A preface was given to ensure clarity and consistency in responses to the scale item, accounting for variations in understanding innovation concepts based on individual perspectives and assessment context (Wells *et al.*, 2010). The following question was used in the survey:

> *Please evaluate the dashboard that you have tried. I think the dashboard is:*
>
> *Innovative* >< *conservative (coded as "innov")*

5.3.2.2 Leading-edge technology

"Leading edge" emerged as another factor perceived by the police that would motivate them to use ICT for work. This theme emphasises the importance of staying at the forefront of technological advancements to maintain competitive advantage and operational efficiency. While similar to innovative technology, leading-edge technology refers to adopting the most advanced and sophisticated technological solutions at a given time (Pech, 2015; Abdullah, 2023), while general innovation can be either incremental (improving existing systems) or disruptive (creating entirely new paradigms) (Charmsaz *et al.*, 2018).

Participant A2 highlighted the necessity of adopting the latest technologies, stating,

> *"In today's fast-paced world, staying updated with leading-edge technologies is beneficial. It ensures that we are using the most efficient and effective tools available, which can make a significant difference in our performance."*

This statement underscores the perceived operational advantages of using the latest technologies, suggesting that staying current is crucial for maintaining high performance.

C2 further illustrated the practical benefits, noting,

> *"Leading-edge ICT like Google Workspace constantly adds new features. It helps my work processes a lot. These frequent updates mean we always have access to the latest tools and functionalities, which keeps us ahead."*

E2's preference for leading-edge ICT applications, such as Tokopedia[2], further exemplifies this point.

> *"Using leading-edge platforms that are always improving ensures that we do not fall behind as technology moves forward,"*

This statement reinforces the idea that access to leading-edge technology is about current capabilities and futureproofing the organisation against technological obsolescence. While both themes highlight the importance of advanced technology, innovative technology focuses on new tools' novelty and problem-solving capabilities, whereas leading-edge technology emphasizes continuous improvement and staying updated with the latest advancements.

These findings suggest that emphasising innovative and leading-edge technologies can motivate officers to adopt new ICT systems. Highlighting how these tools can enhance their efficiency and effectiveness, whether through novel features or staying ahead of technological trends, can further drive adoption rates. Therefore, the survey utilised the following item adopted from UEQ (Laugwitz, Held and Schrepp, 2007):

> *Please evaluate the dashboard that you have tried. I think the dashboard is:*
>
> *Leading-edge* >< *common (lead)*

[2] Tokopedia is an e-commerce in Indonesia (www.tokopedia.com)

5.3.2.3 Speed

Speed emerged as another factor in motivating ICT usage among participants. The police mentioned that fast ICT systems could support the rapid pace and immediate demands of police work. Participant B1 elaborated on this point, stressing,

> *"The speed of application loading is crucial because it should not take too long to get information. We need to access data quickly, especially in critical situations where every second counts."*

This comment underscores the operational importance of fast ICT systems, particularly in time-sensitive scenarios. A1 reinforced this view, asserting,

> *"(ICT) must be fast and responsive. Slow applications can mess up our efficiency and ability to do our jobs well."*

This highlights how slow systems can negatively impact productivity and job performance, suggesting that speed is critical to user satisfaction. Expanding on the speed factor, D3 remarked,

> *"Slow applications can be frustrating and slow us down when we need to act fast. When the system lags, it can delay our response times, which is not preferable in our work."*

This perspective underscores ICT speed's tangible impact on operational effectiveness, highlighting how delays can affect their ability to respond promptly to incidents. Participant E2 emphasised the critical nature of speed in emergencies, noting,

> *"Quick access to information is crucial during our duties, and slow ICT can be a real problem. In emergencies, delays from slow systems can have serious consequences."*

This highlights the potential risks of slow systems in emergency scenarios, where timely information access is critical. B2 added further context, stating,

> *"Fast-loading ICT applications also reduce downtime during traffic stops and help us serve the public more efficiently. Quick systems let us complete our checks and processes without unnecessary delays, which improves overall service delivery."*

This perspective expands the discussion to encompass the broader implications of speedy ICT usage, suggesting that fast systems can enhance public service and operational efficiency. Based on these findings, the survey utilised the speed factor item as one of the measurements of ICT user experience, which was adopted from the UEQ (Laugwitz, Held and Schrepp, 2007).

> *Please evaluate the dashboard that you have tried. I think the dashboard is:*
>
> *Fast >< slow (speed)*

5.3.2.4 Supportive functionality

Supportive functionality was a significant factor for the participants, indicating the importance of ICT systems that actively aid their daily tasks. A supportive ICT system is one that not only provides the necessary tools and information but also enhances the ability to perform duties effectively and efficiently (Goodhue and Thompson, 1995). Participant B1 provided an illustrative example, stating,

> *"ICTs, including a dashboard, should support my daily tasks. For example, the ICT should effectively visualise and share information I need with my colleagues. It needs to do more than just store data; it should help us in our work."*

This highlights the expectation that ICT systems should actively contribute to task performance, not just passively store information. B2 discussed the conditionality of their ICT usage, explaining,

> *"I am more likely to use an ICT if it really supports my job, especially in meeting my specific information needs. It becomes an essential tool if the system can help me track incidents more efficiently or provide real-time updates."*

This underscores the importance of tailored ICT systems to meet specific job requirements, enhancing their practical utility. Participants consistently acknowledged the pivotal role of supportive ICTs in the decision-making process. B3 noted,

> *"With a supportive ICT, I can more efficiently identify potential crash locations, which helps me allocate resources better. This capability is crucial for making data-driven decisions and optimizing our patrol strategies."*

This illustrates how supportive ICTs can enhance strategic decision-making by providing relevant and timely information. D3 emphasised this point, saying,

> *"I am more likely to use ICT if it supports my decision-making. For instance, it can give valuable insights into crash locations and summary statistics when I am planning patrols. These insights help us be more proactive and effective in our actions."*

Here, the participant emphasises the role of supportive ICTs in enhancing decision-making, mainly where timely and precise information is critical. Given the emphasis on the need for ICTs to be supportive, it was included as a survey item. The supportiveness item was adopted from UEQ:

> *Please evaluate the dashboard that you have tried. I think the dashboard is:*
>
> *Supportive >< obstructive (support)*

5.3.3 Dependent variable: behavioural intention to use the dashboard

The dependent variable of this quantitative phase was the behavioural intention (BI) to adopt the dashboard. BI refers to an individual's expressed likelihood or intention to engage in a specific behaviour or action in the future (Fishbein, 1979). BI is not directly measurable and has been treated as a latent construct and measured using several indicators (observed variables) in past studies (e.g., Venkatesh *et al.*, 2003; Venkatesh, Thong and Xu, 2012; Al Nidawy *et al.*, 2020; Nunes *et al.*, 2022). The BI items in the survey were adopted from the UTAUT, only changing "the system" to "the dashboard":

1. I intend to use the dashboard for patrolling allocation (bi1)

2. I predict I would use the dashboard for patrolling allocation (bi2)

3. I plan to use the dashboard for patrolling allocation (bi3)

5.3.4 Cognitive interviewing

This study used cognitive interviewing, a method to evaluate survey questionnaire comprehension for content validity, which is essential for accurate measurement of the intended construct (Drennan, 2003; Beatty and Willis, 2007; Schuler, Lenzi and Yount, 2011; Almanasreh, Moles and Chen, 2019; Aronson *et al.*, 2021). This method involves individuals offering verbal feedback on draft survey questions, explaining their cognitive processes and identifying potential response errors, thereby ensuring the validity of the questions (Drennan, 2003; Willis and Artino, 2013). Since the 1980s, cognitive interviewing has become widely accepted in academic, governmental, and commercial research organisations for its effectiveness in identifying and addressing issues in survey questions, particularly in understanding, responding to, and interpreting questions, especially on complex or sensitive topics (Drennan, 2003; Beatty and Willis, 2007; Sousa, Matson and Lopez, 2016; Goldenhar, Schwatka and Johnson, 2019).

The cognitive interviewing process usually occurs in three stages (Dillman, 2007):

1. Key Informant Interviews: Experts or individuals knowledgeable about the survey's topic provide initial feedback on the draft, identifying potential issues such as ambiguity or sensitive content (Beatty and Willis, 2007).

2. Cognitive Interviews: A revised draft is presented to a small group of participants based on the initial feedback. The focus is on understanding participants' interpretation of the questions and any areas of confusion or misinterpretation (Presser *et al.*, 2004; Willis and Artino, 2013).

3. Pilot Testing: After refining the survey through cognitive interviews, the final version is assessed with a representative sample from the target population. This step ensures the survey's effectiveness and validity. If issues arise during this stage, the questionnaire is further revised before a full-scale deployment (Bryman, 2012).

Ten Jakarta traffic police leaders from the previous requirement elicitation phase agreed to participate in the cognitive interviews conducted online via Zoom application. The sessions ranged from 45 minutes to one hour. They were invited to participate as key informants who understood the context of patrolling allocation. It was expected that they could reflect how the participants in the actual survey interpreted the questions.

Five Indonesian PhD students at UK universities were also invited to help identify possible misunderstandings in the survey translation by presenting them with the survey questionnaires with both the original English and the Indonesian translated survey. The inclusion decision was made because translation quality literature frequently highlights the need to engage bilingual persons with proficiency in both languages to guarantee precise translation and mitigate potential linguistic challenges (Brislin, 1970; Tsai *et al.*, 2023). The students were asked about the clarity and were explained that several items of the survey questionnaire were derived from theories originally in English (Davis, 1986; Venkatesh *et al.*, 2003; Laugwitz, Held and Schrepp, 2007).

Since the survey participants' native language is Indonesian, the questionnaire was translated into "Bahasa Indonesia" (Indonesian language). The survey items regarding interoperability expectations, privacy concerns, social influence, and social incentives derived from the technology acceptance theories adopted the questions' wording of existing studies that employed these theories in Indonesian (e.g., Wang, 2016; Yumami, Budiyanto and Suyoto, 2018; Silaban *et al.*, 2023). On the other hand, UX-related questions, such as innovativeness, leading edge, speed, and supportiveness items, used official translations provided by the original theory developers and are available for download on their website (Schrepp, 2019).

A thinking-aloud procedure was employed for the cognitive interviews, where the participants were asked to read the survey items individually and then told the researcher what they thought the questionnaire meant (Willis, 1999). The researcher asked participants to verbalise their thoughts while expressing their interpretations of survey questions (e.g., *"Tell me what you are thinking... how did you arrive at this answer?"*). These verbalisations provided valuable insights into the thought processes behind the participants' responses from their understanding of the questionnaire items.

During the sessions, the researcher engaged in discussions with the participants, incorporating their suggestions. Seven participants suggested translating all the survey buttons and pop-up messages into Indonesian. Two participants suggested using phrases "at work" and "work-related technologies" in several questions, such as "this dashboard should be able to communicate with other <u>work-related</u>

technologies I use" and "people who are important to me at work think that I should use the dashboard" to avoid confusion. These suggestions were applied to these items:

1. This dashboard should be able to communicate with other work-related technologies I use (inter1)

2. This dashboard should be able to share data with other work-related technologies I use (inter2)

3. People who are important to me at work think that I should use the dashboard (influ1)

4. People who influence my behaviour at work think that I should use the dashboard (influ2)

5. If I use the dashboard, I will increase my chances of being appreciated at work (incen1)

6. If I use the dashboard, I will increase my chances of being recognised at work (incen2)

One participant suggested employing reverse wording for several items to enhance response robustness, such as reversing "If I use the dashboard, I will increase my chances of being recognised" to "If I use the dashboard, I will decrease my chances of being recognised". However, this recommendation was not implemented due to potential negatives, such as response biases where responders can misunderstand the negatively phrased items and the survey measures' internal consistency reliability is reduced (Barnette, 2000; Sauro and Lewis, 2011; van Sonderen, Sanderman and Coyne, 2013).

Finally, a pilot survey was conducted with the ten police participants. This pilot survey was expected to ensure understanding and alignment of the survey items with the study objectives. The participants were requested to take the survey to assess the difficulty level in answering the questions and determine the approximate time needed to complete the test. All participants completed the survey without any issues, and it took an average of seven to ten minutes. The complete survey questionnaire items are in Appendix C.

5.4 Developed hypotheses

The hypothesis development in this research integrated insights from interviews with Jakarta traffic police leaders and the factors from established technology acceptance and user experience theories. This approach offers a contextual understanding of ICT adoption in this research context. Based on these insights, the subsequent survey established hypotheses that the perceived ICT usage motivation factors and demographic characteristics of Jakarta traffic police officers influence their behavioural intention to adopt the dashboard, as depicted in Figure 5.2.

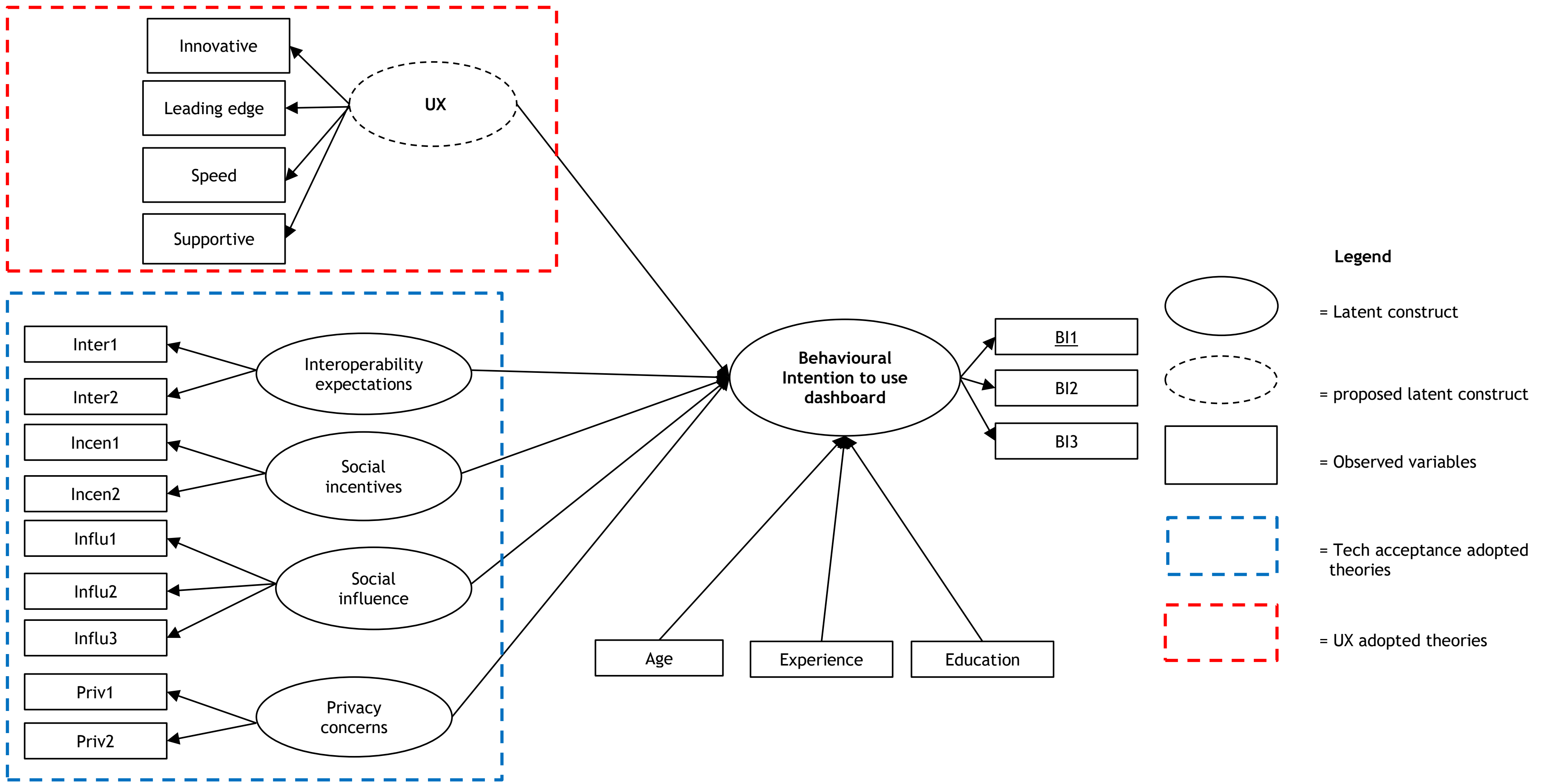


Figure 5.2 Research hypotheses

5.5 Survey data collection

After the hypotheses are established, this phase collects data through a survey, which employs standardised questionnaires to easily compare and collect detailed information on targeted subjects (Trochim and Donnelly, 2001; Nakash *et al.*, 2006; Roopa and Rani, 2012). This method is cost-effective for large population data collection, supports the analysis of various variables, and helps identify trends (Burns, 2000; Verschuren, 2003; Saunders, Lewis and Thornhill, 2009; Bryman, 2012; Pickard, 2013). The questionnaire used in this study was designed to gather demographic and perceptual data regarding the dashboard for patrol allocation, as depicted in Figure 5.2. Responses were collected using a seven-point Likert scale and a semantic differential scale for dashboard evaluation. A detailed version of the questionnaire is provided in Appendix C, which outlines the complete set of questions used to ensure comprehensive data collection and analysis. The following sections describe the sampling approach, sample size estimation, survey distribution, and data preparation.

5.5.1 A priori sample size estimation

Sampling in social science research, a process of selecting a subset of a population for practical and economic reasons, facilitates understanding group behaviour and inferring broader population characteristics from the sample (Kumekpor, 2002; Bhattacherjee, 2012). The chosen sampling strategy should match the research objectives and nature of the investigation, focusing on selecting individuals who can provide meaningful responses to the study questions (Matthews and Ross, 2010; Blaikie and Priest, 2017). This phase's survey was intended to investigate whether the perceived motivation factors can be generalised within the context of the whole population of 2,181 officers of Jakarta traffic police who deal with patrolling activities.

The survey data was analysed using a Structural Equation Modelling (SEM) method, which will be explained in section 5.6. This section outlines the method for calculating the necessary sample size for SEM, emphasising the importance of sufficient sample size or power for identifying genuine relationships (Cohen, 1988; Westland, 2010; Tabachnick, Fidell and Ullman, 2013; Wolf *et al.*, 2013). Standard SEM guidelines suggest a minimum of 200 participants (Boomsma, 1982; Barrett,

2007) or ten observations per variable (Westland, 2010). However, it has been observed that many SEM studies, while adhering to this standard, neglected to predetermine the minimum effect size they aimed to detect, leading to inadequate sample sizes (Westland, 2010).

This study phase targeted a minimum sample of 200 participants and calculated the necessary number based on the model with nineteen observed and six latent variables. Cohen's statistical power analysis (Cohen, 1988; Westland, 2010) guided the a priori sample estimation method. This approach involves two lower constraints on sample size in SEM: one based on the ratio of indicator variables to latent variables and the other considering minimal effect, power, and significance. Equation 1 describes the lower bound sample size for a structural equation model:

$$n = (n_1, n_2) \tag{1}$$

$$n_1 = \left\lceil 50\left(\frac{j}{k}\right)^2 - 450\left(\frac{j}{k}\right)^2 + 1100 \right\rceil$$

$$n_2 = \left\lceil \frac{1}{2H}\left(A\left(\frac{\pi}{6} - B + D\right) + H + \sqrt{\left(A\left(\frac{\pi}{6} - B + D\right) + H\right)^2 + 4AH\left(\frac{\pi}{6} + \sqrt{A} + 2 - C - 2D\right)}\right)\right\rceil$$

$$A = 1 - \rho^2$$

$$B = \rho\arcsin\left(\frac{\rho}{2}\right)$$

$$C = \rho\arcsin(\rho)$$

$$D = \frac{A}{\sqrt{3 - A}}$$

$$H = \left(\frac{\delta}{z_{1-a/2} - z_{1-\beta}}\right)^2$$

Where:

- j = number of observed variables
- k = number of latent variables
- ρ = estimated Gini correlation for a bivariate normal random vector
- δ = anticipated effect size
- α = Sidak-corrected Type I error rate
- β = Type II error rate
- z = a standard normal score

$$F(x;\, \sigma^2) = \frac{1}{2}\left[1 + \text{erf}\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)\right] \qquad 2$$

Equation 2 calculates the z score by using the Cumulative Distribution Function (CDF) of the normal distribution using the mean (μ) and standard deviation (σ) of a distribution.

$$\text{erf}(x) = \frac{2}{\sqrt{\pi}} \int_o^x e^{-t^2} dt. \qquad 3$$

Where:

- μ = mean
- σ = standard deviation
- erf = error function

The error function in Equation 3 calculates the CDF of a normal distribution.

Equations 1, 2, and 3 provided the calculations for SEM's appropriate sample size based on the number of latent variables, observed variables, statistical significance, statistical power level, and anticipated effect size. These formulae allow researchers to estimate the minimum sample size required for their SEM analysis based on several variables, including the number of observed and latent variables, the Gini correlation, the expected effect size, the significance level (α), and the intended power (1 - β). The formula incorporates the ratio of observed to latent variables and the intended effect size to determine the sample size necessary for obtaining reliable results in SEM analysis, considering the Type I and Type II error rates.

The statistical significance/ alpha (α) was set at 0.05, initially proposed by Fisher (1936) and has been widely adopted in statistical practices in social sciences. The statistical power level was set at 0.80, which is commonly accepted in statistics and considered adequate (Cohen, 1988; Maxwell, Kelley and Rausch, 2008; Field, 2013). In other words, this quantitative study wished to have no less than an 80% chance of detecting a medium-sized effect if one is to be detected.

Despite the lack of a universally accepted definition for "small," "medium," and "large" effect sizes, the researcher calculated the minimum sample size using Cohen's (1988) proposed conventions based on Cohen's d, a standardised measure of effect size:

- Small Effect: Cohen's d = 0.20
- Medium Effect: Cohen's d = 0.50
- Large Effect: Cohen's d = 0.80

Cohen (1992) also suggested choosing an effect size that is neither too small nor too large for practical purposes. Using Equations 1, 2, and 3, with the survey's six hypothesised latent and nineteen observed variables, the minimum sample size determined by the lower bound size formulae was 177 for detecting large-size effects and 403 for small-size effects. These numbers were considered when running the survey.

5.5.2 Survey distribution

The survey was conducted online, which was preferred by the Jakarta traffic police administrative office. The office also helped distribute the survey questionnaire to the respondents. The links to the survey and the dashboard prototype were sent to Jakarta's traffic patrol police's administration office for distribution to their officers. The administrative office, which had previously facilitated interviews on the requirement elicitation phase, was requested to circulate the survey link to 2,181 officers. The survey was conducted online through the Qualtrics application provided by the University of Glasgow. It provides automatic response collection in a database, offering advantages like ease of administration and cost-effectiveness (Wright, 2006; Bryman, 2012; Qualtrics, 2021).

The survey process was deployed on March 14th 2022. During the survey, the number of responses received was reported weekly to the administrative office, requesting them to send reminders. Finally, the survey ended on May 26th, 2022, when no new responses were received in several days. The final number of respondents was 714, constituting 32.7% of the target population.

5.5.3 Survey data preparation

The survey's data was prepared after being collected. This step involved retrieving the dataset from Qualtric's online survey platform. Initially presented in CSV format, the dataset was scrutinised to identify potential anomalies. During the examination, several irregularities were identified. Notably, the age column exhibited three observations over 100 years old, while an additional response indicated an age of merely two. These observations were deleted.

In addition, a discrepancy was noted in the working experience duration column. It can be assumed that the participants entered the year they started rather than the total years of experience. There were three observations with 1990, 2004, and 2006 inputs. These discrepancies were rectified by subtracting 2023 (the survey year) from these numbers. The survey items were formatted as ordinal variables.

5.6 Analytical methods: Covariance-Based Structural Equation Modelling (CB-SEM)

This section details the analytical methods of the survey data. The initial stage is a descriptive analysis, which provides a basic understanding and summary of the main characteristics of the dataset. The second stage uses an inferential statistical method to investigate the relationship between ICT usage motivation and demographic factors and the behavioural intention to adopt the dashboard among Jakarta traffic police officers.

The perceived motivation factors for ICT usage were formed as latent variables or constructs. Latent constructs refer to conceptual or theoretical structures that are not immediately observable but are believed to have an impact or provide an explanation for the observed variables (Marsh *et al.*, 2014; Velez *et al.*, 2016). Latent constructs can represent complex and abstract concepts such as intelligence, personality attributes, and attitudes (Hidayat and Wulandari, 2022).

Due to the latent constructs' utilisations, this study employed Structural Equation Modelling (SEM). SEM with latent constructs has two parts: measurement and structural model (Jöreskog, Sörbom and Magidson, 1979). SEM provides a comprehensive framework for estimating measurement models (how observed variables measure latent constructs) and structural models (how latent constructs relate to each other) simultaneously in one analysis (Anderson and Gerbing, 1988; Marsh *et al.*, 2014; Black and Babin, 2019; Kline, 2023).

Generally, there are two types of SEM: partial least squares (PLS-SEM) and covariance-based (CB-SEM). PLS-SEM is commonly used for prediction and theory development (Hair, Ringle and Sarstedt, 2013). Meanwhile, CB-SEM is more suited for testing and confirming theories and hypotheses (Reinartz, Haenlein and Henseler, 2009; Lowry and Gaskin, 2014). This study used a CB-SEM because the survey hypotheses used questions derived from technology acceptance and user experience studies.

The SEM's model fit was evaluated to determine whether the proposed model adequately represents the observed data (section 5.6.4). Several widely adopted fit indices and measures were utilised to assess the fit of SEM models, such as Chi-square, Root Mean Square Error of Approximation (RMSEA), Goodness of Fit index and its adjusted version (GFI and AGFI), Comparative Fit Index (CFI), Normed Fit Index, Incremental Fit Index (IFI), Tucker-Lewis Index (TLI), SRMR (Standardized Root Mean Square Residual), and WRMR (Weighted Root Mean Square Residual).

The SEM model's reliability and validity were also assessed (section 5.6.5). Reliability tests measure the consistency of measurements, verifying how well the observed variables/ indicators measure their respective latent constructs. Meanwhile, the validity tests confirm if measurements accurately represent constructs. These tests ensure that the chosen indicators or measurement items are valid representations of the latent constructs they reflect.

All analytical methods in this quantitative phase are conducted with the Lavaan package in the R programme (Rosseel, 2012; R Core Team, 2021). This package facilitated complex statistical computations, including SEM. Integrating the Lavaan package with R provided a flexible and efficient environment for data manipulation, visualisation, and reproducibility of results.

5.6.1 SEM with ordinal data: DWLS parameter estimator and polychoric correlation

In SEM, a parameter estimator is a statistical method used to estimate the relationships specified in the model (Cepeda-Carrion, Cegarra-Navarro and Cillo, 2019). The choice of an appropriate estimator is crucial for accurate and reliable SEM results (Wang and Rhemtulla, 2021). Based on the observed data, these estimators calculate the model's parameters, such as factor loadings, regression weights, variances, and covariances. In this study, where the outcome variable BI (behavioural intention) was measured in Likert ordinal scales, the appropriate parameter estimator is the Diagonally Weighted Least Squares Mean-Variance (DWLS) using polychoric correlation (Li, 2015).

The mechanisms of SEM with DWLS can be described as follows (Olsson, 1979; Muthén, 1984): The polychoric correlation technique is utilised to analyse the correlations between pairs of ordinal observed variables, taking into account their ordinal nature and their link to latent variables' continuous distribution. The size of the polychoric correlation matrix is determined by the count of observed variables, e.g., a model with three observed variables results in a 3x3 matrix. Values within this matrix vary continuously from -1 to 1, offering insights necessary for the DWLS estimator to weigh the ordinal variables accurately.

The polychoric correlation, as described above, can be calculated as follows:

$$P(X\_i, Y\_j) = \Phi(r\_X_i + 0.5, r\_Y_j + 0.5) - \Phi(r\_X_i - 0.5, r\_Y_j + 0.5) - \Phi(r\_X_i + 0.5, r\_Y_j - 0.5) + \Phi(r\_X_i - 0.5, r\_Y_j - 0.5) \quad 4$$

Equation 4 represents the estimated joint probability of observing two specific ordinal or categorical values, X_i and Y_j. The values X_i and Y_j are assumed to be derived from underlying continuous latent variables and are estimated based on the Cumulative Distribution Function (CDF) of the standard normal distribution (Φ).

$$p(X_i) = \Phi\left(r_{X_i} + 0.5\right) - \Phi\left(r_{X_i} - 0.5\right), p(Y\_j) = \Phi(r\_Y_j + 0.5) - \Phi(r\_Y_j - 0.5) \quad 5$$

Equation 5 calculates the estimated marginal probabilities of observed ordinal or categorical values, X_i and Y_j, respectively. These probabilities are based on the CDF of the standard normal distribution to estimate the polychoric correlation.

$$p\left(X_i, Y_j\right) = p(X_i) * p\left(Y_j\right) \quad 6$$

Equation 6 calculates the expected joint probability of observing X_i and Y_j under the assumption of independence between the underlying continuous latent variables corresponding to X and Y. It is computed as the product of the estimated marginal probabilities $p(X_i)$ and $p(Y_j)$.

$$L = \Sigma \left[X_{ij} * ln\left(P\left(X_i, Y_j\right)\right) + \left(1 - X_{ij}\right) * ln\left(1 - P\left(X_i, Y_j\right)\right)\right] \quad 7$$

The log-likelihood function (equation 7) is used in the context of polychoric correlation to assess the fit of the observed data to the estimated joint probabilities ($P(X_i, Y_j)$) and the expected joint probabilities under the independence assumption ($P(X_i, Y_j)$). It measures how well the estimated probabilities align with the observed data.

5.6.2 Measurement model: Exploratory and Confirmatory Factor Analysis (EFA and CFA)

The measurement model in SEM provides a framework for how observed variables are used to define latent constructs within the theory of measurement (Bollen, 1990; Hair, Ringle and Sarstedt, 2013). In a measurement model, factor analysis is used to identify relationships between latent constructs and their observed variables by uncovering the underlying structure of these variables and their interrelationships (Fabrigar *et al.*, 1999). The factor analysis determines the scores of the measurement instrument for each observed variable and evaluates the potential constructs intended to measure the latent constructs (Byrne, 2013).

Two primary types of factor analysis are Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA), each serving distinct purposes (Thompson, 2004). EFA is employed when researchers have no predetermined assumptions about the relationships between observed variables (Fabrigar *et al.*, 1999). On the other hand, CFA is used when researchers have specific a priori assumptions regarding the factor structure, which refers to the underlying relationships between proposed constructs and their associated observed indicators (Byrne, 2005).

5.6.2.1 Exploratory factor analysis

Exploratory Factor Analysis (EFA) is a statistical method that aims to explore the factor structure of variables and uncover latent constructs within the data by identifying underlying structures in a set of observed variables (Fabrigar *et al.*, 1999; Hair, Ringle and Sarstedt, 2013; Henseler, Ringle and Sarstedt, 2014; Watson, 2017). This study used EFA to analyse the survey items adopted from the User Experience Questionnaire (UEQ) theory: innovativeness, leading edge, speed, and supportiveness. In UEQ, these variables fall under different UEQ quality classifications. The first group is Hedonic (Non-instrumental) Quality, where “leading edge” and “innovative” are in its Novelty sub-group. The second group is Pragmatic/ Instrumental Quality, where “speed” is in the Efficiency sub-group and “supportive” is in the Dependability sub-group (Laugwitz, Held and Schrepp, 2008). Given the overlapping quality groups of these components, it was necessary to uncover their factor structures within the data before they could be analysed in the subsequent CFA and SEM.

In addition, due to the fundamental modifications of the survey items aimed at understanding the interoperability expectations of the respondents, the items were included in the EFA. This inclusion was necessary to ensure that the modified items accurately measure the intended constructs and provide reliable results for the study (Byrne, 2016; Kline, 2023). The results from the EFA will uncover the underlying factor structure of these modified items, illustrating how well they group to measure the intended constructs (Fabrigar and Wegener, 2011; Costello and Osborne, 2019). These insights will then inform the subsequent CFA, confirming and validating the identified factor structure (Brown, 2015). This approach ensures the constructs' robustness and the measurement model's soundness, providing a solid foundation for the overall research (Black and Babin, 2019).

In EFA, choosing a correct rotation method is crucial to simplifying the factor loading matrix and improving factor interpretation. Rotation methods can be broadly categorised into orthogonal and oblique types (Rennie, 1997). Based on the assumption of uncorrelated factors, orthogonal rotations like Varimax are apt for theoretically independent constructs, maximising variance to clarify factor-item relationships (Richman, 1986). On the other hand, oblique rotations such as Promax consider factor correlations, which align with theories that propose interconnected constructs (Finch, 2006; Zhang *et al.*, 2019). Promax, merging an orthogonal rotation with obliqueness, is preferable for strongly correlated factors, whereas Direct Oblimin is effective for moderately correlated factors (Fabrigar *et al.*, 1999).

A preliminary correlation analysis informed the selection of the oblique rotation method for this study. Given that the correlations in the matrix ranged from moderate to high (0.55 to 0.76), Promax was determined to be the most suitable rotation method for this study’s EFA, catering effectively to the observed level of factor correlations. The EFA is calculated as follows (Jöreskog, Sörbom and Magidson, 1979):

$$Y = \lambda F + \delta + \varepsilon \tag{8}$$

Where:

- Y: A matrix (n x p) of observed variables, where n is the number of observations and p is the number of observed variables.

- Λ (Lambda): matrix (p x k) of factor loadings, where k is the number of latent factors.
- F: A matrix (n x k) of latent factors.
- δ (Delta): A matrix (n x p) of unique variances or thresholds for categorical items (relevant when working with categorical data).
- ε (epsilon): A matrix (n x p) of error terms.

Equation 8 describes the factor model ($Y = \Lambda F + \delta + \varepsilon$), which represents the relationship between the observed variables (Y), the estimated factor loadings (λ), the latent factors (F), unique variances or thresholds (δ), and the residual error terms (ε). The goal of EFA is to estimate the factor loadings (λ) and the latent factors ('F') in a way that best explains the observed data ('Y') while minimising the error terms (ε) and accounting for unique variances (δ).

5.6.2.2 Confirmatory factor analysis

CFA was conducted subsequently. CFA is a specific SEM form primarily concerned with examining and validating a proposed measurement model with latent constructs (Ullman, 2006; Zvolensky *et al.*, 2007; Sass, Schmitt and Marsh, 2014). CFA is particularly relevant when researchers aim to verify the factor structure of a measure and examine its reliability and validity (DiStefano and Hess, 2005). CFA was employed because several constructs in the survey items have been identified and defined in past studies, such as TAM and UTAUT (Davis, 1986; Compeau, Higgins and Huff, 1999; Venkatesh *et al.*, 2003). The resulting constructs from the previously conducted EFA were also confirmed in the CFA. Figure 5.3 exemplifies a commonly used CFA diagram to illustrate hypothesised latent variables/ constructs, observed variables, and their relationship (Marsh *et al.*, 2014).

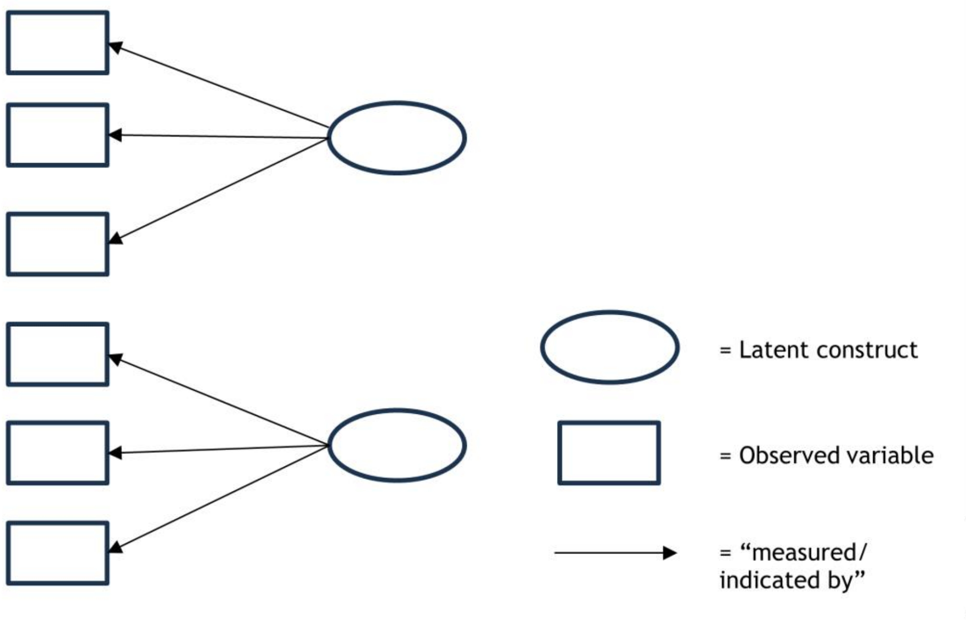


Figure 5.3 Example of CFA diagram of two latent constructs with three observed variables

In addition to displaying the relationships between various variables, the diagram can display the loadings on specific constructs and the error for each observed variable. A CFA is described as follows:

$$Y = \lambda \xi + \varepsilon \qquad 9$$

Where:

- Y: the observed variables or indicators.
- Λ: the factor loadings represent the relationships between the latent factors and the observed variables.
- Ɨ: the latent factors or constructs.
- E: the measurement errors or residuals.

The CFA formula (equation 9) expresses how the observed variables (Y) are related to the latent factors (ξ) through the factor loadings (λ), accounting for the measurement errors (ε). The formula estimates the factor loadings (λ) and the latent factors (ξ) in a way that best explains the observed data (Y) while considering the measurement errors (ε). Factor loadings, which quantify the strength and direction of the correlation between observed variables and their corresponding latent factors, range from -1 to 1 (Wood, 2008), and those exceeding 0.4 are considered acceptable within the social sciences, signifying a moderate to substantial association (Chen and Liu, 2018).

Once CFA has been conducted, assessing whether the fit indices meet the predefined thresholds is essential, allowing for the appropriate interpretation of the results (Anderson and Gerbing, 1988; Hu and Bentler, 1999). This assessment evaluates how well the measurement model aligns with the data and its suitability for subsequent structural analyses, with a more detailed discussion of fit indices in section 5.6.4.

5.6.3 Structural model

The SEM's second component, a structural model, analyses the relationships between latent variables (Jöreskog, Sörbom and Magidson, 1979; Hidayat and Wulandari, 2022). A structural model resembles a regression analysis, where independent or exogenous variables predict the outcomes or endogenous variables (Bagozzi and Yi, 1988; Gallagher and Brown, 2013; Marsh *et al.*, 2014). Equation 10 represents an SEM's structural model, quantifying the relationships between latent outcome variables, latent explanatory variables, and associated error terms:

$$\boldsymbol{\eta} = \boldsymbol{B\eta} + \boldsymbol{\Gamma\xi} + \boldsymbol{\zeta} \qquad 10$$

Where:

- $\boldsymbol{\eta}$ = $q \times 1$ vector of latent outcome variables,
- $\boldsymbol{\xi}$ = $n \times 1$ vector of latent explanatory variables,
- $\boldsymbol{B}$ = $m \times m$ matrix of coefficients of $\boldsymbol{\eta}$ in the structural relationships,
- $\boldsymbol{\Gamma}$ = $m \times n$ matrix of coefficients of $\boldsymbol{\xi}$ in the structural relationships,
- $\boldsymbol{\zeta}$ = $m \times 1$ vector of structural relationships' error terms.

This equation shows how a set of latent variables (η) influences another set of latent variables (ξ). The relationship is quantified using specific numbers (coefficients) that show how much one set impacts the other. These numbers are stored in the matrices B and Γ. The equation also accounts for possible errors (ζ) or unknown factors in these relationships.

5.6.4 Model's goodness of fit indices

SEM's goodness of fit indices evaluate the model's factor loadings, item-to-construct correlations, and constructs' variances to confirm the measurement model's suitability for further structural analysis, entailing an assessment of the agreement between the proposed measuring framework and empirical data (Ryu, 2014). Researchers employ various measurement indices to evaluate the model's representation of the collected data in SEM analysis, such as Chi-square (X^2), Root Mean Square Error of Approximation (RMSEA), Goodness of Fit Index (GFI) and Adjusted Goodness of Fit Index (AGFI), Comparative Fit Index (CFI), normed fit index (NFI), and incremental fit index (IFI), Tucker-Lewis Index (TLI), Standardised/ Weighted Root Mean Square Residual (SRMR/ WRMR) (Hu and Bentler, 1999; Podsakoff *et al.*, 2003; Byrne, 2013; Sass, Schmitt and Marsh, 2014; Tarka, 2017). There is no consensus in the existing literature regarding which model fit indices should be examined and reported, and fit indices should be interpreted carefully (Shi, Lee and Maydeu-Olivares, 2018; Stone, 2021; Kline, 2023). Table 5.1 describes the standard model fit indices and their respective threshold values. The discussions of these indices are in the following subsections.

Fit Index	Threshold value	Reference
Chi-square	p-value insignificant	(Barrett, 2007)
CFI	>0.90	(MacCallum, Browne and Sugawara, 1996; Hu and Bentler, 1999)
TLI (NNFI)	>0.90	(Marsh *et al.*, 2014)
NFI	>0.90	(Bentler and Bonett, 1980)
IFI	>0.90	(Bollen, 1990)
GFI and AGFI	>0.90	(Shevlin and Miles, 1998)
RMSEA	<0.07	(Tabachnick and Fidell, 2007)
SRMR	<0.08	(Hu and Bentler, 1999)

Table 5.1 Threshold values for model fit indices

5.6.4.1 Chi-square test

The significance test of Chi-square (χ^2) shows the differences between a hypothesised model and the data collected, where a minor difference is expected if the model is specified correctly, i.e., fits the model (Barrett, 2007; Hooper, Coughlan and Mullen, 2008). A p-value greater than 0.05 (statistically insignificant) is recommended to indicate a reasonable fit, indicating that the model's implied covariance is reasonably close to the actual covariance of the sample data (Barrett, 2007). In SEM, it is recommended to divide the Chi-square value with df (degree of freedom) (Hu and Bentler, 1999), with the formula as follows:

$$\chi^2 \,/\, df \tag{11}$$

Where:

- x^2= Chi-square value obtained from the model fit test.
- df= degrees of freedom, the difference between the number of observed variables and estimated parameters in the model.

However, a limitation of the Chi-square test is its sensitivity to sample size. As the sample size grows, even small disparities between the actual and anticipated covariance matrices can provide statistically significant Chi-square values (Bryant and Satorra, 2012). The impact of sample size on statistical significance is evident in that larger samples have a higher probability of yielding significant Chi-square values, even when the disparities between the model and the observed data are small and practically insignificant (Byrne, 2013). A common approach to overcoming this limitation in model assessment is to compare the chi-square value of the proposed model with that of a null model (Smith, 1996). Additionally, researchers suggest considering other fit indices to obtain a more comprehensive assessment of model fit (Mulaik *et al.*, 1989; Heene *et al.*, 2011).

5.6.4.2 Root Mean Square Error of Approximation (RMSEA)

Besides the Chi-square, the Root Mean Square Error Of Approximation (RMSEA), which accounts for population approximation error, is a model fit index for evaluating overall fit (Browne and Cudeck, 1992). RMSEA quantifies the mean squared discrepancy between the observed and model-implied covariance matrices, normalised by the degrees of freedom, reflecting the relative improvement of nested models (Bentler, 1990).

An RMSEA value below 0.08 generally indicates a reasonable approximation error (Browne and Cudeck, 1992; Hu and Bentler, 1999), indicating a reasonable fit between the measured model and the observed sample data. RMSEA formula is explained in equation 12 as follows:

$$RMSEA = \sqrt{}[(\chi^2 \,/\, df \; - \; p) \,/\, (n \; - \; 1)] \qquad 12$$

Where:

- RMSEA= Root Mean Square Error of Approximation.
- x^2= Chi-square value obtained from the model fit test.
- df= Degrees of freedom, the difference between the number of observed variables and estimated parameters in the model.
- p= The number of constraints or restrictions imposed on the model.
- n= The total sample size.

5.6.4.3 Goodness of Fit and Adjusted Goodness of Fit (GFI and AGFI)

The goodness of fit (GFI) and adjusted goodness of fit (AGFI) are indices for assessing model fit, particularly with nonnormal data (Doğan, 2022). GFI evaluates how well a hypothesised SEM fits compared to a null model, which assumes no variable relationships. GFI measures the proportion of variance and covariance the model explains relative to the total observed in the data. The GFI is calculated by using the following equation 13:

$$GFI = 1 \; - \; ({\chi^2}_{model} \,/\, {\chi^2}_{null}) \qquad 13$$

Where:

- x^2_{model}= = the Chi-squared statistic calculated from the hypothesised SEM model, which measures the difference between the observed data and the model's prediction.

- x^2_{null}= the Chi-squared statistic obtained from the null model, which assumes no relationships between variables

The Adjusted Goodness of Fit Index (AGFI) modifies the GFI by adjusting for degrees of freedom and penalising models with more parameters, offering a more conservative estimate of fit (Bentler, 1990). GFI and AGFI values above 0.9 signify a robust model fit (Bollen, 1990; Hu and Bentler, 1999), but achieving this benchmark can be challenging with models having more parameters. MacCallum and Hong (1997) suggest a reduced standard of 0.8 in these cases. AGFI Formula can be observed in equation 14:

$$AGFI = (GFI - df_{model}) / (1 - df_{null}) \tag{14}$$

Where:

- df_{model} = the degrees of freedom associated with the hypothesised SEM model.
- df_{null} = the degrees of freedom associated with the null model.

5.6.4.4 Comparative Fit Index, Normed Fit Index, and Incremental Fit Index (CFI, NFI, and IFI)

The Comparative Fit Index (CFI), Normed Fit Index (NFI), and Incremental Fit Index (IFI) are statistical metrics used in multivariate analyses, including SEM, to evaluate a structural model's fit to observed data (Bentler, 1990; Hu and Bentler, 1999). CFI compares the fit of the estimated model to the fit of the null or baseline model, adjusting for differences in degrees of freedom. It evaluates the reduction in chi-square between models and penalises model complexity. CFI is more accurate in smaller samples than the NFI and resilient to sample size effects (Bentler, 1990).

NFI contrasts the sample model's Chi-square with the null model's Chi-square to assess model fit (Bentler and Bonett, 1980). NFI is sensitive to sample size and is therefore not recommended as the singular criterion for evaluating model fit when the sample size is less than 200 (Bentler, 1990; Hooper, Coughlan and Mullen, 2008). IFI, an NFI derivative, addresses the sample size issue (Byrne, 2016). In general, CFI, NFI, and IFI values above 0.90 indicate an acceptable fit, and values above 0.95 indicate an excellent fit (Bentler, 1990; Hooper, Coughlan and Mullen, 2008).

The CFI, NFI, and IFI are formulated in equations 15, 16, and 17 as follows:

$$CFI = (\chi^2{}_{model} - \chi^2{}_{null}) \,/\, (\chi^2{}_{model} + dfmodel - \chi^2{}_{null}) \qquad 15$$

Where:

- $\chi^2{}_{model}$ = Chi-square value obtained from the estimated model fit test.
- $\chi^2{}_{null}$ = Chi-square value obtained from the null or baseline model fit test.
- df_{model} = Degrees of freedom of the estimated model.

$$IFI = (\chi^2{}_{null} - \chi^2{}_{model} + df_{model} - df_{null}) / \chi^2{}_{null} \qquad 16$$

Where:

- df_{model} = the degrees of freedom for the hypothesised model.
- df_{null} = the degrees of freedom for the null/ baseline model.

$$NFI = (\chi^2{}_{null} - \chi^2{}_{model}) / \chi^2{}_{null} \qquad 17$$

Where:

- $\chi^2{}_{model}$ = Chi-square value obtained from the estimated model fit test.
- $\chi^2{}_{null}$ = Chi-square value obtained from the null or baseline model fit test.

5.6.4.5 Tucker-Lewis Index (TLI)/ Non-Normed Fit Index (NNFI)

The Tucker-Lewis Index (TLI), also referred to as the Non-Normed Fit Index (NNFI), evaluates how well a hypothesis fits compared to a null model, factoring in degrees of freedom (Whelehan, 1983; Hu and Bentler, 1999). TLI spans from 0 to 1, where a TLI greater than 0.90 indicates an adequate fit, suggesting that the estimated model significantly improves compared to the null model (Xia and Yang, 2018). This index is advantageous for complex models with correlated errors or nonnormal data, and it offers a more cautious fit estimation by penalising models with more parameters (Whelehan, 1983).

TLI measures the improvement of an estimated model over a null model by comparing the decrease in the chi-square value relative to the maximum possible decrease. Crucially, the TLI considers the differences in degrees of freedom between the estimated and null models, reflecting their respective complexities. This adjustment is significant as it acknowledges that models with more parameters and higher complexity might naturally significantly reduce chi-square. The formula for TLI in SEM is in equation 18:

$$TLI = (\chi^2{}_{null} - \chi^2{}_{model}) / (\chi^2{}_{null} - df_{null}) \qquad 18$$

Where:

- $\chi^2{}_{null}$ = Chi-square value obtained from the null or baseline model fit test.
- $\chi^2{}_{model}$ = Chi-square value obtained from the estimated model fit test.
- df_{null} = Degrees of freedom of the null or baseline model.

5.6.4.6 Standardised Root Mean Square Residual (SRMR)

Standardised Root Mean Square Residual (SRMR) quantifies the difference between the observed covariance matrix and the covariance matrix predicted by the model (Hu and Bentler, 1999; DiStefano *et al.*, 2018). This discrepancy is standardised by dividing it by the square root of the Average Variance Extracted (AVE) (Pavlov, Maydeu-Olivares and Shi, 2020). SRMR with a value below 0.08 indicates a good fit (Hu and Bentler, 1999; DiStefano *et al.*, 2018).

$$SRMR = \sqrt{((\Sigma((S - M)^\wedge 2) / (n(n-1))))} \qquad 19$$

Where:

- S= the observed covariance matrix
- M= the model-implied covariance matrix
- Σ= the sum of squared differences between the observed and model-implied covariances
- n= the number of observed variables

5.6.5 SEM rigour: reliability and validity

This section describes the SEM's reliability and validity assessments. Reliability refers to the extent to which a measurement of a latent construct is consistent and steady across various situations and free from measurement error (Fornell and Larcker, 1981; Bollen, 1990; Zumbo, 2005; Denscombe, 2010; Baalbaki, Malhotra and Nasr, 2013; Ayyıldız, 2020; Kline, 2023). On the other hand, validity measures the extent to which a test or instrument accurately represents the intended concept and reliably supports appropriate inferences about a specific sample and environment (Cook and Campbell, 1979; Zumbo, 2005; Saunders, Lewis and Thornhill, 2009; Zumbo and Chan, 2014; Saunders and Townsend, 2016).

The reliability test employed Cronbach's alpha and coefficient omega (ω) as measures of internal consistency. This step determines how the collected data accurately and consistently represents the underlying constructs of interest. Several tests of validities, namely face, content, construct, convergent, and discriminant, were used to evaluate the psychometric properties and measurement quality of the latent constructs and observed indicators within the proposed SEM model.

5.6.5.1 Reliability

The data collection instrument for this phase was a survey, which then required an internal consistency test to evaluate the reliability of quantitative latent variables/ constructs within the SEM field (Churchill Jr, 1979). Internal consistency assessment in SEM with latent constructs relies on composite reliability, commonly denoted by the ω (Omega) symbol (Fornell and Larcker, 1981). It is calculated by considering the factor loadings and residual variances of the indicators linked with the construct.

Coefficient ω (Omega) can be seen as an alternate measure to Cronbach's alpha, a more often used metric in classical test theory (Ravinder and Saraswathi, 2020). Omega is considered a better measure of reliability for latent variables in SEM because it takes into account the variations in factor loadings and residual variances, a feature lacking in Cronbach's alpha that assumes tau-equivalence, meaning it presumes that all items in a scale have equal factor loadings (i.e., each item contributes equally to the construct) (McNeish, 2018; Flora, 2020).

The coefficient omega (ω) is computed by dividing the sum of squared factor loadings by the sum of squared factor loadings plus the sum of squared residual variances, as denoted by equation 20 below:

$$\omega = (\Sigma\lambda^2) / (\Sigma\lambda^2 + \Sigma\delta) \qquad 20$$

Where:

- $\Sigma\lambda^2$ = the sum of the squared factor loadings for all indicators associated with the latent variable.
- $\Sigma\delta$ = the sum of the residual variances for all indicators associated with the latent variable.

A standard coefficient omega threshold is >0.70, and a value closer to 1 signifies better reliability in measuring the latent variable (Revelle and Zinbarg, 2008; Black and Babin, 2019).

5.6.5.2 Face validity

Face validity, which relates to the extent to which a measurement or structural model is deemed valid based on subjective judgment or expert opinion (Nevo, 1985), is crucial in ensuring that the items in the measurement instrument appear relevant and sensible to the respondents within a given context (Allen, Robson and Iliescu, 2023). If survey respondents are aware of the information sought by the researcher, they can provide more valuable and accurate responses (Hardesty and Bearden, 2004). In this study, aiming to ensure face validity, cognitive interviews were conducted with several Jakarta police leaders in section 5.3.4, and an introduction was provided in the survey to explain the research purpose.

5.6.5.3 Content validity

Content validity in SEM refers to the degree to which the observed items or indicators in a measurement model adequately represent the measured construct, ensuring that the items encompass the full range of the construct and its essential elements (Colquitt *et al.*, 2019). It requires a thorough assessment of these items to confirm that they fully cover and accurately represent all aspects of the construct being studied (Bollen, 1990; Yaghmaie, 2003; Malhotra *et al.*, 2006; Sürücü and Maslakci, 2020). Researchers thoroughly examine current literature to establish SEM content validity and assess the appropriateness and adequacy of the items used in measuring the construct of interest (Hinkin, 1995; Colquitt *et al.*, 2019).

In addition, cognitive interviews and pilot testing can be used to assess the content and its validity (Willis, 1999; MacDermid, 2021). These methods involve administering the survey to a representative sample of participants and collecting their feedback on the intelligibility and relevance of the items (Beatty and Willis, 2007; MacDermid, 2021). The pilot testing and cognitive interviews were conducted as described in section 5.3.4.

5.6.5.4 Construct validity

Construct validity in SEM is essential to how well a research instrument captures and assesses the intended theoretical construct to ensure that the observed variables represent the targeted latent constructs meaningfully (Anderson and Gerbing, 1988; Hair, Ringle and Sarstedt, 2013; Morita and Kannari, 2016; Sürücü and Maslakci, 2020; Wehner, Roemer and Ziegler, 2020; Sjøberg and Bergersen, 2023). The SEM’s factor analysis part is where the model's construct validity is validated (Marsh *et al.*, 2014). The factor analysis will result in factor loadings, which measure how much each variable within a construct predicts its related latent variable. Each factor loading coefficient is accompanied by a P-value (Zumbo, 2005). The factor analysis methods were described in section 5.6.2.

5.6.5.5 Convergent validity

Convergent validity within SEM measures the degree of positive correlation among different assessments of the same construct, typically evaluated by analysing the Average Variance Extracted (AVE) of latent variables to determine how well the indicators capture the same latent construct (Hair, Ringle and Sarstedt, 2013; Henseler, Ringle and Sarstedt, 2014; Engellant, Holland and Piper, 2016; Ab

Hamid, Sami and Sidek, 2017; Cook *et al.*, 2020; Sürücü and Maslakci, 2020). The formula for AVE is as follows (Ayyıldız, 2020):

$$AVE = \Sigma\lambda^{\wedge}2 \,/\, \Sigma(\lambda^{\wedge}2 + \delta) \qquad 21$$

Where:

- $\Sigma\lambda^{\wedge}2$ = the sum of the squared factor loadings for all latent variable indicators.
- $\Sigma(\lambda^{\wedge}2 + \delta)$ = the sum of the squared factor loadings and the measurement error variances (δ) for all indicators of the latent variable.
- AVE = Sum of Squared Factor Loadings (λ^2) / (Sum of Squared Factor Loadings + Sum of Error Variances)

The AVE threshold is typically set at 0.5 or higher as a guideline for acceptable convergent validity (Smith, 1996). This threshold value means that the latent construct should explain at least 50% of the variance in the observed indicators for convergent validity to be established.

5.6.5.6 Discriminant validity

Discriminant validity assesses if each construct in a model is distinct from others within the same model, ensuring that latent variables are unique and the observed relationships are not due to measurement errors or overlaps with other variables (Fornell and Larcker, 1981; Byrne, 2013; Henseler, Ringle and Sarstedt, 2014; Sürücü and Maslakci, 2020). Discriminant validity can be analysed using the Fornell-Larcker criterion that contrasts the square root of the AVE for each construct with the inter-construct correlations (Fornell and Larcker, 1981; Henseler, Ringle and Sarstedt, 2014). The analysis involved a correlation matrix that included the square root of AVE for each variable and its correlation with other variables. It is crucial to ensure that the correlation coefficients between each pair of constructs are not excessively high (Fornell and Larcker, 1981; Taherdoost *et al.*, 2018). It indicates discriminant validity exists if the square root of the AVE for each construct is greater than the correlation between that construct and any other construct in the model. Fornell-Larcker Criterion is calculated as follows:

$$AVEi > Rij \; for \; all \; i \neq j \tag{22}$$

Where:

- AVE_i = the Average Variance Extracted for construct i,
- R_{ij} = the correlation between construct i and construct j.

5.7 Summary of chapter

In summary, this method chapter entailed a systematic and rigorous approach to data analysis. Drawing upon a literature review concerning ICT adoption, acceptance, and user experience, in conjunction with insights from interviews conducted with leaders within the Jakarta traffic police, an analytical framework was methodically formulated.

This framework served as the foundational structure to investigate the determinants influencing ICT adoption intentions within the context of informed decision-making among urban public servants. Subsequently, this framework underwent an empirical test utilising a sample of Jakarta traffic police officers. Before undertaking the primary hypotheses testing, the variables encompassed within the conceptual framework were subjected to rigorous examinations, including Exploratory and Confirmatory Factor Analysis (EFA and CFA) and reliability and validity assessments. These assessments were conducted to ensure the conformance of the model's fit to acceptable benchmarks. The main hypotheses were tested using the SEM technique, and the results are presented in the subsequent chapter.

Chapter 6 Adoption intention examination results

This chapter provides the results from the SEM analysis of the survey data. Descriptive statistics were utilised to summarise the demographic attributes (ages, educational backgrounds, and working experience) and the primary questionnaire responses. Exploratory and Confirmatory Factor Analysis (EFA and CFA) were used to evaluate the validity of the hypothesised measurement models, revealing how well the observed variables represent their respective latent constructs. SEM analysis provided a deeper examination of structural paths to confirm the theoretical framework, ultimately leading to the evaluation of hypotheses.

6.1 Descriptive statistics

The first analysis uses descriptive statistics to summarise the collected survey data. Table 6.1 provides statistical information about survey data variables, including their names, units of measurement, central tendency measures (mean and median), range, minimum, and maximum values.

Variable	Var. unit	Mean	Median	Min	Max
Behavioural intention					
bi1 (intend to use)	Likert scale	6.53	7	2	7
bi2 (predict to use)	Likert scale	6.53	7	2	7
Bi3 (plan to use)	Likert scale	6.54	7	2	7
Age	year	39.2	39	19	58
Work exp	year	11.66	10	0	37
educational level	two-category factor (high school, Bachelor+)	0.51	1	0	1
Interoperability expectations					
inter1 (communication)	Likert scale (1: strongly disagree, 7: strongly agree)	6.46	7	1	7
inter2 (data-sharing)	Likert scale	6.46	7	1	7
Privacy concerns					

Variable	Var. unit	Mean	Median	Min	Max
priv1 (constant tracking)	Likert scale	5.41	6	1	7
priv2 (unguaranteed privacy)	Likert scale	5.22	6	1	7
Social incentives					
incen1 (incentive-appreciation)	Likert scale	5.64	6	1	6
incen2 (incentive-recognition)	Likert scale	5.4	6	1	7
Social influence					
influ1 (influence-important people)	Likert scale	4.48	5	1	5
influ2 (influencing people)	Likert scale	6.38	7	1	7
influ3 (organisation’s support)	Likert scale	5.53	6	1	6
User experience					
speed (speed)	semantic diff. scale fast><slow	5.83	6	1	7
innov (innovativeness)	semantic diff. scale innovative><conventional	6.61	7	1	7
lead (leading edge)	semantic diff. scale leading edge><usual	5.69	6	1	7
support (supportiveness)	semantic diff. scale supportive><obstructive	6.86	7	1	7

Table 6.1 Descriptive statistics of the survey data

6.1.1 The variable of interest: Behavioural intention to use the dashboard (BI)

The BI is a dependent variable which is measured by three observed variables: bi1 (intend to use), bi2 (predict to use), and bi3 (plan to use). These variables represent 7-point Likert scale ratings, ranging from 1 ('Strongly Disagree') to 7 ('Strongly Agree'), with 4 as neutral. The participants’ responses to BI variables can be observed in Figure 6.1.

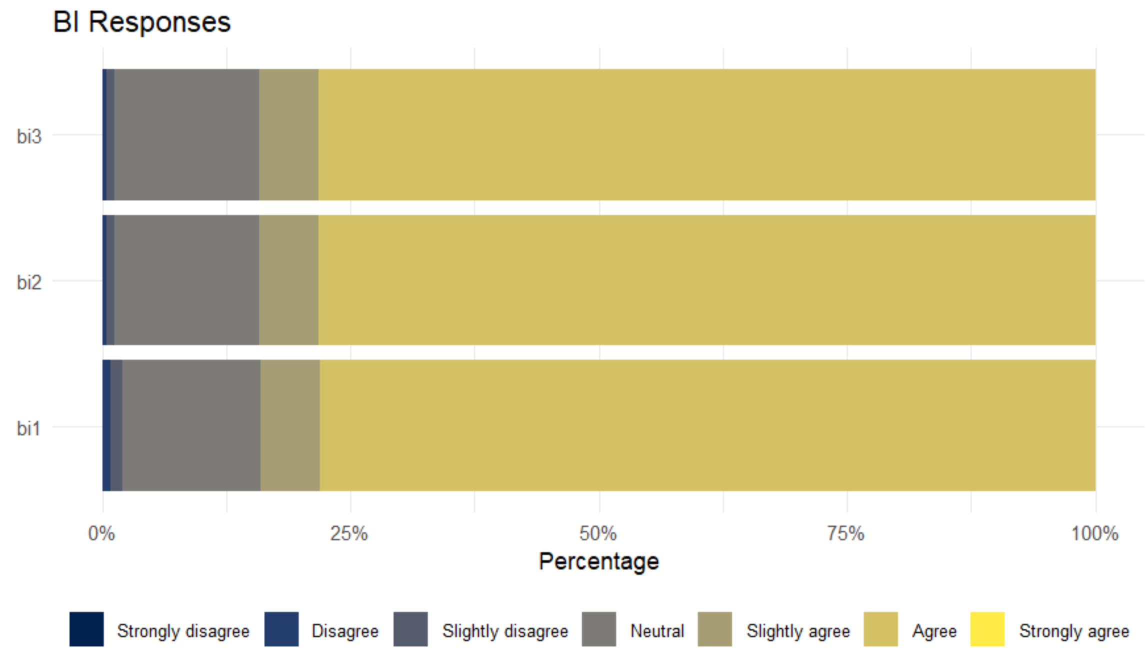


Figure 6.1 Response percentages on BI items

The survey participants gave relatively positive ratings for BI variables, with Means close to 6 ("agree") and no responses with 1 ("strongly disagree"). The participants might have agreed with the dashboard idea because they thought that was the expected response. It can be assumed that the skewness of BI responses was due to social desirability bias, which is the inclination to give socially acceptable answers (Grimm, 2010). Research indicates that participants in studies may tailor their responses to align with their perceived expectations of the researcher (Nichols and Maner, 2008; McCambridge, de Bruin and Witton, 2012) and are often inclined to provide answers that present themselves positively or conform to social norms (Alay and Koçak, 2002).

Additionally, affirmation bias may have played a role, as participants, who were government employees, could have felt an implicit expectation to express support for a dashboard designed to enhance their work. The hierarchical nature of government institutions, including law enforcement, may have influenced responses (Alderfer and Simon, 2002; Thompson and Siciliano, 2021). Research suggests that individuals in structured organisations may provide responses that align with perceived institutional goals rather than their actual opinions, particularly in assessments of workplace-related innovations (Khan, Raya and Viswanathan, 2022; Zhu *et al.*, 2024).

However, the survey was anonymous, which studies found can reduce social desirability bias (Wildman, 1977; Joinson, 1999; Kreuter, Presser and Tourangeau, 2008; De Jong, Pieters and Fox, 2010). The survey was also administered online, and studies found that using the Internet to gather survey data has been linked to reduced levels of social desirability bias (Joinson, 1999; Holbrook and Krosnick, 2010). Additionally, the survey included neutral response options to allow participants to express uncertainty or mixed views, mitigating the tendency to default to agreement (Krosnick *et al.*, 2001; Muñoz van den Eynde and Lobera, 2022).

Furthermore, the SEM analysis used the Diagonally Weighted Least Square (DWLS) as the SEM's estimator, recommended for handling categorical and ordinal data and non-normal/ skewed distributions (Li, 2015). Compared to Maximum Likelihood (ML) estimation, DWLS provides more accurate parameter estimates and a more robust model fit for skewed data (Mîndrilă, 2010; Li, 2015; Isnayanti and Abdurakhman, 2019).

6.1.2 Exploratory factor analysis results

The variables included in the EFA were first analysed with a Scree test (Figure 6.2), commonly used in factor analysis to determine the number of factors to retain (Cattell, 1966). The scree test's plot displays eigenvalues on the y-axis and factor numbers on the x-axis, with each eigenvalue representing the variance explained by a factor. The goal is to identify the "elbow" point where the curve flattens, indicating significant factors on the left and less meaningful factors on the right (Kaiser, 1960).

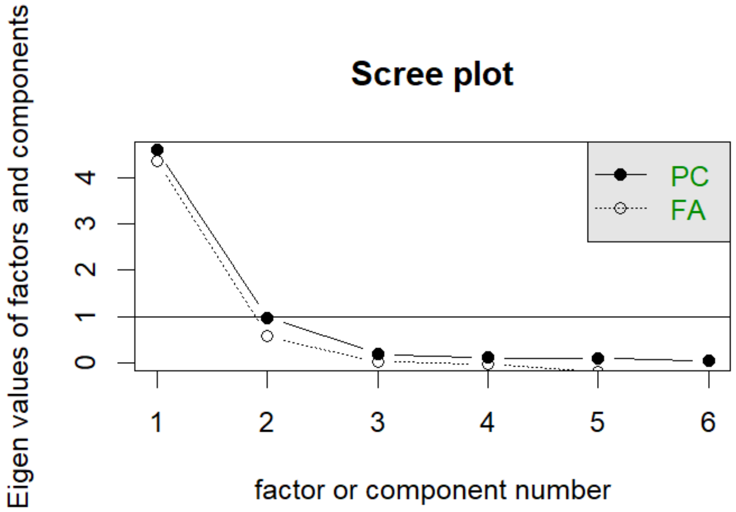


Figure 6.2 Scree plot for the EFA variables

The scree plot, which was generated from the EFA method in section 5.6.2.1, showed a clear "elbow" at the second factor, with a significant drop after the first factor and a smaller drop after the second, suggesting that retaining two factors or less is most appropriate since additional factors beyond the second do not substantially contribute to explaining the variance. Adding more factors would increase the model's complexity without necessarily improving interpretative clarity or fit and could obscure the underlying structure and risk overfitting the sample data (Fabrigar and Wegener, 2011; Costello and Osborne, 2019). Based on this information and the suggested factors, two variations of EFA, one-factor and two-factor models, were conducted for comprehensive analysis.

Standardised loadings (pattern matrix) based upon correlation matrix					
	WLS1	WLS2	h2	u2	com
speed	0.86	0.14	0.93	0.072	1.1
support	0.89	0.11	0.92	0.078	1
innov	1.00	-0.22	0.83	0.174	1.1
lead	0.73	0.29	0.89	0.111	1.3
inter1	-0.04	0.93	0.82	0.182	1
inter2	-0.01	0.92	0.83	0.168	1
	WLS1 WLS2				
SS loadings	3.24 1.98				
Proportion Var	0.54 0.33				
Cumulative Var	0.54 0.87				
Proportion Explained	0.62 0.38				

Cumulative Proportion 0.62 1.00					
With factor correlations of					
WLS1 WLS2					
WLS1 1.00 0.65					
WLS2 0.65 1.00					
Mean item complexity = 1.1					
Test of the hypothesis that 2 factors are sufficient.					
df null model = 15 with the objective function = 8.08					
df of the model are 4 and the objective function was 0.72					
The root mean square of the residuals (RMSR) is 0.03					
The df corrected root mean square of the residuals is 0.06					
Fit based upon off diagonal values = 1					
Measures of factor score adequacy					
WLS1 WLS2					
Correlation of (regression) scores with factors 0.99 0.95					
Multiple R square of scores with factors 0.98 0.90					
Minimum correlation of possible factor scores 0.96 0.81					

Table 6.2 Two-factor EFA results

The two-factor model provided the best results (Table 6.2), showing high standardised loadings (0.86 to 1.00 for Factor 1 and 0.92 to 0.93 for Factor 2), accounting for 87% of the variance (SS loadings = 3.24 for Factor 1 and 1.98 for Factor 2). This model demonstrated significant factor score adequacy with correlations of 0.99 with regression scores for Factor 1 and 0.95 for Factor 2, multiple R squared values of 0.98 and 0.90, and minimum correlations of factor scores at 0.96 and 0.81, respectively. The two-factor model also exhibited strong communalities (h^2 ranging from 0.82 to 0.93) and moderate uniqueness values (u^2 from 0.07 to 0.18). Communalities represent the proportion of each variable's variance that can be explained by the common factors, with high communalities indicating that the factors extracted explain a substantial portion of the variance in the observed variables (Fabrigar and Wegener, 2011). Uniqueness values are the proportion of variance in each variable that is unique to that variable and not explained by the common factors; lower uniqueness values suggest a strong model fit (Costello and Osborne, 2019).

Standardised loadings (pattern matrix) based upon correlation matrix				
	WLS1	h^2	u^2	com
speed	0.94	0.88	0.12	1
support	0.93	0.86	0.14	1
innov	0.79	0.63	0.37	1
lead	0.93	0.87	0.13	1
inter1	0.74	0.55	0.45	1
inter2	0.76	0.58	0.42	1
	WLS1			
SS loadings	4.37			
Proportion Var	0.73			
Mean item complexity = 1				
Test of the hypothesis that 1 factor is sufficient.				
df null model = 15 with the objective function = 8.08				
df of the model are 9 and the objective function was 2.37				
The root mean square of the residuals (RMSR) is 0.13				
The df corrected root mean square of the residuals is 0.17				
Fit based upon off diagonal values = 0.97				
Measures of factor score adequacy				
				WLS1
Correlation of (regression) scores with factors				0.98
Multiple R square of scores with factors				0.97
Minimum correlation of possible factor scores				0.93

Table 6.3 One-factor EFA results

These values indicate a robust factor structure with a good fit, as evidenced by the Root Mean Square Residual (RMSR) of 0.03 and the degrees of freedom (df) corrected RMSR of 0.06. RMSR measures the average discrepancy between observed and predicted correlations, with a lower RMSR indicating a better model fit (Byrne, 2016). Despite a slight increase in item complexity, with a mean item complexity of 1.1, the two-factor model provided more precise interpretative clarity. Item complexity refers to the average number of factors where items load significantly (Pettersson and Turkheimer, 2010); a mean item complexity of 1.1 suggests that items are relatively straightforward, loading primarily on one factor, which aids in interpretative clarity (Gorsuch, 1997).

The one-factor model (Table 6.3), while explaining 73% of the variance, showed a higher RMSR (0.13) and lower overall fit than the two-factor model. The one-factor model did not capture the underlying structure of the data as effectively as the two-factor model. As a result, due to its statistical robustness and interpretative clarity, the two-factor model was selected. This model explained a significant portion of the variance, had a better fit and provided more precise insights into the underlying structure of the data. Therefore, the first factor is defined as User Experience (UX), and the second is Interoperability Expectations (INTER).

6.1.3 Confirmatory factor analysis results

The subsequent Confirmatory Factor Analysis (CFA) was conducted with all the model's latent constructs, including the User Experience (UX) and the Interoperability Expectations (INTER) variables, which were discovered in the prior EFA results. CFA results in Table 6.4 show that all latent constructs demonstrate strong factor loadings (>0.800).

Code	Item	Factor loading
INTEROPERABILITY EXPECTATIONS		
inter1	The dashboard should be able to communicate with other work-related technologies I use	0.914
inter2	The dashboard should be able to share data with other work-related technologies I use	0.981
PRIVACY CONCERNS		
priv1	I am concerned that the dashboard may constantly track my location	0.995
priv2	I am concerned that the dashboard may not guarantee my privacy	0.861
SOCIAL INFLUENCE		
influ1	People who are important to me at work think that I should use the dashboard	0.956
influ2	People who influence my behaviour at work think that I should use the dashboard	0.946
influ3	In general, my organisation will support the use of the dashboard	0.969
SOCIAL INCENTIVES		
incen1	If I use the dashboard, I will increase my chances of being appreciated at work	0.980
incen2	If I use the dashboard, I will increase my chances of being recognised at work	0.963
USER EXPERIENCE		
speed	Fast 1 2 3 4 5 6 7 Slow	0.951
support	Supportive 1 2 3 4 5 6 7 Obstructive	0.999
lead	Leading edge 1 2 3 4 5 6 7 Usual	0.950
innov	Innovative 1 2 3 4 5 6 7 Conservative	0.807
BEHAVIOURAL INTENTION		
bi1	I intend to use the dashboard	0.990
bi2	I predict I will use the dashboard	0.988
bi3	I plan to use the dashboard	0.974

Table 6.4 Items' factor loadings

These loadings represent each item's relationship strength and direction with its corresponding latent construct, indicating how well the items represent their underlying latent construct. High factor loadings suggest that the items are adequate indicators of their respective latent constructs, with a standard threshold above 0.5 considered adequate (Fornell and Larcker, 1981; Bagozzi and Yi, 1988; Hair, Ringle and Sarstedt, 2013). All items in the measurement model exceeded the significant factor loading criterion of 0.5 and were statistically significant ($P<0.05$), indicating a robust and reliable measurement model.

6.1.4 Validity tests

6.1.4.1 Convergent validity

All constructs' AVE (Average Variance Extracted) values are above the standard threshold ≥0.5 (Table 6.5). On average, each construct explains a high percentage of the common variance among its associated variables, ranging from 87% to 97%. These results indicate that the indicators adequately represent their respective latent constructs, and the measurement model is considered appropriate based on convergent validity.

	INTER	INFLU	INCEN	PRIV	UX	BI
AVE	0.91	0.92	0.95	0.87	0.87	0.97

Table 6.5 AVE values

6.1.4.2 Discriminant validity

The discriminant validity calculation results in Table 6.6 indicated that all values are positive, indicating that the independent latent constructs/ variables are distinct and do not overlap (measure the same thing), which is vital for the validity and allowing the interpretation of the measurement model.

	INTER	INFLU	INCEN	PRIV	BI
INTER					
INFLU	0.03				
INCEN	0.12	0.08			
PRIV	0.42	0.33	0.42		
BI	0.03	0.05	0.09	0.50	
UX	0.26	0.22	0.19	0.52	0.18

Table 6.6 Discriminant validity values

6.1.5 Reliability

The calculations for reliability tests consisted of alpha and omega coefficients. All coefficients' values are above the 0.70 threshold for all latent variables (Table 6.7). These results, especially the coefficient omega, which is more appropriate for latent constructs, signify that the variables effectively capture their intended measures.

	INTER	INFLU	INCEN	PRIV	BI	UX
alpha	0.90	0.94	0.92	0.86	0.96	0.86
omega	0.88	0.92	0.90	0.88	0.95	0.89

Table 6.7 Reliability test results

6.1.6 Model fit

The initial assessment of the SEM model fit involved a Chi-square test, which evaluates the model's fit with the data. The Chi-square value for the user-defined model was 291.620, whereas that for the baseline model, which implies no relationships between variables, was 310,056. Both models yielded statistically significant p-values (0.005), indicating that the models and observed data differ. However, it is essential to note that even minor deviations can result in significant p-values with large sample sizes. Despite this, the lower Chi-square value in the user-defined model indicates a better fit between the model and the data than the baseline model. Furthermore, all values of the utilised model fit indices were above threshold values, as shown in Table 6.8.

Fit Index	Value	Threshold
CFI	0.999	>0.90
TLI/ NNFI	0.999	>0.90
NFI	0.998	>0.90
IFI	0.999	>0.90
GFI	0.998	>0.90
AGFI	0.999	>0.90
RMSEA	0.026	<0.08
SRMR	0.038	<0.08

Table 6.8 Model fit indices

6.2 Structural model results

The structural model employed in this study yields coefficients, as presented in Table 6.9.

Hypothesis	Predictor	Coef. Est	P-value	CI_lower	CI_upper
H1	INTER	0.577	0.000	0.465	0.689
H2	PRIV	-0.069	0.027	-0.131	-0.008
H3	INFLU	0.230	0.001	0.089	0.371
H4	INCEN	0.222	0.000	0.121	0.323
H5	UX	0.090	0.018	0.015	0.164
H7	EDU	0.618	0.000	0.436	0.800
H8	EXP	0.017	0.047	0.000	0.033
H9	AGE	-0.036	0.000	-0.051	-0.021

Table 6.9 Structural model coefficients

The structural model's estimated coefficients are in log-odds values. While log-odds provide a practical mathematical framework for modelling, they can be less intuitive than odds ratios or probabilities for interpretation. It is common practice to exponentiate the log odds for a more intuitive and meaningful interpretation of the results (Gortmaker, Hosmer and Lemeshow, 1994). Therefore, the following explanations include odds ratio values resulting from the log-odds exponentiation.

The initial noteworthy finding is the INTER (interoperability expectations) factor, which reveals a statistically significant link with BI, signified by a log-odds coefficient of 0.577 (OR (odds ratio) =1.780, p=0.000). This coefficient interpretation implies that the behavioural intention to use the dashboard increases 78% with each incremental enhancement in interoperability expectations. In other words, as users' expectations for the system to work seamlessly with other systems improve, their intention to adopt the dashboard significantly rises. In practical terms, improving the dashboard's ability to work well with other systems can substantially increase its adoption among the target users.

Conversely, the PRIV (privacy concerns) factor negatively correlates with BI, reflected by a coefficient of -0.069 (OR=0.933, p=0.027). This coefficient means that with each increase in PC, BI diminishes by 6.6%. In practical terms, as users' concerns about privacy increase, their intention to use the dashboard decreases. This suggests that addressing and mitigating privacy concerns is crucial for encouraging users to adopt the dashboard.

The INFLU (social influences) construct has a statistically significant predictive relationship with BI (behavioural intention). The coefficient's estimate of 0.230 (OR= 1.258, p=0.011) indicates that a unit increase in SI corresponds to a 1.26-fold rise (26%) in BI. In practical terms, this means that as social influences, such as peer recommendations or societal norms, become stronger, the intention to adopt the dashboard increases by 26%.

Similarly, the INCEN (social incentives) factor has a significant positive relationship with BI (p=0.000). The regression coefficient of 0.222 (OR=1.248) signifies that for each incremental rise in IN, the likelihood of BI amplifies by a factor of 1.248 (24.8%). Offering social incentives can substantially increase users' intention to use the dashboard. For every unit increase in social incentives provided, there is a 24.8% increase in the likelihood that users will adopt and use the dashboard.

The UX (user experience) construct also exhibits statistical significance, with a coefficient of 0.090 (OR=1.094, p=0.018). This coefficient interpretation suggests that for every incremental unit enhancement in UX, the user's behavioural intention to employ the dashboard experiences a proportional escalation of 9.4%. In practical terms, this means that improving the user experience of the dashboard can lead to a 9.4% increase in the likelihood that users will intend to use it.

The EDU (education) factor, categorised as binary with "high school" and "bachelor+" levels, demonstrates a positive relationship with BI with a coefficient estimate of 0.618 (OR=1.855, p=0.001). This outcome indicates that individuals with bachelor's degrees or higher exhibit an 85.5% increased propensity for intending to use the dashboard compared to their counterparts with a high school degree. In practical terms, higher educational attainment significantly increases the likelihood of adopting the dashboard.

The EXP (work experience) variable has a 0.017 (OR=1.017) coefficient estimate with p value= 0.047. This coefficient suggests that for every additional year in EXP, the user's behavioural intention to employ the dashboard experiences a proportional escalation of 1.7%. Practically, this indicates that as users gain more work experience, their intention to use the dashboard increases slightly.

Lastly, the age variable has a negative coefficient estimate of -0.036 (OR=0.965, p=0.000). This result shows that for every year of age increase, the behaviour of intention to use the dashboard decreases by 3.5%. Practically, this means that older individuals are less likely to intend to use the dashboard.

6.3 Summary of chapter

The survey's collected data were analysed using a Structural Equation Modelling (SEM) technique. The measurement model's validity is rigorously tested, with all Average Variance Extracted (AVE) values exceeding the recommended threshold of 0.5, confirming convergent validity. Discriminant validity is also confirmed, showing that latent variables are distinct. Reliability is high, as evidenced by alpha and omega coefficients exceeding established thresholds.

The fit of the measurement model is assessed using various indices, all of which surpass the recommended threshold values. The Chi-square test confirms the superiority of the user-defined model over the baseline model. Exploratory Factor Analysis (EFA) revealed that the innovativeness, leading edge, speed, and supportiveness items represent a single User Experience (UX) construct and also the interoperability expectations (INTER) construct. Furthermore, Confirmatory Factor Analysis (CFA) validates the measurement model, with all items meeting the significant factor loading criterion of 0.5 and achieving statistical significance at 0.05, reinforcing the strength of the measurement model.

Finally, the SEM's structural model discovered the relationships between Jakarta traffic police officers' ICT usage motivation factors and demographic characteristics with their behavioural intention to use the dashboard (Table 6.10).

No.	**Relationships** (e.g. Interoperability expectations positively influence behavioural intention)	**Estimated effect**
1	Interoperability expectations	+78%***
2	Privacy concerns	-6.6%*
3	Social incentives	+24.8%***
4	Social influence	+26%**
5	User experience	+9.4%*
6	educational level	+85.5%***
7	Working experience	+1.7%*
8	Age	-3.5%***
P-value levels: ***: p<0.001 ** : p<0.01 * : p<0.05		

Table 6.10 SEM's structural model results

The results provided strong support for all the hypotheses. These findings show that interoperability expectations, social influence, social incentives, user experience, educational background, and working experience positively impact individuals' behavioural intentions. The results also showed that privacy concerns and age negatively affect behavioural intention. The next chapter will discuss this examination and the previous requirement elicitation results with the broader literature.

Chapter 7 Discussion

7.1 Introduction

This chapter discusses the study findings with the broader related literature, such as data-driven decision-making, e-government, smart city governance, technology acceptance, user experience, user-centred design, and other relevant fields (Figure 7.1). The first phase explores government employees' decision-making processes and participation in ICT development, using the Jakarta traffic police's patrolling allocation and a dashboard as a case study. This phase involves understanding the police's decision-making process, developing a dashboard prototype to support patrolling allocation, determining the dashboard's content, and identifying preferred features. The insights guide the subsequent dashboard development and inform the adoption intention examination in the next phase. The requirement elicitation phase with Jakarta traffic police leaders, which adopted a User-Centred Design (UCD) approach, provides insights regarding decision-making and feature preferences of the dashboard for patrolling allocations. The application of the UCD approach was intended to make the prototype functional, easy to use, and relevant to officers' daily operations. The phase is intended to provide insights into government employees' decision-making and participation in ICT development.

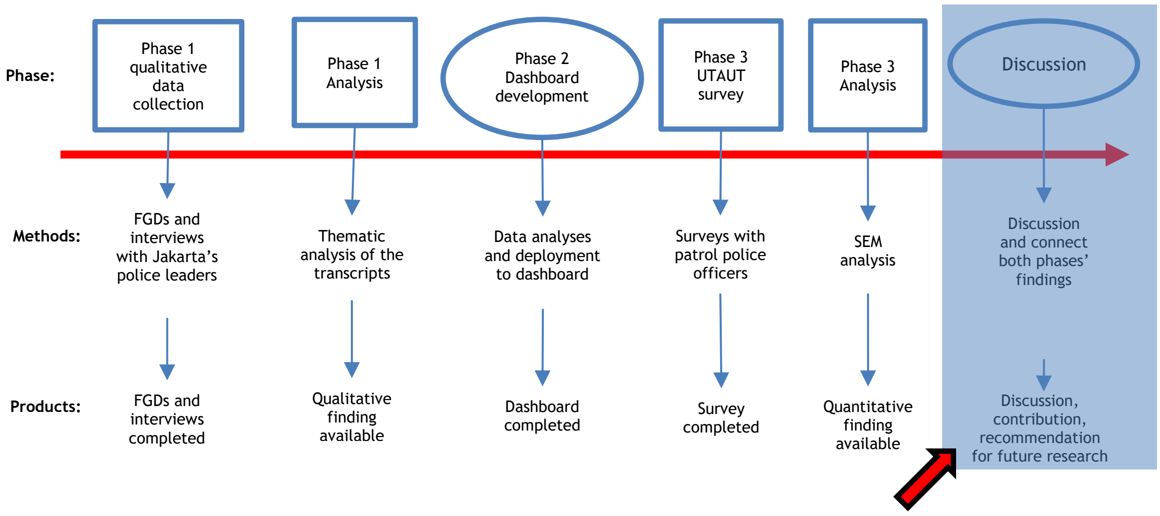


Figure 7.1 Current study phase

Subsequently, the second phase examines the Jakarta traffic police's intention to adopt the developed dashboard. Rather than directly applying established theories like TAM, TPB, and UTAUT, this research develops customised quantitative hypotheses by exploring the police's perceptions of factors that would motivate their ICT use, such as the dashboard. This approach seeks to capture contextual aspects that existing technology acceptance theories may overlook. The survey phase investigated the behavioural intention of urban public servants to adopt ICT for decision-making, with Jakarta traffic police officers' patrolling allocation as the use case. The police's perceived motivation factors for ICT usage and demographic data were integrated into a hypothesis development. A structural equation modelling (SEM) analysis examined the relationships between these original hypotheses and their behavioural intentions to adopt ICT. The development and analysis of the model attempted to provide insights into factors influencing the intention of ICT adoption for decision-making among urban public servants.

7.2 Data-driven decision-making in public sector: Jakarta traffic police's patrolling allocations

This section discusses the decision-making of the Jakarta traffic police's patrolling allocation, namely real-time traffic monitoring, blackspot visualisation, roadside safety campaign, data simplification, crash predictions, and tacit knowledge integration.

7.2.1 Leveraging real-time data for traffic monitoring

Mobile applications such as Google Maps and Waze are essential tools for the Jakarta traffic police's approach to traffic management, as they mentioned that these tools allow them to monitor traffic in real time and make informed decisions about where to deploy patrol resources. The Jakarta traffic police's traffic monitoring focus aligns with the literature that promotes traffic management through proactive traffic management measures (Wu and Lum, 2019; Sieveneck and Sutter, 2021) and is often advocated in smart city and e-government literature to improve public safety by proactively mitigating risks before they escalate (Ma *et al.*, 2018; Yaduvanshi *et al.*, 2019).

Jakarta traffic police's practices of leveraging private-sector data analytics for public policy formulation have gained prominence as public-sector agencies increasingly draw on commercial insights to develop products and services (Kucera and Chlapek, 2014; Choroszewicz and Alastalo, 2021). Private sector data provides insights into urban performance, infrastructure optimisation, service efficiency, and innovative business models for both public and private sectors (Kim *et al.*, 2018; Nicolaï and Boennec, 2018). In smart city developments, the increasing usage of private-sector data and platforms can enhance public services and improve public-sector decision-making (Klievink, Bharosa and Tan, 2016; Cruz and Sarmento, 2017; Liu *et al.*, 2020; OECD, 2022). Combining resources from the public and private sectors in smart city solutions can enhance efficiency and cost-effectiveness, benefiting both the public service and the economy (Leu *et al.*, 2021).

The use of these mobile applications underscores the importance of integrating advanced technology with traditional policing methods. By leveraging real-time data from these platforms, the police can optimise their response strategies, enabling a more dynamic and flexible approach to managing traffic flows and responding to incidents. This technology integration improves operational efficiency and enhances the police's ability to anticipate and address potential traffic issues before they become severe (Bedford *et al.*, 2021; Watson, Burtch and Greenwood, 2024). This proactive use of technology is consistent with predictive policing, where data analytics and real-time monitoring are used to foresee and prevent incidents, enhancing overall public safety (Bachner, 2013; Hung and Yen, 2021).

7.2.2 Visualising data to identify crash blackspots

The Jakarta traffic police leaders' attempts to identify blackspots—areas with a high frequency of crashes—using crash data provide an example of applying data-driven decision-making strategies in urban governance. These blackspot strategies, which are rooted in the principles of evidence-based decision-making, advocating for data analysis, information-based decision-making, and data visualisation, play a crucial role in comprehending complex datasets (Iqbal *et al.*, 2020; Wan, He and Zhou, 2021; Cui *et al.*, 2022). Enhancing urban management and safety involves integrating various data types, such as geospatial data, to identify and map crash-prone areas to optimise patrol allocation (Mesquitela *et al.*, 2022; Sarker, 2022). This strategy is crucial for improving management efficiency, enabling swift decision-making, and securing sustained enhancements in urban safety (Horng *et al.*, 2021).

However, the Jakarta traffic police's desire to visualise traffic crash data can be challenging due to its complexity and heterogeneity. Traditional crash data sources, like the police's IRSMS, often have incomplete datasets due to underreporting, particularly for minor incidents. This can affect visual analysis (Stiles, Li and Miller, 2022). The spatial heterogeneity of the environment is a primary challenge for capturing and representing diverse crash conditions (Yu, Xu and Gu, 2019). The complexity of traffic data requires appropriate visualisation techniques to represent congestion and crash patterns in urban networks (Singh and Mohan, 2019).

Despite the challenges, visualisation can provide a powerful tool for identifying crash hotspots and understanding patterns in traffic incidents. The Jakarta police underscored the usefulness of using map visualisation to identify blackspots and past crash locations, which they perceived as aids in informing patrol deployment decisions to mitigate future crash risks. This method exemplifies how integrating historical crash data with geospatial technology can lead to more informed decision-making and effective public safety management (Miller, 2000; Gregoriades and Chrystodoulides, 2018; Liu and Khattak, 2020). By leveraging advanced visualisation techniques, the police can gain deeper insights into congestion and crash trends, enabling more informed decision-making (Kalamaras *et al.*, 2018; Dong *et al.*, 2023).

Furthermore, even with incomplete datasets, visualisations such as line graphs and bar charts, which are used in the developed dashboard prototype in this study, can help highlight areas where underreporting occurs, guiding efforts to improve data collection and accuracy (Song and Szafir, 2019). Incorporating maps, spatial data analytics, and geographic visualisation into geospatial dashboards, along with visual analytics techniques, is crucial for practical decision support, real-time monitoring, and identifying the movement of blackspot areas over time (Jing *et al.*, 2019; Praharaj, Solís and Wentz, 2022).

7.2.3 Employing data to promote road safety

Using data to increase public safety awareness is crucial in the police approach. Displaying recent crash statistics on roadside billboards encourages road users to drive safely by reaching a broader audience and promoting a road safety culture. The Jakarta police's public awareness campaigns utilise these visible reminders of crash statistics to influence driver behaviour. Participants in strategy discussions noted that such billboards remind road users to drive safely, as seeing the number of crashes and victims can prompt individuals to reconsider their driving habits, fostering a safety culture among road users. This data-driven approach leverages crash statistics to encourage drivers to be more cautious and responsible, demonstrating the potential of data-driven public awareness campaigns in enhancing road safety and underscoring the importance of integrating such strategies into broader traffic management and safety programs (Oviedo-Trespalacios *et al.*, 2019; Steinhardt, 2020; Desjardins and Lavallière, 2023).

By making crash data publicly available, the police aim to raise awareness and promote responsible driving. Sharing crash statistics through public displays is intended to reach a broader audience and instil a sense of accountability among drivers. Visualising crash data is a deterrent and encourages safer driving practices (Desjardins and Lavallière, 2023). In low- and middle-income countries, where road traffic injuries are disproportionately high, sharing crash statistics through billboards could be a vital component of broader road safety programs, which have shown promise in reducing fatalities and injuries when evidence-based interventions are employed (Oviedo-Trespalacios *et al.*, 2019). Visualisation in public spaces can support social and civic purposes, increase social awareness and discourse, and influence meaningful participation and behaviour change related to traffic safety (Steinhardt, 2020).

Despite its benefits, Jakarta traffic police's roadside advertising poses several potential risks to road safety, primarily through driver distraction and increased cognitive workload. Research indicates that roadside advertising, particularly digital billboards, can divert drivers' attention from critical driving tasks, leading to impaired driving performance and increased crash risk (Hinton, Watson and Oviedo-Trespalacios, 2022). Young drivers, in particular, are more susceptible to these distractions due to their lower capacity to discriminate between relevant and irrelevant information, which can result in higher cognitive workload and changes in driving behaviour, such as increased speed in billboard-saturated environments (Oviedo-Trespalacios *et al.*, 2019). The introduction of digital technology in billboards, which often includes changing luminance and interactive elements, further exacerbates this issue by capturing attention involuntarily and reducing the cognitive capacity available for driving, especially in cognitively demanding situations (Mackun and Żukowska, 2017). Additionally, the lack of consistent regulations and management criteria for roadside advertising across different jurisdictions complicates efforts to mitigate these risks (Young *et al.*, 2009; Tarnowski, Olejniczak-Serowiec and Marszalec, 2017).

7.2.4 Simplifying data to enhance accessibility

The Jakarta police's engagement with the Integrated Road Safety Management System (IRSMS) traffic crash database revealed a fundamental challenge: their perceptions about the complexity and granularity of the spreadsheet structured data in the IRSMS database. They expressed the need for a simplified overview of past crashes for planning patrol routes and timings, guiding the deployment of patrol officers by analysing recent crash locations and times. The participants' summarisation needs point to a common trend in decision-making: extracting actionable insights from large, detailed datasets. Jakarta traffic police's hesitancy in interacting with this extensive database underscores the need for e-government initiatives to balance technological sophistication, like IRSMS, with user accessibility to ensure effective and widely used services (Alshira'h, 2020; Al-Rahmi *et al.*, 2022).

Jakarta traffic police's intention to transform "Big Data" into "Small Data" is essential for making datasets more accessible and informative, particularly in fields such as urban planning and transportation, where large datasets are abundant (García-Arteaga and Lotero, 2023). Smart city initiatives focus on transforming complex datasets into actionable insights, a trend also underscored in urban governance discourse (Townsend, 2013; Castro, 2016; Kitchin and McArdle, 2016; Carmichael and Marron, 2018). Summarising large volumes of data is crucial for enhancing policy-making, resource allocation, and governance within the public sector (Janssen, Charalabidis and Zuiderwijk, 2012; Benfeldt Nielsen, 2017). It facilitates more effective decision-making to prevent traffic crashes (Al

Najada and Mahgoub, 2016; Elamrani Abou Elassad, Mousannif and Al Moatassime, 2020).

However, the Jakarta police’s desire for data summarisation and simplification also has potential challenges, such as reducing the richness and scope of the data and potentially overlooking crucial details necessary for creating accurate and effective interventions (Hogarth and Soyer, 2014; Liu *et al.*, 2018). As a result, the data's usefulness in developing focused and effective policy measures may be diminished (Janssen, Charalabidis and Zuiderwijk, 2012). This problem highlights the necessity of policymakers and data scientists working together to guarantee appropriate insights (Verstraete *et al.*, 2021). In smart cities, integrating policymakers and data scientists to transform data into actionable insights is essential for supporting data-driven policies (Levenson and Fink, 2017; van Veenstra and Kotterink, 2017; Verstraete *et al.*, 2021). This collaboration positively impacts policy outcomes (Choi *et al.*, 2005), such as effectively allocating resources and implementing measures to prevent traffic incidents and improve road safety (Machluf *et al.*, 2017).

The implementation of e-government services, as demonstrated by the Jakarta police's use of the IRSMS and their need for simplified data, relies on finding the right balance between presenting data in a way that decision-makers can easily understand without losing any vital information or insights in the process (Liu *et al.*, 2018; Elamrani Abou Elassad, Mousannif and Al Moatassime, 2020). This need for balance highlights the importance of initiatives that improve not only technological capabilities but also prioritise user-centred design principles (Alshira’h, 2020; Al-Rahmi *et al.*, 2022) and the need for collaboration between stakeholders and scientists to extract meaningful data insights (Choi *et al.*, 2005; Machluf *et al.*, 2017; Verstraete *et al.*, 2021).

7.2.5 Analysing data for predictive traffic crash prevention

The participants expressed concerns about the unpredictable nature of traffic crashes and their desire for predictive crash analytics. The literature on crash prevention supports this anticipatory approach through proactive measures (Wu and Lum, 2019; Sieveneck and Sutter, 2021). In smart cities, data analytics are leveraged to enhance urban life, including road traffic safety, to identify and reduce traffic safety issues pre-emptively (Prakash, Suresh and Pn, 2019; Mehdizadeh *et al.*, 2020; Sieveneck and Sutter, 2021; Ismagilova *et al.*, 2022). Predictive analytics can play a significant role in smart city and e-government initiatives, using historical data to anticipate future challenges, allowing for better resource allocation and proactive measures (Shikhar *et al.*, 2016; Leigh, Dunnett and Jackson, 2019) to improve public safety by mitigating risks before they escalate (Ma *et al.*, 2018; Yaduvanshi *et al.*, 2019).

The police's perceptions of the usefulness of historical crash data to inform patrol assignments and monitor high-crash areas align with the literature that emphasises the importance of analysing historical crash data alongside real-time traffic and environmental information to develop models for traffic crash risk prediction and traffic safety improvement (Yu *et al.*, 2016; Chen, Chen and Ma, 2018; Cheng *et al.*, 2018). The Jakarta traffic police's request to generate a crash prediction from the IRSMS data can be related to the concept of predictive policing, which involves developing statistical models for predicting future crashes (Wang, Quddus and Ison, 2013; Aggarwal, 2015; Chen, Chen and Ma, 2018; Hamad *et al.*, 2020). The participants thought having crash predictions should improve traffic safety by enabling them to identify crash-prone locations and deploy patrol resources effectively. The literature also suggests that a predictive capability could enable the optimal allocation of patrolling resources to address and mitigate crash risks pre-emptively (Al-Harthei *et al.*, 2017; Feng, Wang and Quddus, 2020; Sieveneck and Sutter, 2021).

Jakarta traffic police's desire aligns with studies' findings that emphasise the importance of accurate crash prediction models that use real-time traffic information (Lee, Hellinga and Saccomanno, 2006; Hossain *et al.*, 2019). These models establish associations between traffic flow characteristics and crash risks, enabling proactive measures to prevent crashes (Lee, Hellinga and Saccomanno, 2006; Dong *et al.*, 2018). Advanced technologies, such as machine learning and deep learning models, subsets of artificial intelligence, have improved crash prediction accuracy and can effectively extract valuable insights from complex datasets that challenge traditional statistical methods or human analysis (Xu *et al.*, 2013; Sharmin *et al.*, 2020; Olokun *et al.*, 2022; Paderno *et al.*, 2022).

7.2.6 Integrating data and tacit knowledge in decision-making

The Jakarta police's interactions with the Integrated Road Safety Management System (IRSMS) traffic crash database highlight the manifestation of e-government, where digital tools are employed to streamline government operations (Engin and Treleaven, 2019; Mittal, 2020). Their interactions reflect the essential role of informed decision-making in public service, where strategic decisions are based on accurate and relevant data (Abdulhafedh, 2017; Hamad *et al.*, 2020; Hossin *et al.*, 2023). The reliability and accuracy of data sources are foundational for effective public sector decision-making (Müller and Steen, 2019).

The Jakarta police leaders exemplify the essential role of data in enhancing public service efficiency and responsiveness. They demonstrate the data-driven decision-making practice in urban governance, which integrates empirical data and traditional practices to improve urban management and decision-making processes (Sun *et al.*, 2014; Kitchin, 2016; Zhang *et al.*, 2016). For instance, personal experience plays a crucial role in patrol allocation decisions. Officers rely on their experience with past traffic incidents to allocate patrols to locations where crashes are more likely to occur. This understanding, developed through hands-on experience, helps identify high-risk areas that may not be immediately apparent from data alone.

The police's use of real-time communication to monitor traffic conditions further exemplifies this integration. By sharing information about traffic build-ups via police radios, officers can quickly deploy resources to manage traffic flow and reduce the risk of crashes. By combining real-time data with situational awareness, this approach is informed by past experiences and enables officers to respond effectively to dynamic traffic situations. It demonstrates the critical role of tacit knowledge in anticipating and mitigating potential risks, ensuring that technology enhances rather than replaces the human element in public service (Meijer and Bolívar, 2016; Kattel, Lember and Tõnurist, 2020).

Managing and utilising tacit knowledge improves organisational performance and contributes to achieving long-term objectives (Pathirage, Amaratunga and Haigh, 2007; Chen and Mohamed, 2010). The strategic decision-making process heavily relies on tacit knowledge based on experience and intuition (Guthrie, 1996; Khatri and Ng, 2000; Brockmann and Anthony, 2002; Richards, 2002). This is particularly crucial in unpredictable environments like police work, where preset responses are often inadequate, and officers must navigate novel scenarios (Mintzberg, Raisinghani and Theoret, 1976; Khatri and Ng, 2000; Lucena and Popadiuk, 2019). For example, Jakarta traffic police officers prevent traffic disruptions by waking long-haul truck drivers parked on roadsides, urging them to move to safer locations before morning traffic builds up. This proactive intervention, informed by the police's experience, mitigates risks that may not be immediately evident from available data, thereby preventing crashes and maintaining traffic flow.

The Jakarta traffic police believe that accurate, data-backed information complements their real-world experiences, thus enhancing their ability to make informed decisions. The psychological and organisational effects of data-driven governance are profound, with access to accurate and comprehensive data bolstering decision-makers' confidence (Meijer and Bolívar, 2016; Brous and Janssen, 2020). In fast-paced environments such as police duties, where quick decision-making is crucial, having tacit knowledge becomes even more critical for strategic positioning and decision-making (Jones and Mahon, 2012). The Jakarta police's practices in integrating their experiences with data-driven approaches underscore the importance of balancing technological efficiency with a human-centred approach in public service. This ensures that the police can effectively manage and mitigate potential risks, thus enhancing public safety.

7.2.7 Overarching discussion: enhancing public sector decision-making through data-driven approaches and tacit knowledge integration

This study of Jakarta traffic police's current practices and aspirations for data-driven strategies in patrolling allocations offers an insightful use case in the broader context of public sector decision-making. This discussion synthesises the themes of real-time traffic monitoring, crash blackspot visualisation, data simplification, predictive analytics, and integrating tacit knowledge to highlight the complexities and benefits of leveraging data in urban governance.

Using real-time data from mobile applications such as Google Maps and Waze illustrates proactive traffic management. These tools enable immediate and informed decisions regarding patrol deployment, aligning with the broader smart city and e-government paradigms that emphasize risk mitigation before issues escalate (Wu and Lum, 2019; Sieveneck and Sutter, 2021). Integrating private-sector data into public policy formulation reflects an increasing trend where commercial insights enhance urban performance and infrastructure optimization (Kucera and Chlapek, 2014; Choroszewicz and Alastalo, 2021). However, this practice necessitates a delicate balance between leveraging such data and maintaining public service universality and privacy (Tzermias, Prevelakis and Ioannidis, 2014).

Employing data to promote road safety awareness is a critical strategy in police efforts, exemplified by displaying the recent crash statistics on roadside billboards to encourage safe driving. These billboards aim to foster a road safety culture by visually reminding drivers of crash data, potentially prompting safer driving habits (Desjardins and Lavallière, 2023). This approach is particularly impactful in low- and middle-income countries, where road traffic injuries are high (Oviedo-Trespalacios *et al.*, 2019). However, despite its benefits, roadside advertising, especially digital billboards, poses risks by distracting drivers and increasing cognitive workload, particularly among young drivers (Hinton, Watson and Oviedo-Trespalacios, 2022). The lack of consistent regulations further complicates mitigating these risks, highlighting the need for balanced strategies that promote safety without compromising driver attention (Young *et al.*, 2009; Tarnowski, Olejniczak-Serowiec and Marszalec, 2017).

Additionally, the Jakarta traffic police aim to implement evidence-based decision-making using data visualisation to identify crash blackspots. This is a clear demonstration of their commitment to making informed choices. By integrating geospatial data, they aim to pinpoint high-frequency crash areas, facilitating optimized patrol allocations and enhanced urban safety (Iqbal *et al.*, 2020; Wan, He and Zhou, 2021). The strategic use of geospatial dashboards underscores the importance of visual analytics in transforming complex data into actionable insights, thereby supporting more effective public safety management (Jing *et al.*, 2019; Praharaj, Solís and Wentz, 2022).

Furthermore, the police's challenge of interacting with the IRSMS traffic crash database highlights the need for data simplification. Simplifying complex datasets is crucial for making information accessible and actionable, particularly in urban planning and transportation domains, where large volumes of data are prevalent (García-Arteaga and Lotero, 2023). The transformation of "Big Data", such as the IRSMS, into "Small Data", such as the crash summary in the dashboard prototype, is essential for effective decision-making, although it must be managed carefully to avoid losing critical details necessary for accurate interventions (Hogarth and Soyer, 2014; Liu *et al.*, 2018).

Moreover, predictive analytics represents a forward-looking approach to traffic crash prevention, leveraging historical data to anticipate and mitigate future risks (Wu and Lum, 2019; Sieveneck and Sutter, 2021). The Jakarta traffic police's interest in crash predictions underscores the value of integrating predictive models into urban safety strategies. These models, enhanced by advanced technologies like machine learning, significantly improve accuracy and effectiveness, enabling proactive resource allocation and risk management (Xu *et al.*, 2013; Sharmin *et al.*, 2020).

In addition to these technological advancements, integrating data-driven decision-making with tacit knowledge underscores the need for a balanced approach to urban governance. While empirical data provides a robust foundation for strategic decisions, the nuanced understanding derived from on-the-ground experience is equally critical (Sun *et al.*, 2014; Kitchin, 2016). This balance ensures that technological advancements enhance rather than replace the human element in public service, fostering a more holistic decision-making framework (Meijer and Bolívar, 2016; Kattel, Lember and Tõnurist, 2020). Addressing the gap between data-driven methods and tacit knowledge involves fostering collaboration, promoting a culture of information sharing, and providing adequate training to integrate these approaches effectively (Bennett, 1998; Brockmann and Anthony, 2002).

This study's findings regarding DDDM tools' potential to enhance resource allocation and operational efficiency among the Jakarta traffic police must also be contextualised within the broader ethical challenges associated with DDDM. For instance, while predictive tools and data visualisation can provide valuable insights for patrolling allocations, they risk reflecting and perpetuating historical inequities embedded in the underlying data (Hadjimatheou and Nathan, 2022;

Hiller, 2022). The ethical impact of predictive analytics and data visualisation is profound, as their deterministic ‘pre-emptive power’ can shape individual choices and opportunities, raising concerns about agency and fairness (Cavallo, 2022). Such biases may disproportionately affect specific communities, undermining the fairness and inclusivity of decision-making processes (Browning and Arrigo, 2021; Alikhademi *et al.*, 2022; Purves, 2022; Montana *et al.*, 2023; Rajiv, Roshan and Sankaradass, 2023).

Additionally, the importance of trust and transparency, highlighted by participants, resonates with the need to address the "black box" nature of algorithms, which can obscure the rationale behind decisions (Brożek *et al.*, 2024). This aligns with concerns in the literature about ensuring that technological tools remain explainable and accountable (Samek, Wiegand and Müller, 2017; Chen, Chien and Yu, 2023). The lessons from predictive policing systems, which have faced criticism for reinforcing systemic biases (Hung and Yen, 2023; Ziosi and Pruss, 2024), serve as a cautionary parallel for adopting data-driven approaches in traffic management. By embedding ethical safeguards, such as participatory design and regular bias audits (D’Ignazio *et al.*, 2020; Dekker *et al.*, 2022), DDDM tools can be tailored to promote equity and accountability alongside efficiency.

The Jakarta traffic police's aspirations for data-driven strategies in patrolling allocations exemplify a sophisticated approach to urban governance that seeks to leverage real-time data, geospatial visualisation, public safety awareness, data simplification, predictive analytics, and integrating tacit knowledge. These envisioned practices aim to enhance public safety and management efficiency while highlighting the ongoing challenges in balancing technological sophistication with human expertise. Addressing these challenges involves fostering collaboration, promoting a culture of information sharing, and providing adequate training to integrate data-driven methods with tacit knowledge. This study underscores the importance of a nuanced approach that values both technological advancements and the irreplaceable insights human experience provides, aiming to foster more resilient and adaptive public sector decision-making.

7.3 Government employees' participation in ICT development: Jakarta traffic police's dashboard feature requirements

The following sections discuss the Jakarta traffic police's dashboard feature preferences: responsive web design, simple interface, user guidance, and the general need for user-friendly ICT.

7.3.1 Responsive web design: compatible dashboard across devices

The Jakarta traffic police leaders' requirements for the dashboard's device compatibility reveal the essential role of responsive web design in public sector ICT. Responsive web design involves using fluid frameworks to craft user interfaces that adjust to diverse viewing environments like computers, laptops, and mobile devices (Marcotte, 2011; Nebeling and Norrie, 2013; Zanella *et al.*, 2014). Participants emphasised the necessity of the dashboard being mobile-friendly and expressed a preference for using mobile ICT. This focus on mobile accessibility aligns with the growing importance of mobile government (m-government) applications (Al-Hubaishi, Ahmad and Hussain, 2017), which have been acknowledged as a platform for enhancing government ICT by offering convenient access to government resources (Zhu and Hou, 2021).

Jakarta traffic police's preference for responsive web design aligns with the growing range of devices used by government officials, resulting in the emergence of smart governments (Von Lucke, 2016; Engin and Treleaven, 2019). Studies emphasise that government platforms need to be user-friendly on all devices (Cordella and Bonina, 2012; Efe and Özdamarlar, 2021). The Jakarta traffic police's call to prioritise responsive web design for effortless access across devices aligns with e-government studies emphasising the accessibility of government services, which promotes inclusivity and engagement (Robertson, Buie and Murray, 2011; Andreasson and Snaprud, 2014; Akgül, 2016). Research emphasises that the usability of government platforms across all devices, coupled with user-friendly interfaces, is crucial for the effectiveness and adoption of ICT in the public sector (Berg, Giest and Kraaij, 2022).

While responsive web design enhances flexibility and accessibility across various platforms, it also presents drawbacks, particularly in user experience on smaller screens, such as smartphones, where navigation difficulties and reduced content visibility can degrade usability (Hussain and Mkpojiogu, 2015). Furthermore, it faces issues like compatibility with older browsers, longer loading times, and challenges in optimising user experience (Almeida and Monteiro, 2017), with unresponsive websites negatively impacting user convenience and information access (Patel *et al.*, 2015; Zimmermann, Strobbe and Ziegler, 2019; Rehan Anwar, Hardini and Anggraeni, 2021).

In the broader context of smart city governance, the importance of responsive web design is reinforced by research integrating it into ICT development and innovation to provide diverse viewing options (Khan *et al.*, 2017; Rocha *et al.*, 2019). This focus also aligns with ICT acceptance research, indicating that users are more likely to engage with ICTs accessible through their preferred devices (Bröhl *et al.*, 2018; Shimray and Ramaiah, 2019). Moreover, responsive web design has been widely applied in desktop-to-mobile adaptation (Laine *et al.*, 2021), reflecting the need for adaptability in design and aligning with the inclusive and ubiquitous nature of smart city services (Anthopoulos and Reddick, 2016; Berg, Giest and Kraaij, 2022).

7.3.2 Simple interface

The Jakarta traffic police preferred straightforward, user-friendly interfaces and stressed the significance of an accessible and easy-to-understand system. The insights regarding a simple interface highlighted the necessity of an interface that is easy to understand and navigate, aligning with the broader visualisation trend towards intuitive technology designs (Tanahashi *et al.*, 2010; Granic, 2017). The significance of presenting comprehensible complex data is supported by literature indicating that well-designed dashboards can mitigate information overload, especially with large datasets (Anderson *et al.*, 2023), and should minimise cognitive load to generate insights (Ahn *et al.*, 2019).

The police’s preference for a familiar and user-friendly dashboard further underscores the importance of intuitive interfaces that leverage users' existing knowledge. The participants associated simplicity with increased productivity, echoing research that suggests straightforward interfaces can increase performance, satisfaction, and user productivity (Ruijten, Kruyt-Beursken and IJsselsteijn, 2018; Anderson *et al.*, 2023). This productivity is crucial in e-government services and smart city applications where quick and accurate decision-making is essential (Mills *et al.*, 2021; Kaluarachchi, 2022).

The Jakarta police's recommendation of a simple dashboard interface aligns with studies that emphasise the importance of user-friendliness and accessibility in e-government systems, emphasising the importance of UCD (Norman and Draper, 1986; Bertot and Jaeger, 2006; Sambasivan, Wemyss and Rose, 2010; Twizeyimana, 2017). The literature emphasises the critical feature of "information at a glance" for effective dashboard designs (Foth, Choi and Satchell, 2011; Maheshwari and Janssen, 2014; Foth, 2018; Sarikaya *et al.*, 2019; Islam, Bouwman and Islam, 2020). Such designs enable users to comprehend information and make decisions quickly, fostering ICT acceptance and user confidence (Laugwitz, Held and Schrepp, 2007; Smith, 2013). It is crucial to prioritise a human-centred approach when rethinking the implementation of learning technologies to ensure that technology adoption is in line with the needs and abilities of individuals (Norman and Draper, 1986; Bertot and Jaeger, 2006; Liu, 2022).

However, it is also crucial to balance simplicity with functionality to avoid oversimplifying complex governmental processes, which could undermine the effectiveness of e-government solutions (Goldkuhl and Röstlinger, 2014). Integrating technological proficiency with ease of use is necessary to make the dashboard practical and accessible for all users (Bertot and Jaeger, 2006; Schall *et al.*, 2017). While simplicity is desirable, the design should also consider the audience and their specific needs to tailor the dashboard effectively (Schall *et al.*, 2017; Magdalena *et al.*, 2019; Vázquez-Ingelmo *et al.*, 2020).

7.3.3 User guidance

The Jakarta traffic police leaders' recommendations for including built-in user instructions align with the concept of 'onboarding,' which involves guiding users through a system's features and functions (Dhanoa *et al.*, 2022). Effective onboarding is essential for modern dashboard design, as it facilitates non-expert users' understanding of complex datasets (Dhanoa *et al.*, 2022). During the early stages of user engagement, it is crucial to carefully plan the design elements and flow to support the engagement of new users (Cascaes Cardoso, 2017). Participants' suggestion of incorporating a simple guidance text box within the dashboard reflects this approach.

The Jakarta police underscored the value of a guidance textbox, stating that it would be helpful to ensure everyone can effectively navigate and use the dashboard. Including user instructions in the interface of e-government systems has been acknowledged as a crucial element in enhancing accessibility and usability (Venkatesh, Chan and Thong, 2011; Chillakuri, 2020). This desire for a system accessible to all team members, regardless of their familiarity with technology, mirrors a user-centric design philosophy essential in public sector design (Norman and Draper, 1986; Bertot and Jaeger, 2006; Twizeyimana, 2017).

The participants' proposal for a plain, descriptive instruction box in instructional design further underscores the importance of creating user-friendly dashboard guidance. Onboarding is crucial in modern dashboard design, ensuring users can fully leverage the dashboard's capabilities (Chillakuri, 2020). Such guidance should cater to users with diverse levels of technological proficiency, aligning with practical e-government service design principles that emphasise straightforward and clear instructions (Anderson *et al.*, 2023).

7.3.4 Overarching discussion: The desire for user-friendly ICT

This study's requirement elicitation phase implemented a user-centred design (UCD) approach to involve the end users. By exploring the users' decision-making practices and feature preferences, the dashboard prototype aimed to be functional, user-friendly, and relevant to officers' daily operations, following the arguments that an effective e-government system must incorporate user participation to meet their needs (Bertot and Jaeger, 2006; Al-Yawer and Ahmad, 2018). The involvement of users has also been shown to enhance inclusivity and effectiveness in smart city governance (Paskaleva *et al.*, 2017).

A major theme that emerged from the findings is the Jakarta traffic police's desire for a user-friendly ICT solution. This is evident in their emphasis on the need for a responsive web design (RWD), which underscores the necessity for adaptable and versatile user interfaces in government ICT. RWD's role is pivotal in ensuring that public sector platforms are accessible across various devices, including desktops, laptops, and mobile devices (Marcotte, 2011; Nebeling and Norrie, 2013). The emphasis on mobile-friendliness aligns with the broader shift towards mobile government (m-government) applications, which enhance accessibility to government services (Al-Hubaishi, Ahmad and Hussain, 2017).

Furthermore, the police department's preference for mobile-friendly solutions indicates a movement towards smart governance, where the flexibility of accessing services from multiple devices is crucial (Von Lucke, 2016; Engin and Treleaven, 2019). Studies confirm that government platforms must be user-friendly on all devices to promote inclusivity and engagement (Cordella and Bonina, 2012; Efe and Özdamarlar, 2021). However, challenges such as navigation issues on smaller screens and compatibility with older browsers must be addressed to maximise the benefits of RWD (Hussain and Mkpojiogu, 2015; Almeida and Monteiro, 2017)).

In addition to responsive web design, the Jakarta traffic police emphasise the importance of a simple and user-friendly interface. Simple interfaces are essential for reducing cognitive load and enhancing user productivity, mainly when quick decision-making is critical (Ruijten, Kruyt-Beursken and IJsselsteijn, 2018). The emphasis on familiar and straightforward interfaces aligns with the broader trend towards user-centred design (UCD) in e-government services. It aims to make technology accessible to all users regardless of technical proficiency (Norman and Draper, 1986; Bertot and Jaeger, 2006).

However, the challenge lies in balancing simplicity with functionality. Oversimplification can undermine the effectiveness of e-government solutions by failing to capture the complexity of governmental processes (Goldkuhl and Röstlinger, 2014). Therefore, it is crucial to integrate technological proficiency with ease of use, ensuring that the dashboard remains practical and accessible for all users (Schall *et al.*, 2017). The design should be tailored to meet the specific needs of its audience, maintaining a balance between simplicity and comprehensive functionality (Magdalena *et al.*, 2019; Vázquez-Ingelmo *et al.*, 2020).

Finally, the recommendation for built-in user guidance reflects the importance of onboarding in modern dashboard design. Onboarding helps non-expert users navigate complex systems, enhancing their understanding and effective use of the technology (Dhanoa *et al.*, 2022). The Jakarta traffic police's suggestion of incorporating a simple guidance text box within the dashboard aligns with this concept, emphasizing the need for clear and accessible instructions (Cascaes Cardoso, 2017).

Practical user guidance is essential for the accessibility and usability of e-government systems, particularly for users with varying levels of technological proficiency (Venkatesh, Chan and Thong, 2011; Dhanoa *et al.*, 2022). Including plain, descriptive instruction boxes can significantly enhance user experience, ensuring that all team members can effectively utilise the dashboard (Chillakuri, 2020). This approach supports a user-centric design philosophy crucial in public sector technology, promoting greater adoption and satisfaction (Norman and Draper, 1986; Bertot and Jaeger, 2006).

Considering these findings, the emphasis on creating a user-friendly ICT solution is paramount. The Jakarta traffic police's dashboard requirements highlight the critical aspects of responsive web design, simple interfaces, and user guidance in developing effective ICT solutions for the public sector. These elements collectively contribute to the overall goal of creating user-friendly, accessible, and efficient government platforms. A user-driven approach enhances employee engagement and service delivery and aligns with the broader goals of smart governance and effective e-government. Future research should continue to explore and validate these design principles across different contexts and user groups to refine our understanding of user-centric ICT in the public sector.

It is worth noting that the survey responses revealed that the Jakarta traffic police officers generally intended to use the dashboard, as indicated by the BI variables' responses, which were measured using three indicators: the participants' "intend to use", "predict to use", and "plan to use". These variables used Likert scales and received positive ratings from the participants. The positive responses suggest a possible match between the dashboard's content and features and the officers' requirements, which indicates that the user-centred design approach in developing technology solutions might encourage adoption intention.

Past studies have consistently demonstrated the positive impact of UCD on user experience in different areas, such as e-government services (Bertot and Jaeger, 2006; Athmay, Fantazy and Kumar, 2016; Alshira'h, 2020). The importance of being informed and involved in ICT has played an essential role in encouraging user adoptions in the government-to-business (G2B) and government-to-citizens (G2C) fields (Conroy and Evans-Cowley, 2005; Teo, Srivastava and Jiang, 2008), and this study result suggested that it also might be the case in the government-to-employees (G2E).

7.4 Factors influencing dashboard adoption intention

The following sections discuss the factors influencing Jakarta traffic police's behavioural intention to use the dashboard: social influence, education, work experience, age, privacy concerns, interoperability expectations, social incentives, and user experience.

7.4.1 Social influence

The concept of social influence plays a pivotal role in the adoption of ICT among Jakarta traffic police officers, as identified during the requirement elicitation phase. Social influence can be defined as the effect of external factors on individuals' inclination to comply and conform, often driven by the need for social acceptance or a sense of belonging (Cialdini and Goldstein, 2004). Social influence can significantly affect motivation and behaviour, even without explicit rewards (Crawford *et al.*, 2020).

One participant's comment about using ICT to feel more connected with coworkers illustrates the impact of peer behaviour and the need for social inclusion on technology usage (Venkatesh *et al.*, 2003; Isaac *et al.*, 2019). Similarly, other participants recognised the impact of social influence in fostering cooperation and discipline, especially in a hierarchical organisation like their police force. Research suggests that within the police force, the sense of belonging to a group or team can significantly enhance officers' readiness to work together and uphold established norms and standards (Goette, Huffman and Meier, 2006; Okimoto, Hornsey and Wenzel, 2019).

The study's SEM analysis confirms these interview insights. All three social influence indicators showed high factor loadings (influ1= 0.956, influ2= 0.946, influ3= 0.969). The structural model revealed a significant predictive relationship between social influence (SI) and the dashboard adoption's behavioural intention (BI), showing that increased SI correlates with a 26% increase in BI. This result underscores the importance of a supportive social environment in technology adoption, particularly in government settings.

The broader literature establishes the role of social influence in the technology adoption field. It describes how individuals' decisions to adopt technology are influenced by the behaviours and attitudes of others in their social or professional circles (Venkatesh and Bala, 2008; Graf-Vlachy, Buhtz and König, 2018). Social influence, driven by peer behaviour and the need for social acceptance, is crucial for formulating strategies that acknowledge and leverage social dynamics to enhance ICT usage in e-government and smart city governance contexts. Acknowledging social influence in promoting cooperation and discipline, especially in structured organisations like the police force, significantly impacts technology adoption and usage (Alhaderi and Ahmed, 2015; Graf-Vlachy, Buhtz and König, 2018; Donne and Fortin, 2020). Understanding and leveraging these social dynamics in the public sector is crucial, as they play a vital role in determining how technology is adopted and utilised (Alhaderi and Ahmed, 2015; Donne and Fortin, 2020).

7.4.2 Educational level

The study's quantitative analysis observed a significant relationship between education and the behavioural intention (BI) to adopt the dashboard among Jakarta traffic police officers. Police officers with a bachelor's degree or higher demonstrated an 85.5% increased likelihood of intending to use the dashboard compared to their counterparts with only a high school education. This finding underscores the impact of educational background on the propensity of traffic police officers to adopt the dashboard.

Existing literature supports the finding that individuals with higher education levels, often more digitally literate and resourceful, show an increased intention to adopt ICT (Nikou and Aavakare, 2021). Education predicts technology adoption by influencing an individual's ability and willingness to engage with new technologies (Riddell and Song, 2017). Higher education levels increase the likelihood of using e-government services owing to increased familiarity and comfort with technology (Pérez-Morote, Pontones-Rosa and Núñez-Chicharro, 2020).

The observed likelihood of officers with varying education levels adopting the dashboard can be attributed to the benefits of higher education, such as enhanced critical thinking, problem-solving skills, and the ability to integrate complex systems like ICT solutions (Costello, Jackson and Moreton, 2013; Bates *et al.*, 2015; Biswas *et al.*, 2020). However, formal education might not always directly translate into practical skills or readiness for technological changes (Uematsu and Mishra, 2010; Riddell and Song, 2017), highlighting the importance of hands-on experience and continuous training (Cheney, Mann and Amoroso, 1986; Nelson, Kattan and Cheney, 1991).

Enhancing public servants' engagement with advanced ICT tools requires elevating their education level, improving digital literacy, and considering their varying technological competencies in e-government system design (Chohan and Hu, 2020; Morte-Nadal and Esteban-Navarro, 2022). This approach highlights the need for diverse training methods, as formal education and practical training are crucial to ensuring the effective use of e-government and smart city technologies. The findings reveal the need to consider educational backgrounds in ICT adoption strategies and the importance of addressing formal education and practical training to ensure the effective use of e-government and smart governance technologies.

7.4.3 Work experience

The SEM analysis provides significant insights into how the working experience of Jakarta's traffic police officers influences their likelihood of adopting dashboard technology in patrol allocation duties. The results indicate a positive, albeit slight, relationship between an officer's experience and their intention to use the dashboard technology. Specifically, with a coefficient estimate of 0.017, an odds ratio (OR) of 1.017, and a p-value of 0.047, the analysis suggests that for each additional year of experience, there is a 1.7% increase in the probability of an officer using the dashboard for patrol-related decisions.

This discovered relationship aligns with research findings that more professional experience may lead to a higher inclination to adopt new technologies as individuals become more familiar with the evolving technological landscape (Aggarwal *et al.*, 2015; Goeke *et al.*, 2016). The finding that each additional year of experience contributes to a 1.7% increase in the likelihood of adopting the dashboard for patrol decisions might suggest familiarity and comfort with operational procedures, which grow with experience and can enhance the adoption of job-related technologies (Aggarwal *et al.*, 2015; Goeke *et al.*, 2016).

Public sector research suggests the importance of experience in facilitating employees' adeptness at integrating new technologies into their existing practices (Smith, Collins and Clark, 2005; Goeke *et al.*, 2016). More experienced employees might better understand how technology can streamline operations and enhance efficiency and effectiveness in their roles (Weinberg, 2004; Lee and Xia, 2010; Mittal, 2020). The SEM finding that links working experience to an increased inclination to adopt dashboard technology among Jakarta's traffic police officers can help formulate strategies that acknowledge and leverage varying experience levels in successfully deploying ICT in e-government and smart governance initiatives.

7.4.4 Age

The SEM analysis showed a 3.5% decrease in the intention to adopt dashboard technology for each additional year of age among Jakarta traffic police officers. This trend was observed across the surveyed age range, which spanned from 19 to 58 years old. However, it is crucial to consider the limitations of interpreting this decrease as a strictly linear relationship over the entire age range. The cumulative effect of a 3.5% decrease per year, when applied from ages 19 to 58, could theoretically result in a substantial reduction in adoption intention. While the DWLS method used in the SEM analysis is well-suited for handling the ordinal nature of the survey data, the interpretation of a linear decrease across a wide age range should be cautiously approached. In practice, the intention to adopt technology is unlikely to decrease indefinitely and may plateau or reach a lower limit, particularly among older officers who might already have low levels of adoption intention (Mannheim *et al.*, 2023).

This finding supports research suggesting that younger individuals, often more technologically familiar and adaptable, tend to have a higher propensity and a more positive attitude towards adopting new technologies (Venkatesh *et al.*, 2003; Berkowsky, Sharit and Czaja, 2017; Ginters, 2020). The negative relationship between age and the intention to adopt the dashboard also brings to light the issue of the digital divide, which encompasses both access to technology and the ability and willingness to use it (Van Dijk, 2006, 2017). Age is a crucial factor in this divide, with older individuals facing more challenges in adopting new technologies (Van Dijk, 2006, 2017; Given, 2008; Bhattacharjee, Baker and Waycott, 2020; Pang *et al.*, 2021).

The results underscore the importance of tailored training and support for officers. Specialised training programs and user-centric approaches can mitigate the negative impact of age on ICT adoption by accommodating the varied learning styles and technology comfort levels of older individuals (Olphert and Damodaran, 2013; Berkowsky, Sharit and Czaja, 2017). The decreased adoption intention with age among Jakarta traffic police officers may reflect generational attitudes towards technology, as research indicates that different generations vary in their approach to technology use in the workplace (Statnickė, Savanevičienė and Šakys, 2019).

Understanding the impact of age on ICT adoption is crucial for e-government and smart city initiatives. This understanding can inform the design and marketing of initiatives to different age groups, ensuring wider adoption and highlighting the necessity of considering demographic factors, including age, in designing and implementing e-government services (Budding, Faber and Gradus, 2018). The study finding highlights the need to consider age as a significant factor in ICT adoption strategies, including the need for tailored training and support approaches.

7.4.5 Privacy concerns

Jakarta traffic police leaders indicated that privacy concerns influence their motivation to use ICT. These concerns stem from worries about the security of their information, impacting their trust in ICT systems and willingness to share data. Participants shared privacy concerns about using applications with non-disabling continuous location trackers and expressed unease with GPS location-monitored devices, especially those that cannot be deactivated. These concerns reflect a broader issue known as surveillance creep, or function creep, which refers to expanding surveillance technologies beyond their original purpose (Koops, 2021). This issue is driven by the widespread use of GPS-enabled mobile devices and the development of location-based applications (Riaz, Dürr and Rothermel, 2015; Bernot, Trauth-Goik and Trevaskes, 2021).

The participants' concerns about continuous location tracking and the desire for privacy guarantees highlight broader worries about personal data security and user autonomy in technological systems. Ensuring strong privacy safeguards is crucial for encouraging the use of ICT tools (Clayton and Sibbald, 2020). This stance on privacy protection is critical to technology acceptance, especially in professional settings like public service (Bhave, Teo and Dalal, 2019; Schomakers, Lidynia and Ziefle, 2022). The integration of privacy considerations into the early stages of ICT design, known as Privacy by Design (PbD), emphasises the necessity of including privacy characteristics in the initial design and implementation of ICT systems (Wu, Vitak and Zimmer, 2019; Mavroeidi, Kitsiou and Kalloniatis, 2021). According to the PbD method, privacy considerations should always be included in the design and implementation process (Wu, Vitak and Zimmer, 2019).

The quantitative phase supports these insights. The SEM's measurement model revealed that all the indicators for the privacy concerns construct have high factor loadings (priv1=0.995, priv2= 0.861). The structural model results showed a negative correlation between Privacy Concerns and Behavioural Intention, with a coefficient of -0.069 (OR=0.933, p=0.027). This finding indicates that with each increase in privacy concerns, behavioural intention diminishes by 6.6%, aligning with research that suggests privacy concerns can act as a barrier to adopting new technologies (Brous and Janssen, 2020; Chan and Saqib, 2021; Trkman, Popovič and Trkman, 2023).

The concerns expressed by Jakarta traffic police leaders about privacy, particularly regarding continuous location tracking, influence their intention to adopt the dashboard, underscoring the need for robust privacy protections and trust-building measures in developing and implementing such technologies. This significant finding also supports the importance of including negative emotions and experiences in models as they are frequently encountered in the real-world implementation and utilisation of technology (Hornbæk and Hertzum, 2017).

7.5 Novel influencing factors

During the hypothesis development interviews, several Jakarta police officers identified interoperability as a crucial ICT feature. Given the emphasis placed on this factor, it was included in the survey to examine its potential influence on the officers' intention to adopt the dashboard. It is important to note that while the dashboard is not yet interoperable, the expectation itself may play a significant role in shaping adoption intentions. The rationale is grounded in the theory that user expectation could enhance their initial willingness to adopt technology despite the current limitations (Davis, 1986; Venkatesh *et al.*, 2003). Therefore, this study seeks to determine whether the mere expectation of this feature might influence stated intentions to use the dashboard.

During the development of the hypothesis, no other studies were identified that examine interoperability factors, specifically in terms of expectations. Existing research primarily focuses on existing interoperability features (e.g., DeNardis, 2010; Zhan, Wang and Xia, 2011; Santos and Reinhard, 2012; Tripathi, Gupta and Bhattacharya, 2012; Dukić, Dukić and Bertović, 2017; Shahzad *et al.*, 2019; Albahlal, 2021). There appears to be a notable gap in the literature regarding the role of anticipated interoperability in technology adoption. Therefore, the survey questions were refined to capture these expectations, which were further validated through exploratory factor analysis before inclusion in the SEM analysis, as detailed in section 6.1.2.

In addition, regarding the social incentives factor, existing government ICT adoption studies have primarily focused on other incentive forms, such as financial (e.g., Gupta, Dasgupta and Gupta, 2008; Wickramasinghe and Wickramasekara, 2022; Chen, Meng and Yu, 2023), educational (e.g., Gupta, Dasgupta and Gupta, 2008), career promotion (e.g., Yap, Thong and Raman, 1994; Chung, Lee and Kuo, 2016; Camarena and Fusi, 2022), and reward-punishment systems (e.g., Liang, Xue and Wu, 2013; Camarena and Fusi, 2022). While one qualitative study examined incentives such as recognition, status, and a sense of accomplishment (H. Zhang *et al.*, 2022), this current study is, to the best of the researcher's knowledge, the first to quantitatively hypothesise recognition and appreciation as a social incentive construct and explore their impact on public servants' ICT adoption intention.

Finally, Jakarta traffic police identified UX-related factors as motivators for ICT use. While most UX studies rely on summary statistics to assess user experience (Laugwitz, Held and Schrepp, 2008; Forster *et al.*, 2018; Díaz-oreiro *et al.*, 2019; Schrepp, 2019), a few have utilised UX as a latent construct in SEM, yielding varied factor structures (e.g., Deng *et al.*, 2010; Mlekus *et al.*, 2020; Idkhan and Idris, 2023). Therefore, this study explores and examines UX factors to contribute to understanding UX's role in ICT adoption.

7.5.1 Interoperability expectations

Interoperability is a factor that Jakarta traffic police perceived as motivating them to adopt ICT. They highlighted the need for system interoperability in their work, exemplifying the integration of traffic crash and civil registry systems for better communication. The police described challenges with using separate systems for vehicle registration and crash reports, advocating for improved system compatibility. Their preference aligns with literature suggesting that interoperability can reduce redundancy and enhance the user experience in e-government services (Luna-Reyes and Gil-Garcia, 2014; Athmay, Fantazy and Kumar, 2016).

The Jakarta traffic police favoured interoperable applications to replace isolated systems for vehicle registration and crash reporting, stating that such integration would increase efficiency and streamline their tasks. Prioritising interoperability in data and communication exchange is acknowledged in smart city and e-government literature as essential for enhancing operational effectiveness and decision-making (Pardo, Nam and Burke, 2012; Wimmer, Boneva and di Giacomo, 2018). The interoperability feature facilitates smooth communication and data exchange between different systems, devices, or platforms and is essential in public sector ICT systems (Whitman, Santanu and Panetto, 2006; Handley, 2013). It plays a significant role in the success and utility of ICT in government settings (Luna-Reyes and Gil-Garcia, 2014; Athmay, Fantazy and Kumar, 2016).

The subsequent SEM analysis measures the interoperability expectations factor using indicators inter1 (ability to communicate) and inter2 (ability to share data). The measurement model showed high factor loadings (ii1=0.914, ii2=0.981). The structural model revealed a significant correlation between interoperability expectation and behavioural intention, indicating a 78% increase in behavioural intention with an additional increase in interoperability expectations. This result demonstrates that adoption intention is higher among Jakarta police officers who favour an interoperable dashboard.

Interoperability is crucial in e-government and smart cities, enabling services through a unified platform for a convenient experience and integrating diverse devices and services to facilitate the digital transformation of urban environments (Sharma and Panigrahi, 2015; Weber and Žarko, 2019). Seamless integration of systems, data, and applications in smart city designs, involving the effective coordination of various technologies and platforms, is crucial for reducing costs and improving efficiency by ensuring smooth data flow and interoperability (Nuaimi *et al.*, 2015; Albouq *et al.*, 2022). Interoperability can lead to cohesive services and increased efficiencies (Pliatsios, Kotis and Goumopoulos, 2023). Moreover, developing regulatory frameworks and good practice examples is necessary to ensure legal certainty and protect stakeholders' interests, facilitating the broader adoption of interoperable smart city services (Santos and Reinhard, 2012).

7.5.2 Social Incentives

Several Jakarta traffic police leaders revealed the impact of social incentives on their technology usage. They observed that social incentives like recognition or appreciation from commanders influence officers' decisions to use ICTs, indicating the crucial role of recognition as a social incentive. Social incentives, defined as crucial motivators that drive individuals to adopt behaviours aligned with social norms or driven by intrinsic or extrinsic motivations (Nguyen-Van, Stenger and

Tiet, 2021), play a significant role in their ICT usage decision-making process. This perspective aligns with the concept of social reinforcement in technology adoption (Graf-Vlachy, Buhtz and König, 2018; H. Zhang *et al.*, 2022), emphasising the role of positive reinforcement in motivating individuals to engage with new technologies.

Participants' comments on reputation resonate with studies on organisational norms influencing technology adoption (Kamal, 2006; Melitski, Gavin and Gavin, 2010; Talukder, 2012). In the public service sector, the significance of personal reputation for an individual's job satisfaction is well-documented. Research indicates that a positive personal reputation can increase overall work satisfaction (Zinko *et al.*, 2011; Sofyan *et al.*, 2016; H. Zhang *et al.*, 2022). Moreover, personal reputation factors include self-esteem, a sense of belonging, and the desire for rewards (Zinko and Rubin, 2015). Additionally, there is a correlation between employee pride, job satisfaction, and the external reputation of their organisation (Helm, 2013; Zhou, Luo and Tang, 2017). This context allows the understanding of the reasons behind officers' ICT utilisation. These efforts focus on earning respect and are viewed as a way to showcase discipline and obedience, viewed as essential for advancing their careers. These findings underscore the need for strategies that acknowledge and leverage these incentives in ICT adoption among public servants.

The quantitative result confirms the hypothesis, where the measurement model of social incentives showed high factor loadings on both indicators (incen1= 0.980, incen2= 0.963). The SEM's structural model results demonstrated a strong correlation between social incentives and the behavioural intention to adopt the dashboard. The social incentives construct showed a statistically significant predictive relationship with behavioural intention (BI), with a coefficient estimate of 0.220 (OR= 1.248, p=0.000), suggesting a 24.8% increase in BI for each unit increase in social incentives. Users' inclination to use the dashboard can be significantly increased by providing social incentives. The chance that users will accept and use the dashboard increases by 24.8% for every unit increase in social incentives offered.

These insights regarding how recognition and appreciation can drive technology adoption and usage contribute to the discussion of the role of social incentives in encouraging ICT use among government employees. Research indicates that nonfinancial incentives, such as education (e.g., Gupta, Dasgupta and Gupta, 2008), career promotion (e.g., Yap, Thong and Raman, 1994; Chung, Lee and Kuo, 2016; Camarena and Fusi, 2022), reward-punishment systems (e.g., Liang, Xue and Wu, 2013; Camarena and Fusi, 2022), recognition, status, and a sense of accomplishment (H. Zhang *et al.*, 2022), significantly enhance productivity and motivation, which can be extended to adopting ICT in the public sector. Recognising and leveraging these dynamics is critical to encouraging ICT tool usage in professional settings (Scherer *et al.*, 2018), where technology can significantly enhance operational efficiency and decision-making (Pereira *et al.*, 2018; Contreras-Figueroa *et al.*, 2021). Addressing social and organisational challenges is crucial to fully realise the benefits of ICT, as it can transform government operations and improve service delivery (Rehouma and Hofmann, 2018).

7.5.3 User experience-related factors

The survey results confirmed that the UX latent variable/ construct influences the Jakarta traffic police's intention to adopt the dashboard. These findings support the literature, which has argued that when studying ICT acceptance and adoption, it is essential to combine UX factors, which focus on the experiential aspect, with technology acceptance factors that prioritise utilitarian aspects (Balaji *et al.*, 2015; Hornbæk and Hertzum, 2017; Mlekus *et al.*, 2020). The UX construct, measured by four indicators (innovativeness, leading edge, speed, and supportiveness), has a significant relationship with the BI construct with a coefficient of 0.090 (Odds Ratio/OR=1.094, p=0.018). This result suggests that for every incremental unit enhancement in UX, the user's behavioural intention to employ the dashboard experiences a proportional escalation of 9.4%.

This finding further validates positive user experience's significant influence on user satisfaction and intention to use e-government services (Al-Rahmi *et al.*, 2022). However, there is inconclusiveness among a few studies that examined the influence of User Experience (UX) on ICT adoption. These studies yielded different outcomes regarding the factor structures (e.g., Deng *et al.*, 2010; Mlekus *et al.*, 2020; Idkhan and Idris, 2023). Therefore, the SEM results of each UX indicator will be provided in detail in the following sections to contribute to the UX literature.

7.5.3.1 Innovativeness

The hypothesis development interviews showed that the inclination for innovativeness drove ICT usage among Jakarta traffic police officers. Innovativeness, the readiness to accept new and emerging technologies, reflects a desire to remain at the forefront of technological progress (Bibri and Krogstie, 2017a). Participants expressed a strong interest in exploring and utilising cutting-edge ICT solutions like virtual and augmented reality, emphasising innovation as a defining characteristic of efficient ICT. This perspective reflects the practical advantages of keeping up with continuous technological advancements and using these innovations effectively. The participants' view that innovation signifies high-quality ICT aligns with the literature emphasising the critical role of creative and innovative solutions in enhancing the efficacy of ICT (Pereira *et al.*, 2018).

The SEM's Confirmatory Factor Analysis (CFA) supports these insights, revealing a substantial factor loading of 0.807 for the innovativeness indicator within the User Experience (UX) construct. The high factor loading of the CFA highlights the importance of innovativeness in enhancing user experience and, as a result, increasing the likelihood of Jakarta traffic police officers adopting the dashboard. The findings emphasise the desire for innovative features in ICT design among Jakarta traffic police officers. The results also support the importance of staying current with technological advancements, which are crucial to enhancing the adoption and effective use of these technologies in public sector environments, balanced with responsible and sustainable approaches.

The technology acceptance literature identifies innovativeness as a critical trait influencing the speed at which an individual or organisation adopts new technologies (Dedehayir, Mäkinen and Ortt, 2018). Innovative technologies like virtual and augmented reality are increasingly being explored for their potential to enhance public services and governance (Komninos, Pallot and Schaffers, 2013; Schrom-Feiertag *et al.*, 2018). Furthermore, fostering an innovative culture and embracing new technologies can facilitate the adoption of smart governance practices, leading to improved decision-making and service delivery (Nam and Pardo, 2011; Caird and Hallett, 2018). The importance of innovativeness in the UX design of ICT is highlighted, where incorporating innovative elements can significantly enhance the adoption and usage of e-government services (Kilicer, Bardakci and Arpaci, 2018).

However, to ensure responsible and sustainable technological advancement and to avoid technocratic governance, innovation in ICT must be responsible by considering ethical and social implications (Kitchin, 2015; Stahl and Jirotka, 2017; Kummitha, 2020; Tocci, 2020; Sengupta and Sengupta, 2022). Failure to recognise the significance of organisational culture, norms, and standards in ICT-driven innovations can also result in difficulties and inconsistencies in public administration settings (van Duivenboden and Thaens, 2008; Ravishankar, 2013). Adopting responsive governance strategies is vital to managing technological risks, as these strategies involve regulatory frameworks that adapt swiftly to the rapid evolution of digital platforms (Taeihagh and Lim, 2019). There is a delicate balance between ensuring safety and fairness through necessary governance and avoiding excessive regulation that could potentially stifle innovation in emerging or unproven technologies (Perrier, 2022).

7.5.3.2 Leading edge

The Jakarta police leaders stated that the leading-edge quality of ICT motivates them to use these technologies. "Leading edge" in the ICT context signifies being at the forefront of technical innovation (Abdullah, 2023). One participant stressed the importance of keeping up with the latest technical advancements, suggesting that this benefits the rapidly evolving technological landscape. Studies suggest that people with preferences for new technology are committed to staying up-to-date with ICT by adopting appropriate advancements (Qu and Weston, 2015; Taherdoost *et al.*, 2018).

They discussed Google Workspace for practical examples, highlighting how its continuous incorporation of new features streamlines work processes. The practical benefits of engaging with leading-edge technologies demonstrate how adopting them can streamline work processes and enhance efficiency (Anthopoulos and Reddick, 2016; Warner and Wäger, 2019). These technologies can enhance service delivery, lower costs, and increase transparency for e-government solutions (Archmann and Iglesias, 2010; Reddick, Chatfield and Jaramillo, 2015; Anthopoulos and Reddick, 2016; Di Giulio and Vecchi, 2023).

However, carefully considering elements like the accessibility of information data infrastructure and the application of knowledge management systems is necessary to implement these technologies successfully (Yang *et al.*, 2006; Onyshchuk *et al.*, 2020; Di Giulio and Vecchi, 2023).

The police's comments align with the principles of smart governance, where advanced technologies are vital to enhancing public services and improving decision-making processes (Gil-Garcia, Helbig and Ojo, 2014; Pereira *et al.*, 2018). Moreover, the CFA's high factor loading of 0.950 for the leading-edge indicator in the UX construct suggests a strong correlation between the perception of technology as leading-edge and user experience, aligns with literature highlighting the role of advanced features and continuous innovation in enhancing user satisfaction and adoption of ICT solutions in e-government (Lee and Xia, 2010; Craddock *et al.*, 2012; Gil-Garcia, Helbig and Ojo, 2014; Verkijika, 2018; Choi *et al.*, 2021; Neelu and Kavitha, 2021). Combining leading-edge technologies, innovation, and principles of good governance is essential for developing smart, creative, innovative, and sustainable cities (Lopes, 2017). The significance of leading-edge technology in user adoption is also evident in various sectors, including e-government, where technological advancements can motivate public sectors to adopt new ICT solutions (Mergel, 2016).

7.5.3.3 Speed

Jakarta traffic police leaders emphasised 'speed' as a crucial motivator for their ICT use, highlighting the importance of quick application loading times for practical app usage. The negative impact of slow applications, as discussed by the police, aligns with studies that have explored how system performance issues affect user perceptions and willingness to use e-government services (Papadomichelaki and Mentzas, 2012; Fan and Yang, 2015; Sharma, 2015). The police also mentioned the role of speedy ICT in emergencies, which studies found particularly relevant in law enforcement and emergency response scenarios (Bharosa, Lee and Janssen, 2010; Verhulst and Rutkowski, 2017).

The police also stated that rapid loading is vital for efficient access to information and is essential in utilising technology for daily tasks, stressing the need for ICT applications to be fast and responsive. Fast and responsive ICT systems are linked to improved efficiency in government operations and service delivery (Verhulst and Rutkowski, 2017; Mergel, Edelmann and Haug, 2019). The Jakarta traffic police's collective viewpoint indicates a strong preference for efficient ICT experiences, with participants believing that faster applications enhance performance and productivity. Their comments reflect a broader theme in e-government research, exploring the connection between ICT efficiency, reduced downtime, and increased user satisfaction (Mahmoodi and Nojedeh, 2016; Sachan, Kumar and Kumar, 2018; Nam *et al.*, 2022). Studies suggest that system response time is an ICT-supportive factor influencing user satisfaction (Shaw, DeLone and Niederman, 2002; David, Chalon and Delomier, 2013).

Supporting these qualitative insights, the SEM's CFA for User Experience (UX) showed a high factor loading of 0.951 for the speed indicator, suggesting that ICT speed significantly impacts the user experience of Jakarta traffic police leaders. This finding is consistent with a broader topic in e-government research, which suggests the relationship between decreased downtime, ICT efficiency, and improved user happiness (Laugwitz, Held and Schrepp, 2007; Mahmoodi and Nojedeh, 2016; Sachan, Kumar and Kumar, 2018; Díaz-oreiro *et al.*, 2019). The focus on 'speed' by Jakarta traffic police leaders underscores the essential role of fast ICT systems in improving operational efficiency and emergency responsiveness. These insights suggest the importance of high-speed ICT infrastructure in enhancing government service delivery and operational productivity.

7.5.3.4 Supportiveness

The participants stated that ICT tools should be supportive of their tasks. They highlighted the importance of using ICT, like dashboards, to streamline daily tasks, primarily visualising and sharing information for better collaboration with colleagues. This finding emphasises the need for ICT tools that can help improve job efficiency by making information more accessible and facilitating better sharing. Participants' emphasis on ICT tools like dashboards aiding in daily tasks resonates with the concept that perceived usefulness is a critical factor influencing technology adoption in public service delivery (Weerakkody *et al.*, 2015; Engin and Treleaven, 2019; Velsberg, Westergren and Jonsson, 2020; Chohan *et al.*, 2021; Chohan and Hu, 2022).

The role of supportive ICT in decision-making was a recurring theme among participants. For example, the participants noted that supportive ICT could increase efficiency in identifying potential crash locations and optimising resource allocation. Their emphasis on ICT offering valuable insights aligns with the focus on data-driven decision-making in e-Government and smart city governance (Wang and Feeney, 2016; El-Haddadeh *et al.*, 2019; Soomro *et al.*, 2019; Choi *et al.*, 2021; Todisco *et al.*, 2021; Sarker, 2022; Hossin *et al.*, 2023).

Participants also pointed out the conditional nature of ICT adoption, pointing out that they are more inclined to use ICT solutions that genuinely support their work by fulfilling specific informational needs. This pragmatic approach, aligning with research findings, shows that public officials increasingly recognise the value of ICT tailored to their specific needs, resulting in improved efficiency and effectiveness in their roles (Dawes, Cresswell and Pardo, 2009; Wang and Feeney, 2016; Todisco *et al.*, 2021). Studies suggest that individuals' subjective perceptions of ICT supportiveness in products or services are shaped by factors like system response time, user understanding, effectiveness, effort, and performance expectations, which collectively influence user satisfaction (Shaw, DeLone and Niederman, 2002; Al-Maskari and Sanderson, 2010; David, Chalon and Delomier, 2013; Helin *et al.*, 2018).

The SEM result reinforces these insights. The CFA showed a high factor loading of 0.999 for the supportiveness indicator, confirming the contribution of ICT supportiveness in the overall user experience of Jakarta traffic police officers. This CFA result aligns with literature findings that when ICT solutions actively contribute to their work, public officials are more likely to have a positive user experience, encouraging adoption (Gupta, Dasgupta and Gupta, 2008; Papadomichelaki and Mentzas, 2012; Kant and Jaiswal, 2017). The findings demonstrated the importance of supportive ICT in the work of Jakarta traffic police officers. The emphasis on ICT tools that assist in task performance, cater to specific informational needs, and enhance decision-making processes underscores the need to design ICT solutions that are closely aligned with the practical and operational requirements of users in the public sector.

7.6 Overarching discussion of the influencing factors for ICT adoption intention

This study integrated interview insights to develop quantitative hypotheses to examine the factors affecting IT adoption, a key yet understudied part of government ICT acceptability (Ives and Olson, 1984; Bano and Zowghi, 2015; Raimondo and Newcomer, 2017; Rehouma, 2017, 2020; Rehouma and Hofmann, 2018). This comprehensive approach aimed to uncover the complex dynamics between technology, governance, and human factors, thereby providing a holistic view that is important for understanding the influence of government employee involvement in IT system adoption and offering contextually rich and generalisable insights.

The Jakarta traffic police's perceived factors motivating their ICT usage were elicited. By directly engaging with officers, the research attempted to capture the nuanced experiences, attitudes, and expectations often missed by quantitative analyses alone. Utilising these qualitative findings to formulate quantitative hypotheses enabled the statistical identification of relationships grounded in the experiences of the target users. This approach was intended to make the subsequent quantitative analysis more relevant and applicable and ensure the findings were statistically robust and contextually meaningful.

The study's survey on the factors influencing the behavioural adoption intention of a dashboard by traffic police officers in Jakarta has revealed several essential drivers. The findings uncover a complex interplay of technological, social, and individual determinants. These overarching themes provide a multifaceted understanding of ICT adoption in the public sector and highlight the interconnectedness of various factors that shape adoption's behavioural intentions.

A significant focus is placed on the need for technological sophistication, including critical aspects such as interoperability, speed, innovativeness, and leading-edge technology. This theme emphasises the preference for advanced and user-friendly systems that support seamless communication and data exchange, underlining the importance of technological capabilities in improving operational efficiency and decision-making processes within the public sector.

The analysis further reveals the profound impact of social dynamics, including social influence and incentives like recognition and appreciation. This aspect demonstrates the extent to which ICT adoption is influenced by the broader social environment, including peers, superiors, and the prevailing organisational culture, underscoring the role of social factors in encouraging or hindering technology adoption in professional settings and the public sector (Pereira *et al.*, 2018; Scherer *et al.*, 2018; Contreras-Figueroa *et al.*, 2021; H. Zhang *et al.*, 2022).

The study also highlights how individual characteristics such as educational level, work experience, and age significantly affect the inclination toward ICT adoption. This insight points to the varied responses to technology based on demographic factors, suggesting that a deeper understanding of these characteristics can inform strategies to enhance technology uptake (Aggarwal *et al.*, 2015; Berkowsky, Sharit and Czaja, 2017; Riddell and Song, 2017; Van Dijk, 2017; Ginters, 2020; Nikou and Aavakare, 2021).

Privacy concerns are pivotal, indicating a critical barrier to ICT adoption. This aspect stresses the need for robust privacy measures and transparent data handling practices to build trust in ICT systems, signalling the necessity of addressing privacy and security from the outset of technology implementation, especially in professional environments such as public service (Bhave, Teo and Dalal, 2019; Clayton and Sibbald, 2020; Schomakers, Lidynia and Ziefle, 2022).

Lastly, the importance of user experience, encompassing supportiveness, speed, innovativeness, leading edge, and the alignment of ICT tools with users' needs, is identified as a critical factor. This theme underlines the necessity of developing ICT solutions that are not only technologically advanced but also tailored to fit users' work practices and expectations, thereby enhancing satisfaction and adoption rates (Balaji *et al.*, 2015; Hornbæk and Hertzum, 2017; Mlekus *et al.*, 2020; Al-Rahmi *et al.*, 2022).

These insights suggest that achieving a successful ICT adoption among Jakarta traffic police leaders requires a multidimensional approach. This approach must simultaneously address the technological capabilities of the dashboard system, the social dynamics within the police force, the individual characteristics of the officers, privacy considerations, and the overall user experience. By acknowledging the complexity of factors influencing ICT adoption, this analysis underscores the need for holistic strategies that consider the technological, social, and individual dimensions to effectively enhance the adoption and utilisation of ICT tools in public service delivery.

7.7 Summary of chapter

This study explores ICT development and examines the behavioural intention to adopt it among Jakarta's traffic police officers, adopting User-Centred Design (UCD) to meet their decision-making needs. It begins by focusing on eliciting requirements for a patrolling allocation dashboard, identifying the police's decision-making practices and feature expectations. These include real-time traffic monitoring, crash data visualisation, road safety campaigns, predictive analytics for crash locations, and support for tacit knowledge in decision-making, reflecting a comprehensive understanding of urban governance and e-government applications.

The study investigates the motivations behind ICT adoption among officers, revealing key factors such as system interoperability expectations, privacy concerns, social incentives, educational level, age, work experience, and user experience. Notably, expectations for interoperability between various government systems, social recognition, higher educational levels, and positive user experiences emerged as significant motivators. Conversely, privacy concerns and older age appeared as deterrents.

Through its findings, the study contributes to the broader literature on e-government and smart city governance by highlighting the critical role of user-centred design in uncovering users' requirements and promoting ICT adoption among public servants. It underscores the need for ICT solutions that are not only technologically advanced but also align with users' practical needs and concerns, thereby enhancing the effectiveness of urban governance initiatives.

Chapter 8 Conclusion

8.1 Introduction

This chapter provides the conclusion for this study. The first section is the study summary, followed by the findings. The next sections provide theoretical, practical, and policy implications. The study limitations and recommendations for future research are also described.

8.2 Study summary

This section provides a concise overview of the research conducted on ICT development participation and adoption intention among Jakarta's traffic police officers. The dashboard development phase adopted a User-centred Design (UCD) by including Jakarta traffic police as end-users in the design process to ensure that the resulting dashboard is practical, relevant, and user-friendly. Interviews were conducted to gather requirements from Jakarta traffic police leaders for dashboard development. These interviews provided insight into the police's decision-making practices. The police's participation in the dashboard development also revealed their preferences for the dashboard features.

The subsequent adoption intention examination phase used a multi-method approach to understand the factors influencing the intention to adopt the developed dashboard for patrolling allocations. This phase developed a set of quantitative hypotheses by interviewing the officers regarding the perceived factors that motivate their use of ICT. Subsequently, a survey was conducted to gather data, which were then quantitatively analysed using an SEM method. This research phase revealed the main factors influencing the intention to adopt the dashboard among Jakarta traffic police officers.

8.3 Findings from research questions

8.3.1 Decision-making in Jakarta traffic police' patrolling allocations

RQ1: How do government employees conduct decision-making within the data-driven decision-making framework?

This study provides a comprehensive analysis of the Jakarta traffic police's decision-making for patrolling allocations, offering contributions to the empirical evidence supporting the practical application of data-driven decision-making (DDDM) theories in the public sector.

The findings contribute to the noted gap in empirical evidence for DDDM by illustrating how the Jakarta traffic police effectively utilise real-time traffic monitoring tools like Google Maps and Waze. These tools facilitate proactive traffic management and illustrate the practical steps in integrating commercial data into public sector decision-making. This aligns with the broader smart city and e-governance paradigms, emphasising risk mitigation, thus bridging the gap between theoretical potential and practical application (Brynjolfsson and McElheran, 2016; Dingelstad, Borst and Meijer, 2022).

Another aspect revealed by this study is the Jakarta traffic police's recognition of the need for advanced geospatial data and predictive analytics. Although these tools are not yet implemented, there is a clear aspiration to use geospatial data to visualise traffic black spots and predictive analytics to forecast traffic crash risks. This need highlights the importance of such technologies in optimising patrol allocations and enhancing urban safety. The study underscores the potential for these tools to transform complex data into actionable insights and proactively prevent traffic incidents, contributing to understanding which data types and analytics tools function best in specific situations.

The Jakarta police’s use of data to enhance road safety awareness, particularly through displaying recent crash statistics on roadside billboards, can be an effective strategy for promoting road safety. The visibility of crash data prevents unsafe driving practices and fosters a culture of caution and responsibility among road users (Desjardins and Lavallière, 2023). By publicly sharing crash data, the police aim to raise awareness and instil accountability, motivating drivers to reconsider their habits and ultimately reducing traffic crashes. This data-driven approach underscores the potential of public awareness campaigns in improving road safety and highlights the importance of integrating such strategies into broader traffic management initiatives.

The desire to integrate predictive analytics reflects a forward-looking strategy to prevent crashes before they occur. By leveraging historical data and advanced technologies such as machine learning, the Jakarta traffic police aim to adopt a proactive approach to resource allocation. This finding contributes to the empirical need to explore the practices of integrating computational models and predictive analytics into public sector decision-making.

Additionally, integrating tacit knowledge with empirical data is emphasised, showcasing the need for a balanced approach in urban governance. This blend of data-driven methods and on-the-ground experience ensures that technological advancements enhance rather than replace the human element in public service. This aspect of the study informs practitioners on effectively integrating these approaches, promoting a culture of collaboration and information sharing within government agencies.

The findings also stress investing in technology and human resources to create a solid foundation for DDDM. Ensuring that all government agencies have the necessary infrastructure and trained personnel is crucial for successfully implementing data-driven practices. This highlights the need for adequate resources and infrastructure to integrate data analytics into public administration consistently.

Overall, this study contributes to the academic understanding of DDDM in the public sector and provides practical insights for policymakers and urban planners. By illustrating the practical application of data-driven strategies in traffic management, the study complements theoretical propositions and offers evidence-based recommendations to refine DDDM theories and practices. This nuanced approach values both technological advancements and the irreplaceable insights human experience provides, aiming to foster more resilient and adaptive public sector decision-making.

8.3.2 Participation in ICT development

RQ2: "What features do government employees prefer in an ICT for decision-making, and how does their participatory involvement in its development provide insights into user-centred design practices?"

This study provides empirical insights into the expectations of Jakarta traffic police for features in a patrolling allocation dashboard, underscoring the importance of user participation in developing ICT solutions for the public sector. The findings address significant gaps in the existing research by highlighting the critical role of government employee participation in developing ICT solutions, a topic often overlooked in the literature. The results also address the gap in policing literature by involving police in the research process and exploring how research findings should be disseminated to bridge the gap between research and policing practices.

The research highlights a strong need for user-friendly ICT solutions, as evidenced by the traffic police's strong preference for a responsive web design (RWD). This preference underscores the necessity for adaptable and versatile user interfaces that can be accessed across various devices, including desktops, laptops, and mobile devices. The emphasis on mobile-friendliness aligns with broader trends towards m-government applications, which enhance accessibility to government services and support smart governance initiatives. Studies affirm that user-friendly government platforms on all devices promote inclusivity and engagement, although challenges such as navigation issues on smaller screens and compatibility with older browsers must be addressed to realise the full benefits of RWD.

Moreover, the importance of simple and user-friendly interfaces was a recurring theme. Simple interfaces are essential for reducing cognitive load and enhancing productivity, especially in high-stakes environments like traffic management, where quick decision-making is crucial. This focus aligns with the broader trend towards user-centred design (UCD) in e-government services, which aims to make technology accessible to all users regardless of their technical proficiency. However, balancing simplicity with functionality remains a challenge, as oversimplification can undermine the effectiveness of e-government solutions. Thus, it is vital to integrate technological proficiency with ease of use to ensure that the dashboard is both practical and accessible.

The recommendation for built-in user guidance underscores the importance of onboarding in modern dashboard design. Onboarding helps non-expert users navigate complex systems, enhancing their understanding and effective use of the technology. The Jakarta traffic police's suggestion to incorporate simple guidance text boxes within the dashboard reflects this need for clear and accessible instructions, which can significantly enhance user experience and ensure effective dashboard utilisation by all team members.

The positive survey responses from Jakarta traffic police officers regarding their intention to use the dashboard can be seen as validating the user-centred design approach. The high ratings on the “intend to use”, “predict to use”, and “plan to use” the dashboard indicate that the developed features likely align well with the officers' requirements. This suggests that involving end users in the design and development process can significantly enhance the likelihood of adopting new technology solutions in the public sector.

Past studies have consistently demonstrated the positive impact of UCD on user experience across various domains, including e-government services. The findings of this study extend these insights to the government-to-employees (G2E) context, suggesting that informed and involved users are more likely to adopt new ICT solutions. This reinforces the importance of user participation in developing government ICT solutions to meet user needs and encourage their adoption effectively.

By focusing on the perspectives and participatory roles of the Jakarta traffic police, this study fills the gap in understanding how employee participation influences ICT development in the public sector. The critical role of government employee participation in enhancing public sector IT project outcomes is acknowledged yet underexplored in existing research. The experiences, perceptions, and challenges faced by public servants, who are the primary users of ICT in urban governance, are crucial for the effectiveness of e-government initiatives. This study addresses these aspects, providing empirical evidence highlighting the benefits of engaging employees in the ICT development process.

Overall, the study contributes to knowledge by offering empirical insights into the importance of creating user-friendly, accessible, and efficient government platforms by incorporating elements such as responsive web design, simple interfaces, and user guidance. This user-driven approach enhances employee engagement and service delivery and aligns with the broader goals of smart governance and effective e-government.

8.3.3 Influencing factors of ICT adoption intention

The research questions for the adoption intention examination phase are:

RQ3: What factors are perceived as motivating government employees' adoption of ICT tools, and how can these insights inform the understanding of technology acceptance in the public sector?

RQ4: "What are the relationships between identified motivational factors and the behavioural intention of government employees to adopt ICT, and how do these findings contribute to the refinement of ICT adoption theories in public sector settings?"

Overall, the research on the factors that influence the intention of Jakarta traffic police officers to adopt a dashboard uncovers a landscape of motivations for using ICT. This study reveals that interoperability expectations, privacy concerns, social incentives, social influence, educational level, work experience, age, and user experience influence public servants' decisions to use ICT tools.

Interoperability became crucial as officers expected smooth communication and data exchange between systems. The emphasis on interoperable applications highlights the significance of smooth workflows and practical information sharing in improving operational effectiveness.

Privacy concerns were also significant, indicating a sense of unease regarding data security and personal privacy. These concerns highlight the importance of strong privacy protections in ICT systems, especially in sensitive domains such as public service.

Social incentives and social influence played a substantial role, emphasising the importance of recognition, respect, and appreciation in motivating officers to embrace ICT tools. The significance of social dynamics in technology adoption within hierarchical organisations cannot be overstated.

The level of education played a significant role in predicting the adoption of technology, as officers with higher education levels were more likely to use the dashboard. This discovery highlights the importance of being digitally literate and understanding technology when influencing one's adoption intentions.

Previous work experience demonstrated a connection to adoption intention, indicating that familiarity with operational procedures and the ever-changing technological landscape increases the likelihood of embracing job-related technologies.

Age negatively correlated with adoption intention, underscoring the importance of addressing the digital divide and providing customised training and support for older officers to encourage wider adoption.

Ultimately, the user experience influenced the intention to adopt, which included factors such as innovation, leading edge, speed, and support. Officers favoured ICT tools that are cutting-edge, technologically advanced, speedy, and helpful for their tasks, highlighting the importance of user-focused, efficient, and state-of-the-art ICT solutions.

These findings contribute to knowledge by offering insights into the dynamics of ICT adoption among public servants. Taking a comprehensive approach when designing and implementing ICT tools is crucial. Factors like interoperability, privacy, social dynamics, education, experience, age, and user experience should be considered to improve adoption and effective use in e-government and smart city initiatives. A thorough understanding of these factors is essential to develop effective strategies that maximise the use of ICT in professional settings, especially in public service delivery.

8.4 Theoretical implication

This study offers insights into e-government, smart city governance, public sector DDDM, and policing literature. The research enriches the theoretical understanding of decision-making and technology integration within public service by examining the application of data-driven strategies and ICT tools.

The study reinforces the significance of tacit knowledge in data-driven decision-making in public administration, highlighting the role of personal experience in governance processes. This finding aligns with the public sector DDDM theory, emphasising the critical role of tacit knowledge of data in the public sector's informed decision-making.

By involving the police in dashboard development for patrolling allocation, this study provides insights into employees' participation in government ICT development, which is the field that has received less focus. The dashboard development phase provides empirical insights into developing user-centred public sector ICT and the vital need for user-friendly ICT. This finding confirms existing literature on the necessity of government technology to focus more on the human element, providing valuable insights into the discourse on human-centric technology development in e-government and smart governance. The involvement also contributes to the gap in the policing literature that calls for studies into police involvement in the research process and the dissemination of research findings between departments, especially in showing how a user-centred dashboard can be potentially valuable.

Exploring interoperability within public sector ICT, the research enhances the theoretical grasp by showing that even in the early form of expectation, seamless communication and data exchange between different systems can elevate user adoption intention for Government ICT. It highlights the necessity of considering interoperability early in government ICT development.

This study also provides new insights into how social incentives positively influence behavioural intention to adopt ICT among government employees. It highlights the potential impact of well-structured incentive mechanisms, such as appreciation and recognition, on accelerating ICT adoption within government sectors.

Lastly, the research's focus on user experience (UX) in public sector ICT offers contributions to theories of UX, drawing attention to the importance of innovativeness, leading-edge quality, speed, and supportiveness in fostering positive adoption intentions of ICT among public servants.

Overall, this study provides a multifaceted view of data-driven decision-making, development participation, and adoption of ICT in public sector governance, offering theoretical and practical insights that advance our understanding of e-government, smart city initiatives, and the critical interplay between technology, policy, and human factors in public administration.

8.5 Practical implication

On a practical level, this study offers insights for public sector IT developers and administrators tasked with implementing ICT solutions. The dashboard prototype development highlighted critical user needs, such as data accuracy, simplicity, device compatibility, and integrated guidance, emphasising the importance of aligning technological tools with real-world operational demands and ensuring reliable databases like the IRSMS support them. In addition, the findings concerning interoperability and user-friendly interfaces suggest that these features should be prioritised to mitigate user frustration and enhance system integration into daily operations. These results underline the necessity of involving end-users in the design process to ensure that the technological tools are robust, practical, and tailored to the specific contexts of their use. These insights can guide future refinements of the dashboard and similar ICT solutions.

Furthermore, the study recommends proactive approaches to privacy concerns and suggests incorporating demographic variables such as age and education into training programs to improve technology adoption rates. Practically, this means developing customised training programs that address the distinct needs of various user demographics and embedding robust privacy protections to increase trust and user acceptance.

In summary, the practical implications derived from this study offer a roadmap for enhancing urban governance and public service delivery through strategic ICT integration, highlighting the importance of user-centric design, predictive analytics, interoperability, privacy considerations, and the leveraging of social dynamics in the development and deployment of ICT solutions in the public sector.

8.6 Policy implication

From a policy perspective, the study advocates for formulating government policies that promote extensive user engagement from the early stages of ICT project development. Policies should encourage collaborative approaches involving users, developers, and policymakers in co-creating ICT solutions. Moreover, such policies should enforce strict privacy measures and maintain transparency in managing and using user data to build trust. By implementing these recommendations, governments can enhance the effectiveness, acceptance, and accountability of e-government services, leading to improved public sector performance.

Collectively, these policy implications offer a roadmap for leveraging ICT to enhance smart city governance, improve public service delivery, and foster a more engaged, safe, and efficient urban environment. Policymakers play a pivotal role in translating these insights into actionable strategies that can transform urban governance and elevate the quality of life for citizens.

8.7 Limitations of the study

A potential limitation of this study is response bias, as it is possible that individuals who are more inclined to use the dashboard technology may have been more motivated to respond to the survey. This possibility could result in an overrepresentation of positive perceptions and intentions, potentially affecting the generalisability of the findings. However, it should be noted that there is no clear evidence to confirm this bias.

Another possible limitation concerns the influence of power relationships, where participants may have felt inclined to provide socially desirable responses, aligning with perceived expectations from senior management. While measures were taken to ensure anonymity and voluntary participation, a potential bias could have influenced the results. Nevertheless, no direct evidence suggests that affirmation bias significantly impacted the study.

The study's findings may also have limited applicability due to its narrow focus on Jakarta traffic police. The circumstances and challenges public services face in other regions may differ significantly. Insights derived from a specific group may not fully encompass public servants' diverse perspectives. In addition, the study focuses on the design and presentation of a dashboard prototype but does not extensively examine its practical use or evaluate its long-term sustainability in operational settings. As a result, there is a limited understanding of how effective the dashboard would be in real-world scenarios.

Highlighting the technological aspects of the dashboard could potentially overshadow important non-technical factors like organisational culture, the need for training, and user motivation, which are crucial for the successful adoption and utilisation of the technology. The demographic characteristics of the study participants, such as age, education level, and work experience, could limit the applicability of the findings to a broader population beyond the specific group of Jakarta traffic police officers involved.

It is essential to consider a wide range of ICT solutions relevant to governments and public service rather than solely focusing on one dashboard technology. The interview data heavily depends on personal perceptions, which may not fully capture ICT adoption's actual conditions or outcomes. Finally, it is essential to note that the study's cross-sectional design may not fully capture the changing dynamics of technology use and adoption over time. This limitation highlights the importance of conducting longitudinal research to understand these processes, especially in public service.

8.8 Recommendations for future research

Future studies on ICT in public service should aim to broaden their geographic and demographic scope. Research can provide insights with broader applicability by incorporating a diverse range of participants from various cities or countries and spanning multiple roles and ranks within public service departments. Longitudinal research is essential for tracking how the adoption of ICT tools and their impacts evolve, particularly in response to changes in technology and urban dynamics.

Comparative studies across different cities or public service agencies can yield a more comprehensive understanding of best practices and challenges in using ICT for public service operations. It is also crucial to explore non-technological factors, such as organisational culture, leadership styles, and individual attitudes of public servants, which significantly influence decision-making processes. Research focusing on the user-centric design of ICT tools could provide valuable insights for developing more effective and user-friendly systems.

Further investigation into predictive analytics in public service management, including its effectiveness, challenges, and ethical considerations, would be beneficial. Future research may investigate the long-term effects of UCD on technology adoption and user satisfaction in similar contexts. Future research should continue to explore and validate these design principles across different contexts and user groups to refine our understanding of user-centric ICT in the public sector.

Appendices

Appendix A Research ethics

A.1 Requirement elicitation phase

University of Glasgow

College of Social Sciences

25 October 2021

Dear Taufiq Syahrial

College of Social Sciences Research Ethics Committee

Project Title: Using traffic crash data to develop a dashboard to improve the effectiveness of Jakarta's police patrolling allocations

Application No: 400210027

The College Research Ethics Committee has reviewed your application and has agreed that there is no objection on ethical grounds to the proposed study. It is happy therefore to approve the project, subject to the following conditions:

- Start date of ethical approval: 01/11/2021
- Project end date: 30/09/2024
- Any outstanding permissions needed from third parties in order to recruit research participants or to access facilities or venues for research purposes must be obtained in writing and submitted to the CoSS Research Ethics Administrator before research commences. Permissions you must provide are shown in the *College Ethics Review Feedback* document that has been sent to you as the Collated Comments Document in the online system.
- The data should be held securely for a period of ten years after the completion of the research project, or for longer if specified by the research funder or sponsor, in accordance with the University's Code of Good Practice in Research: (https://www.gla.ac.uk/media/media_490311_en.pdf)
- The research should be carried out only on the sites, and/or with the groups and using the methods defined in the application.
  - **Approval has been granted in principal:** no data collection must be undertaken until the current research restrictions as a result of social distancing and self-isolation are lifted. You will be notified once this restriction is no longer in force.
- Any proposed changes in the protocol should be submitted for reassessment as an amendment to the original application. The **Request for Amendments to an Approved Application** form should be used: https://www.gla.ac.uk/colleges/socialsciences/students/ethics/forms/staffandpostgraduateresearchstudents/

Yours sincerely,

Dr Muir Houston
College Ethics Officer

Muir Houston, Senior Lecturer
College of Social Sciences Ethics Officer
Social Justice, Place and Lifelong Education Research
University of Glasgow
School of Education, St Andrew's Building, 11 Eldon Street
Glasgow G3 6NH
0044+141-330-4699 Muir.Houston@glasgow.ac.uk

A.1.1 English version

A.1.1.1 Consent form

University of Glasgow

College of Social Sciences

Consent Form

Title of Project: Using traffic crash data to develop a dashboard to improve the effectiveness of Jakarta's police patrolling allocations.

Name of Researcher: Taufiq Syahrial
Principal Supervisor: Dr Jinhyun Hong
Co-Supervisor: Dr David McArthur

I confirm that I have read and understood the Participant Information Sheet for the above study and have had the opportunity to ask questions.

I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason.

I acknowledge that participants will be referred to by pseudonym.

I understand that confidentiality may be impossible to be guaranteed, due to the limited size of the participant sample.

All names and other material likely to identify individuals will be anonymised.

The material will be treated as confidential and always kept in secure storage.

The material will be retained in secure storage for use in future academic research.

The material may be used in future publications, both print and online.

I understand that other authenticated researchers will have access to this data only if they agree to preserve the confidentiality of the information as requested in this form.

I understand that other authenticated researchers may use my words in publications, reports, web pages, and other research outputs, only if they agree to preserve the confidentiality of the information as requested in this form.

I acknowledge the provision of a Privacy Notice in relation to this research project.

A.1.1.2 Privacy notice

Privacy Notice for Participation in Research Project:
"Using traffic crash data to develop a dashboard to improve the effectiveness of Jakarta's police patrolling allocations".
Researcher: Taufiq Syahrial
GUID:

Your Personal Data

The University of Glasgow will be what's known as the 'Data Controller' of your personal data processed in relation to your participation in the research project 'Using traffic crash data to develop a dashboard to improve the effectiveness of Jakarta's police patrolling allocations'. This privacy notice will explain how The University of Glasgow will process your personal data.

Why we need it

We are collecting basic personal data such as your name and contact details in order to conduct our research. We need your name and contact details to arrange for an online interview.

We only collect data that we need for the research project, and we will not mention your identity in the research and only name you with pseudonym and your general duty in the Jakarta's traffic police. Please note that your confidentiality may be impossible to guarantee for example due to the size of the participant group and location.

Please see accompanying **Participant Information Sheet**.

Legal basis for processing your data

We must have a legal basis for processing all personal data. As this processing is for Academic Research we will be relying upon **Task in the Public Interest** in order to process the basic personal data that you provide. For any special categories data collected we will be processing this on the basis that it is **necessary for archiving purposes, scientific or historical research purposes or statistical purposes**

Alongside this, in order to fulfil our ethical obligations, we will ask for your **Consent** to take part in the study Please see accompanying **Consent Form**.

What we do with it and who we share it with

All the personal data you submit is processed by:

Taufiq Syahrial (researcher), Dr Jinhyun Hong, and Dr David Philip McArthur (researcher's supervisors).

In addition, security measures are in place to ensure that your personal data remains safe:

A.1.1.3 Participant Information Sheet

University of Glasgow

College of Social Sciences

Participant Information Sheet

"Using traffic crash data to develop a dashboard to improve the effectiveness of Jakarta's police patrolling allocations".

Name of Researcher: Taufiq Syahrial

Principal Supervisor: Dr Jinhyun Hong

Co-Supervisor: Dr David McArthur

You are being invited to take part in a research study. The purpose of this research is to use Jakarta's traffic crash data to develop a dashboard to improve the effectiveness of police patrolling allocations. This research is intended to mitigate traffic crashes, their casualties, and fatalities. Before you decide to take part, it is important for you to understand why the research is being done and what it will involve. Please read the following information carefully and discuss it with others if you wish. Ask the researcher if there is anything that is not clear or if you would like more information. Take some time to decide whether or not you wish to take part.

You will be interviewed via Zoom application and will be asked several questions about what your current practice is to allocate your patrolling activities and what your unmet information needs to improve your patrolling allocations are. Should you choose to take part, the interview will last for approximately an hour. The interview will be audio and video recorded.

The aim of the research is to identify unmet information needs and then to use Jakarta's traffic crash data to meet some of these needs. It is expected that this will be of benefit to you and your decision-making process. This dashboard can be accessed with mobile phones, tablets, and any internet connected browsers. There should be no significant risk associated with this research. You may withdraw from this study any time without any consequences to your job or well-being and without providing a reason.

Research's benefits:
This research should benefit Jakarta's traffic police in the process of improving the effectiveness of traffic patrolling activities to mitigate traffic crashes. Furthermore, there is a possibility that the findings of this research can be adopted in other cities in Indonesia, and hopefully many other parts of the world.

A.1.2 Indonesian version

A.1.2.1 Consent form

University of Glasgow

College of Social Sciences

Formulir Persetujuan

Judul Studi: Penggunaan data kecelakaan lalu lintas untuk mengembangkan dasbor dalam rangka meningkatkan efektivitas alokasi patroli kepolisian di Jakarta.

Nama Peneliti: Taufiq Syahrial
Pembimbing Utama: Dr Jinhyun Hong
Pembimbing Kedua: Dr David McArthur
Pembimbing Ketiga: Dr Mark Livingston

Saya mengkonfirmasi bahwa saya telah membaca dan memahami lembar informasi peserta untuk studi di atas dan memiliki kesempatan untuk mengajukan pertanyaan.

Saya mengerti bahwa partisipasi saya sukarela dan saya bebas untuk menarik kapan saja, tanpa memberikan alasan apa pun.

Saya mengakui bahwa peserta akan dirujuk dengan nama samaran.

Saya mengerti bahwa kerahasiaan mungkin mustahil untuk dijamin, karena jumlah peserta penelitian yang terbatas.

Semua nama dan bahan lain yang cenderung mengidentifikasi individu akan dianonimkan.

Materi penelitian ini akan diperlakukan sebagai rahasia dan selalu disimpan dalam penyimpanan yang aman.

Materi penelitian ini akan disimpan secara aman untuk digunakan dalam penelitian akademik di masa depan.

Materi penelitian ini mungkin akan digunakan dalam publikasi masa depan, baik cetak maupun online.

A.1.2.2 Privacy notice

Privacy Notice for Participation in Research Project:
"Penggunaan data kecelakaan lalu lintas untuk mengembangkan dasbor dalam rangka meningkatkan efektivitas alokasi patroli kepolisian di Jakarta".
Peneliti: Taufiq Syahrial
GUID:

Data Pribadi Anda

The University of Glasgow akan menjadi apa yang dikenal sebagai 'pengontrol data' dari data pribadi Anda yang diproses sehubungan dengan partisipasi Anda dalam studi penelitian Penggunaan data kecelakaan lalu lintas untuk mengembangkan dashboard untuk meningkatkan efektivitas alokasi patroli kepolisian di Jakarta'. Pemberitahuan privasi ini akan menjelaskan bagaimana Universitas Glasgow akan memproses data pribadi Anda.

Kenapa Ini Diperlukan?

Kami mengumpulkan data pribadi dasar seperti nama dan detail kontak Anda untuk melakukan penelitian kami. Kami membutuhkan nama dan detail kontak Anda untuk mengatur pertemuan wawancara online.

Kami hanya mengumpulkan data yang kami butuhkan untuk proyek penelitian, dan kami tidak akan menyebutkan identitas Anda dalam penelitian dan hanya memberi nama Anda dengan nama samaran dan tugas umum Anda di polisi lalu lintas Jakarta. Harap dicatat bahwa kerahasiaan Anda mungkin tidak mungkin untuk dijamin misalnya karena ukuran grup dan lokasi peserta.

Silakan lihat **lembar informasi peserta** terlampir.

Dasar Hukum untuk Memproses Data Anda

Kami harus memiliki dasar hukum untuk memproses semua data pribadi. Karena pemrosesan ini untuk penelitian akademik, kami akan mengandalkan **tugas dalam kepentingan publik (Task in the Public Interest)** untuk memproses data pribadi dasar yang Anda berikan. Untuk setiap data kategori khusus yang dikumpulkan, kami akan memproses ini berdasarkan **keperluan pengarsipan, tujuan penelitian ilmiah atau historis atau tujuan statistik.**

Di samping ini, untuk memenuhi kewajiban etis kami, kami akan meminta **persetujuan** Anda untuk mengambil bagian dalam penelitian, silakan lihat **Lembar Persetujuan** terlampir.

Apa yang kami lakukan dan siapa saja yang memproses data anda

Semua data pribadi yang Anda kirim diproses oleh:

Taufiq Syahrial (peneliti), Dr Jinhyun Hong, Dr David Philip McArthur, and Dr Mark Livingston (pembimbing peneliti).

Selain itu, langkah-langkah keamanan tersedia untuk memastikan bahwa data pribadi Anda tetap aman:

A.1.2.3 Participant information sheet

University of Glasgow

College of Social Sciences

Lembar Informasi Peserta

"Penggunaan data kecelakaan lalu lintas untuk pengembangan dashboard dalam rangka meningkatkan efektivitas alokasi Patroli Kepolisian di Jakarta".

Nama Peneliti: Taufiq Syahrial

Pembimbing Utama: Dr Jinhyun Hong

Pembimbing Kedua: Dr David McArthur

Pembimbing Ketiga: Dr Mark Livingston

Anda diundang untuk mengambil bagian dalam studi penelitian ini. Tujuan dari penelitian ini adalah dengan menggunakan data kecelakaan lalu lintas Jakarta untuk mengembangkan dashboard untuk meningkatkan efektivitas alokasi patroli polisi. Penelitian ini dimaksudkan untuk mengurangi kecelakaan lalu lintas, korban, dan kematian. Sebelum Anda memutuskan untuk mengambil bagian, penting bagi Anda untuk memahami mengapa penelitian ini dilakukan dan apa yang akan dilibatkan. Silakan baca informasi berikut dengan hati-hati dan diskusikan dengan orang lain jika Anda mau. Tanyakan kepada peneliti apakah ada sesuatu yang tidak jelas atau jika Anda ingin informasi lebih lanjut. Luangkan waktu untuk memutuskan apakah Anda ingin ambil bagian atau tidak.

Anda akan diwawancarai melalui aplikasi zoom dan akan ditanyakan beberapa pertanyaan tentang apa praktik Anda saat ini untuk mengalokasikan kegiatan patroli Anda dan apa yang dibutuhkan informasi Anda yang tidak terpenuhi untuk meningkatkan alokasi patroli Anda. Jika Anda memilih untuk ambil bagian, wawancara akan berlangsung sekitar satu jam. Wawancara akan direkam secara audio dan video.

Tujuan dari penelitian ini adalah untuk mengidentifikasi kebutuhan informasi yang tidak terpenuhi dan kemudian menggunakan data kecelakaan lalu lintas Jakarta untuk memenuhi beberapa kebutuhan ini. Diharapkan bahwa ini akan bermanfaat bagi Anda dan proses pengambilan keputusan Anda. Dashboard ini nantinya dapat diakses dengan ponsel, tablet, dan browser yang terhubung internet. Seharusnya tidak ada risiko signifikan yang terkait dengan penelitian ini. Anda dapat menarik diri dari penelitian ini kapan saja tanpa konsekuensi terhadap pekerjaan atau kesejahteraan Anda dan tanpa memberikan alasan.

Manfaat penelitian ini:
Penelitian ini semestinya memberikan benefit kepada polisi lalu lintas dalam proses meningkatkan efektivitas kegiatan patroli lalu lintas untuk mengurangi kecelakaan lalu lintas. Selanjutnya, ada kemungkinan bahwa temuan penelitian ini dapat diadopsi di kota-kota lain di Indonesia, dan mudah-mudahan pada banyak tempat lain di dunia.

A.2 Adoption intention examination phase

University of Glasgow

College of Social Sciences

29 March 2022

Dear Taufiq Syahrial

College of Social Sciences Research Ethics Committee

Project Title: Using traffic crash data to develop a dashboard to improve the effectiveness of Jakarta's police patrolling allocations (3rd Phase)

Application No: 400210153

The College Research Ethics Committee has reviewed your application and has agreed that there is no objection on ethical grounds to the proposed study. It is happy therefore to approve the project, subject to the following conditions:

- Start date of ethical approval: 29/03/2022
- Project end date: 30/09/2024
- Any outstanding permissions needed from third parties in order to recruit research participants or to access facilities or venues for research purposes must be obtained in writing and submitted to the CoSS Research Ethics Administrator before research commences: socsci-ethics@glasgow.ac.uk
- The research should be carried out only on the sites, and/or with the groups and using the methods defined in the application.
- The data should be held securely for a period of ten years after the completion of the research project, or for longer if specified by the research funder or sponsor, in accordance with the University's Code of Good Practice in Research: (https://www.gla.ac.uk/media/media_490311_en.pdf)
- Any proposed changes in the protocol should be submitted for reassessment as an amendment to the original application. The **Request for Amendments to an Approved Application** form should be used: https://www.gla.ac.uk/colleges/socialsciences/students/ethics/forms/staffandpostgraduateresearchstudents/

Yours sincerely,

Dr Susan A. Batchelor
College Ethics Lead

Susan A. Batchelor, Senior Lecturer
College of Social Sciences Ethics Lead
University of Glasgow
School of Social and Poitical Sciences &
Scottish Centre for Crime and Justice Research
Ivy Lodge, 63 Gibson Street, Glasgow G12 8LR.
0044+141-330-6167 socsci-ethics-lead@glasgow.ac.uk

A.2.1 English version

A.2.1.1 Consent form

University of Glasgow

College of Social Sciences

Consent Form

Title of Project: Using traffic crash data to develop a dashboard to improve the effectiveness of Jakarta's police patrolling allocations.

Name of Researcher: Taufiq Syahrial
Principal Supervisor: Dr Jinhyun Hong
Co-Supervisors: Dr David McArthur and Dr Mark Livingston

I confirm that I have read and understood the Participant Information Sheet for the above study and have had the opportunity to ask questions.

I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason.

I acknowledge that the survey participants will be anonymous.

The material will be treated as confidential and always kept in secure storage.

The material will be retained in secure storage for use in future academic research.

The material may be used in future publications, both print and online.

I understand that other authenticated researchers will have access to this data only if they agree to preserve the confidentiality of the information as requested in this form.

I understand that other authenticated researchers may use my survey responses in publications, reports, web pages, and other research outputs, only if they agree to preserve the confidentiality of the information as requested in this form.

I acknowledge the provision of a Privacy Notice in relation to this research project.

<u>**Please tick your preference**</u>

Yes ☐ No ☐ I agree to take part in this study.

A.2.1.2 Privacy notice

Privacy Notice for Participation in Research Project:
"Using traffic crash data to develop a dashboard to improve the effectiveness of Jakarta's police patrolling allocations".
Researcher: Taufiq Syahrial
GUID:

Your Personal Data

The University of Glasgow will be what's known as the 'Data Controller' of your personal data processed in relation to your participation in the research project 'Using traffic crash data to develop a dashboard to improve the effectiveness of Jakarta's police patrolling allocations'. This privacy notice will explain how The University of Glasgow will process your personal data.

Why we need it

We are collecting your responses in a technology acceptance survey in order to conduct our research. The survey is anonymous, and we will not ask for your personal information.

We only collect data that we need for the research project. The survey is anonymous by design, and we will not collect your personal data. However, your confidentiality maybe impossible to guarantee due to the sample size.

Please see accompanying **Participant Information Sheet**.

Legal basis for processing your data

We must have a legal basis for processing all personal data. As this processing is for Academic Research, we will be relying upon **Task in the Public Interest** in order to process the survey responses that you provide. For any special categories data collected we will be processing this on the basis that it is **necessary for archiving purposes, scientific or historical research purposes or statistical purposes**

Alongside this, in order to fulfil our ethical obligations, we will ask for your **Consent** to take part in the study Please see accompanying **Consent Form** on the first page of the online survey.

What we do with it and who we share it with

All the survey responses you submit are processed by:

Taufiq Syahrial (researcher), Dr Jinhyun Hong, Dr David Philip McArthur, and Dr Mark Livingston (researcher's supervisors).

A.2.1.3 Participant information sheet

1

University of Glasgow

College of Social Sciences

Participant Information Sheet

Title: "Using traffic crash data to develop a dashboard to improve the effectiveness of Jakarta's police patrolling allocations". This research is undertaken as a part of the researcher's PhD degree.

Name of Researcher: Taufiq Syahrial

Principal Supervisor: Dr Jinhyun Hong

Co-Supervisor: Dr David McArthur and Dr Mark Livingston

You are being invited to take part in this research study which aims to use Jakarta's traffic crash data to develop a dashboard to improve the effectiveness of police patrolling allocations. This research is intended to mitigate traffic crashes, their casualties, and fatalities. Before you decide to take part, you need to understand why the research is being done and what it will involve. Please read the following information carefully and discuss it with others if you wish. Ask the researcher if there is anything unclear or more information required. Take some time to decide whether or not you wish to take part.

This research has three phases. The first phase was interviews and focus groups with Jakarta patrol police's leaders to investigate the unmet needs of their patrolling allocations' decision making. The interview results led to developing an online information dashboard in the second phase. Subsequently, the dashboard prototype was given feedback by the leaders. Finally, this survey will be the third and last phase of this research.

Prior to this survey, you should have been given a link to access an online dashboard from Urmin PJR (the police's administrative office). Please only

A.2.2 Indonesian version

A.2.2.1 Consent form

Consent form

Lembar Persetujuan Peserta

Judul: "Menggunakan data kecelakaan lalu lintas untuk mengembangkan dasbor guna meningkatkan efektivitas alokasi patroli polisi Jakarta".

Nama Peneliti : Taufiq Syahrial

Supervisor 1: Dr David McArthur

Supervisor 2: Dr Mark Livingston

Saya mengerti bahwa partisipasi saya bersifat sukarela dan saya bebas untuk mengundurkan diri kapan saja, tanpa memberikan alasan apapun.

Saya mengerti bahwa peserta survei akan anonim (tanpa identitas pribadi).

Materi survei ini akan diperlakukan sebagai rahasia dan selalu disimpan dalam penyimpanan yang aman untuk digunakan dalam penelitian akademis di masa depan.

Materi survei ini dapat digunakan dalam publikasi mendatang, baik cetak maupun online.

Saya memahami bahwa peneliti lain yang diautentikasi akan memiliki akses ke data ini hanya jika mereka setuju untuk menjaga kerahasiaan informasi seperti yang diminta dalam formulir ini.

Saya memahami bahwa peneliti lain yang diautentikasi dapat menggunakan tanggapan survei saya dalam publikasi, laporan, halaman web, dan hasil penelitian lainnya, hanya jika mereka setuju untuk menjaga kerahasiaan informasi seperti yang diminta dalam formulir ini.

Saya menyatakan bahwa saya telah membaca dan memahami Lembar Informasi Peserta dan Pemberitahuan Privasi untuk penelitian ini dan telah memiliki kesempatan untuk mengajukan pertanyaan.

○ Klik disini apabila anda setuju berpartisipasi, kemudian klik tombol "lanjut" dibawah (1)

A.2.2.2 Privacy notice

Pemberitahuan Privasi untuk Partisipasi dalam Proyek Penelitian:

"Menggunakan data kecelakaan lalu lintas untuk mengembangkan dasbor guna meningkatkan efektivitas alokasi patroli polisi Jakarta".

Peneliti : Taufiq Syahrial
GUID:

Data anda

University of Glasgow akan menjadi 'Pengendali' data anda yang diproses sehubungan dengan partisipasi Anda dalam proyek penelitian 'Menggunakan data kecelakaan lalu lintas untuk mengembangkan dasbor untuk meningkatkan efektivitas alokasi patroli polisi Jakarta'. Pemberitahuan privasi ini akan menjelaskan bagaimana University of Glasgow akan memproses data pribadi Anda.

Mengapa kami membutuhkannya?

Kami mengumpulkan tanggapan Anda dalam survei ini untuk melakukan penelitian kami. Survei ini anonim sehingga kami tidak akan meminta informasi pribadi Anda. Kami hanya mengumpulkan data yang kami butuhkan untuk proyek penelitian. Namun, kerahasiaan Anda mungkin tidak dapat dijamin karena ukuran sampel. Silakan lihat Lembar Informasi Peserta terlampir.

Landasan hukum untuk memproses data Anda

Kami harus memiliki landasan hukum untuk memproses semua data pribadi. Karena pemrosesan ini untuk Riset Akademik, kami mempedomani "Tugas untuk Kepentingan Umum" untuk memproses tanggapan survei yang Anda berikan. Untuk data kategori khusus apa pun yang dikumpulkan, kami akan memprosesnya berdasarkan data yang diperlukan untuk **tujuan pengarsipan, tujuan penelitian ilmiah atau historis, atau tujuan statistik.**

Bersamaan dengan ini, untuk memenuhi kewajiban etis kami, kami akan meminta **Persetujuan** Anda untuk ikut serta dalam penelitian. Silakan lihat **Formulir Persetujuan** yang menyertai di halaman pertama survei online.

Apa yang kami lakukan kepada data anda dan dengan siapa kami membagikannya

Semua tanggapan survei yang Anda kirimkan diproses oleh:
Taufiq Syahrial (peneliti),Dr David Philip McArthur, Dr Mark Livingston, dan Dr Jinhyun Hong (pembimbing peneliti).

Selain itu, langkah-langkah keamanan diterapkan untuk memastikan bahwa data respons survei Anda tetap aman. Data akan disimpan di penyimpanan aman University of Glasgow. Semua data yang terkait dengan penelitian ini akan dienkripsi dan dilindungi kata sandi. Karena sifat penelitian ini, sangat mungkin bahwa peneliti lain dapat menganggap data yang dikumpulkan berguna dalam menjawab pertanyaan penelitian masa depan. Kami akan meminta persetujuan eksplisit Anda agar data Anda dibagikan dengan cara ini. Kami akan memberi Anda salinan temuan studi dan rincian publikasi atau keluaran berikutnya berdasarkan permintaan.

Apa hak Anda?*

GDPR menetapkan bahwa individu memiliki hak tertentu termasuk: untuk meminta akses ke, salinan, dan

A.2.2.3 Participant information sheet

Lembar Informasi Peserta

Judul: "Menggunakan data kecelakaan lalu lintas untuk mengembangkan dasbor guna meningkatkan efektivitas alokasi patroli polisi Jakarta".

Penelitian ini dilakukan sebagai bagian dari studi PhD peneliti.

Nama Peneliti : Taufiq Syahrial
Pembimbing Utama: Dr David McArthur
Pembimbing Kedua: Dr Mark Livingston

Anda diundang untuk berpartisipasi dalam studi penelitian yang bertujuan untuk menggunakan data kecelakaan lalu lintas Jakarta untuk mengembangkan dashboard untuk meningkatkan efektivitas alokasi patroli polisi. Penelitian ini dimaksudkan untuk memitigasi kecelakaan lalu lintas, korban jiwa, dan korban jiwa. Sebelum Anda memutuskan untuk mengambil bagian, Anda perlu memahami mengapa penelitian ini dilakukan dan apa yang akan terlibat.

Silakan baca informasi berikut dengan seksama dan diskusikan dengan orang lain jika Anda mau. Tanyakan kepada peneliti jika ada sesuatu yang tidak jelas atau informasi lebih lanjut yang diperlukan. Luangkan waktu untuk memutuskan apakah Anda ingin mengambil bagian atau tidak.

Penelitian ini memiliki tiga fase. Tahap pertama (sudah terlaksana) adalah wawancara dan focus group dengan pimpinan polisi patroli Jakarta untuk menyelidiki kebutuhan informasi yang belum ada dari pengambilan keputusan alokasi patroli mereka. Hasil wawancara mengarah pada pengembangan dasbor informasi online pada fase kedua. Selanjutnya prototipe dashboard tersebut diberi feedback oleh pimpinan. **Terakhir, survei ini akan menjadi tahap ketiga dan terakhir dari penelitian ini.**

Sebelum survei ini, Anda seharusnya sudah diberikan link untuk mengakses dashboard online dari Urmin PJR (kantor administrasi kepolisian). Harap hanya berpartisipasi dalam survei ini jika Anda telah mengakses dasbor karena survei ini dimaksudkan untuk mengukur penerimaan teknologi Anda terhadapnya.

Anda diminta untuk berpartisipasi dalam survei online dengan 65 pertanyaan. Jika Anda memilih untuk ikut serta, survei akan berlangsung selama kurang lebih setengah jam. Tanggapan Anda akan bersifat anonim, dan kami tidak akan mengumpulkan informasi apa pun yang dapat digunakan untuk mengidentifikasi peserta.

Penelitian ini bertujuan untuk memberikan informasi yang bermanfaat melalui dasbor untuk membantu pengambilan keputusan Anda dalam alokasi patroli lalu lintas. Dasbor ini dapat diakses dengan ponsel, tablet, dan browser apa pun yang terhubung ke internet. Seharusnya tidak ada risiko signifikan yang terkait dengan penelitian ini. Anda dapat menolak untuk berpartisipasi dalam penelitian ini tanpa konsekuensi apa pun terhadap pekerjaan atau kesejahteraan Anda dan tanpa memberikan alasan. Namun, jika Anda telah menyelesaikan survei, kami tidak dapat menghapus tanggapan Anda karena bersifat anonim, dan kami tidak dapat mengidentifikasi tanggapan khusus Anda.

Manfaat Penelitian:
Penelitian ini diharapkan dapat bermanfaat bagi kepolisian lalu lintas Jakarta dalam meningkatkan efektivitas kegiatan patroli lalu lintas untuk mengurangi kecelakaan lalu lintas. Lebih lanjut, tidak menutup kemungkinan bahwa hasil penelitian ini dapat diadopsi

Appendix B Dashboard development

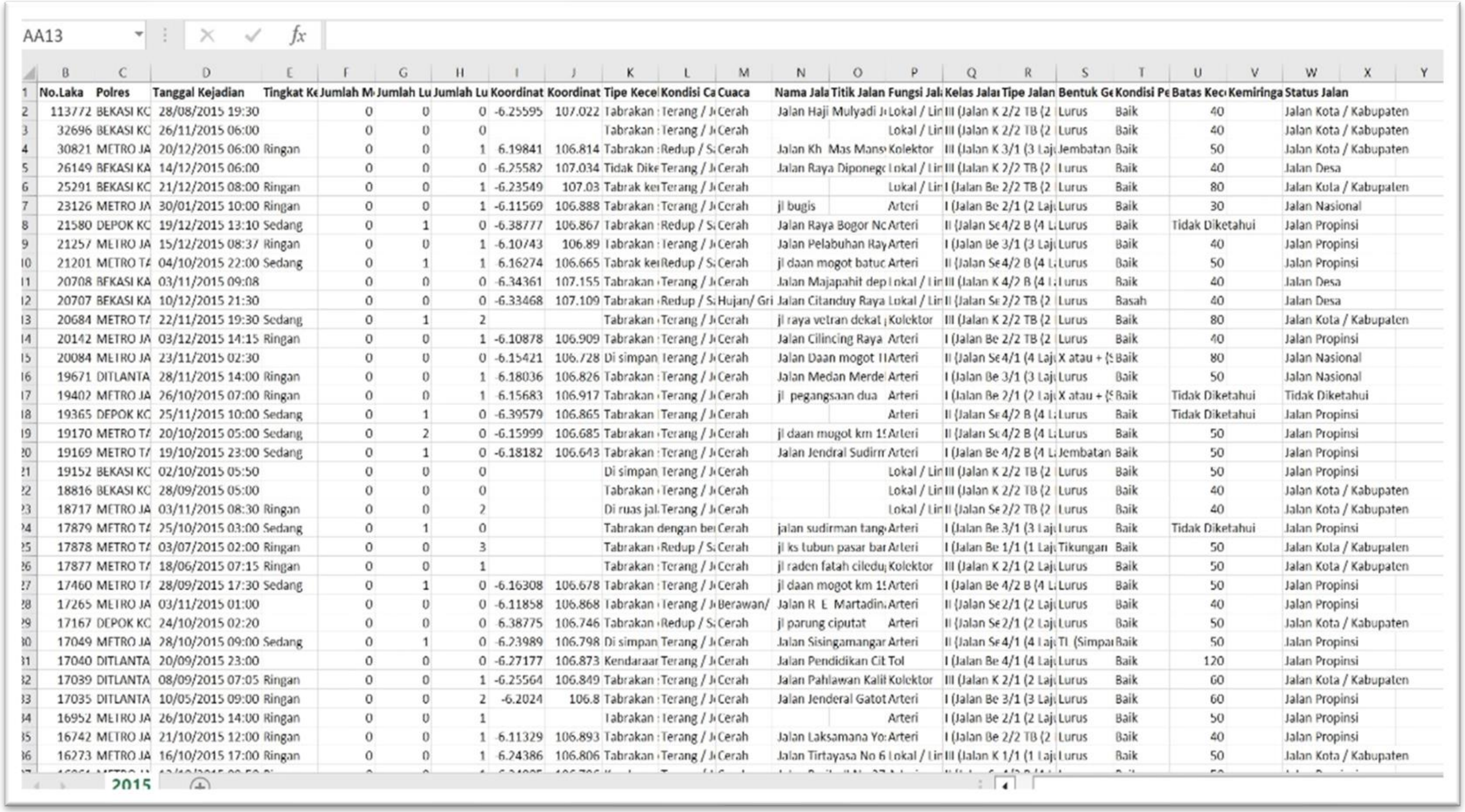
This chapter describes the development of the dashboard prototype, which was led by the results of the requirement elicitation phase. The dashboard is intended as a subject to represent ICT in the survey phase. Section B.1 presents the development's platform, tools, and data. Section B.2 explains the development approach. Section B.3 describes the validation session. Finally, Section B.4 presents the prototype.

B.1 Platform, tools, and data

The dashboard was developed using the R programming language and its Shiny package for creating interactive web applications (R Core Team, 2021; Posit, 2023). R's open-source environment is widely used for statistical analysis, visualisation, and data manipulation. The "shinydashboard" package provides additional tools for building dynamic dashboards that update in real-time based on user inputs, leveraging server-side R code for interactive work (Chang and Borges Ribeiro, 2018). Shiny extends R's functionality, enabling developers to construct web-based interfaces that allow users to interact dynamically with data and visualisations. The application's logic and interface are designed using R, with Shiny facilitating the web interface creation.

The deployment process for the Shiny app dashboard involved initial setup in R and RStudio, followed by coding the application, local testing, and using "shinydashboard" for the layout design. For making the dashboard accessible online, Shinyapps.io, a cloud-based service by RStudio, offers an efficient solution by simplifying the deployment process, eliminating the need for complex server setups or specialised hosting knowledge (Posit, 2023). This service provides a robust platform for sharing interactive dashboards with a broader audience without technical hassles.

Leveraging the R programming language, the Shiny package, and the "shinydashboard" framework, this study produced an interactive dashboard that facilitates dynamic user interaction with data. Shinyapps.io was used to deploy and share this dashboard online, providing an accessible and efficient avenue for reaching a broad audience. This approach also ensures the replicability of the dashboard while streamlining the development process. It also promotes consistency and thorough documentation, making it easier for future researchers to build upon and expand the work. The utilised Jakarta's traffic crash data were downloaded from IRSMS at www.irsms.korlantas.polri.go.id (Figure 8.1).



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	No.Laka	Polres	Tanggal Kejadian	Tingkat Ke	Jumlah M	Jumlah Lu	Jumlah Lu	Koordinat	Koordinat	Tipe Kecel	Kondisi Ca	Cuaca	Nama Jala	Titik Jalan	Fungsi Jal	Kelas Jala	Tipe Jalan	Bentuk Ge	Kondisi Pe	Batas Kec	Kemiringa	Status Jalan
2	113772	BEKASI KC	28/08/2015 19:30		0	0	0	-6.25595	107.022	Tabrakan	Terang / J	Cerah	Jalan Haji Mulyadi J		Lokal / Lin	III (Jalan K	2/2 TB (2	Lurus	Baik	40		Jalan Kota / Kabupaten
3	32696	BEKASI KC	26/11/2015 06:00		0	0	0			Tabrakan	Terang / J	Cerah			Lokal / Lin	III (Jalan K	2/2 TB (2	Lurus	Baik	40		Jalan Kota / Kabupaten
4	30821	METRO JA	20/12/2015 06:00	Ringan	0	0	1	6.19841	106.814	Tabrakan	Redup / S	Cerah	Jalan Kh Mas Mans		Kolektor	III (Jalan K	3/1 (3 Laj	Jembatan	Baik	50		Jalan Kota / Kabupaten
5	26149	BEKASI KA	14/12/2015 06:00		0	0	0	-6.25582	107.034	Tidak Dike	Terang / J	Cerah	Jalan Raya Diponeg		Lokal / Lin	III (Jalan K	2/2 TB (2	Lurus	Baik	40		Jalan Desa
6	25291	BEKASI KC	21/12/2015 08:00	Ringan	0	0	1	-6.23549	107.03	Tabrak ke	Terang / J	Cerah			Lokal / Lin	I (Jalan Be	2/2 TB (2	Lurus	Baik	80		Jalan Kota / Kabupaten
7	23126	METRO JA	30/01/2015 10:00	Ringan	0	0	1	-6.11569	106.888	Tabrakan	Terang / J	Cerah	jl bugis		Arteri	I (Jalan Be	2/1 (2 Laj	Lurus	Baik	30		Jalan Nasional
8	21580	DEPOK KC	19/12/2015 13:10	Sedang	0	1	0	-6.38777	106.867	Tabrakan	Redup / S	Cerah	Jalan Raya Bogor Nc		Arteri	II (Jalan Se	4/2 B (4 L	Lurus	Baik	Tidak Diketahui		Jalan Propinsi
9	21257	METRO JA	15/12/2015 08:37	Ringan	0	0	1	-6.10743	106.89	Tabrakan	Terang / J	Cerah	Jalan Pelabuhan Ray		Arteri	I (Jalan Be	3/1 (3 Laj	Lurus	Baik	40		Jalan Propinsi
10	21201	METRO TA	04/10/2015 22:00	Sedang	0	1	1	6.16274	106.665	Tabrak ke	Redup / S	Cerah	jl daan mogot batuc		Arteri	II (Jalan Se	4/2 B (4 L	Lurus	Baik	50		Jalan Propinsi
11	20708	BEKASI KA	03/11/2015 09:08		0	0	0	6.34361	107.155	Tabrakan	Terang / J	Cerah	Jalan Majapahit dep		Lokal / Lin	III (Jalan K	4/2 B (4 L	Lurus	Baik	40		Jalan Desa
12	20707	BEKASI KA	10/12/2015 21:30		0	0	0	-6.33468	107.109	Tabrakan	Redup / S	Hujan/ Gri	Jalan Citanduy Raya		Lokal / Lin	II (Jalan Se	2/2 TB (2	Lurus	Basah	40		Jalan Desa
13	20684	METRO TA	22/11/2015 19:30	Sedang	0	1	2			Tabrakan	Terang / J	Cerah	jl raya vetran dekat		Kolektor	III (Jalan K	2/2 TB (2	Lurus	Baik	80		Jalan Kota / Kabupaten
14	20142	METRO JA	03/12/2015 14:15	Ringan	0	0	1	-6.10878	106.909	Tabrakan	Terang / J	Cerah	Jalan Cilincing Raya		Arteri	I (Jalan Be	2/2 TB (2	Lurus	Baik	40		Jalan Propinsi
15	20084	METRO JA	23/11/2015 02:30		0	0	0	-6.15421	106.728	Di simpan	Terang / J	Cerah	Jalan Daan mogot I		Arteri	II (Jalan Se	4/1 (4 Laj	X atau + (S	Baik	80		Jalan Nasional
16	19671	DITLANTA	28/11/2015 14:00	Ringan	0	0	1	6.18036	106.826	Tabrakan	Terang / J	Cerah	Jalan Medan Merde		Arteri	I (Jalan Be	3/1 (3 Laj	Lurus	Baik	50		Jalan Nasional
17	19402	METRO JA	26/10/2015 07:00	Ringan	0	0	1	6.15683	106.917	Tabrakan	Terang / J	Cerah	jl pegangsaan dua		Arteri	I (Jalan Be	2/1 (2 Laj	X atau + (S	Baik	Tidak Diketahui		Tidak Diketahui
18	19365	DEPOK KC	25/11/2015 10:00	Sedang	0	1	0	-6.39579	106.865	Tabrakan	Terang / J	Cerah			Arteri	II (Jalan Se	4/2 B (4 L	Lurus	Baik	Tidak Diketahui		Jalan Propinsi
19	19170	METRO TA	20/10/2015 05:00	Sedang	0	2	0	-6.15999	106.685	Tabrakan	Terang / J	Cerah	jl daan mogot km 1		Arteri	II (Jalan Se	4/2 B (4 L	Lurus	Baik	50		Jalan Propinsi
20	19169	METRO TA	19/10/2015 23:00	Sedang	0	1	0	-6.18182	106.643	Tabrakan	Terang / J	Cerah	Jalan Jendral Sudirn		Arteri	I (Jalan Be	4/2 B (4 L	Jembatan	Baik	50		Jalan Propinsi
21	19152	BEKASI KC	02/10/2015 05:50		0	0	0			Di simpan	Terang / J	Cerah			Lokal / Lin	III (Jalan K	2/2 TB (2	Lurus	Baik	50		Jalan Propinsi
22	18816	BEKASI KC	28/09/2015 05:00		0	0	0			Tabrakan	Terang / J	Cerah			Lokal / Lin	III (Jalan K	2/2 TB (2	Lurus	Baik	40		Jalan Kota / Kabupaten
23	18717	METRO JA	03/11/2015 08:30	Ringan	0	0	2			Di ruas jal	Terang / J	Cerah			Lokal / Lin	II (Jalan Se	2/2 TB (2	Lurus	Baik	40		Jalan Kota / Kabupaten
24	17879	METRO TA	25/10/2015 03:00	Sedang	0	1	0			Tabrakan dengan be		Cerah	jalan sudirman tang		Arteri	I (Jalan Be	3/1 (3 Laj	Lurus	Baik	Tidak Diketahui		Jalan Propinsi
25	17878	METRO TA	03/07/2015 02:00	Ringan	0	0	3			Tabrakan	Redup / S	Cerah	jl ks tubun pasar bar		Arteri	I (Jalan Be	1/1 (1 Laj	Tikungan	Baik	50		Jalan Kota / Kabupaten
26	17877	METRO TA	18/06/2015 07:15	Ringan	0	0	1			Tabrakan	Terang / J	Cerah	jl raden fatah ciledu		Kolektor	III (Jalan K	2/1 (2 Laj	Lurus	Baik	50		Jalan Kota / Kabupaten
27	17460	METRO TA	28/09/2015 17:30	Sedang	0	1	0	-6.16308	106.678	Tabrakan	Terang / J	Cerah	jl daan mogot km 1		Arteri	I (Jalan Be	4/2 B (4 L	Lurus	Baik	50		Jalan Propinsi
28	17265	METRO JA	03/11/2015 01:00		0	0	0	-6.11858	106.868	Tabrakan	Terang / J	Berawan/	Jalan R E Martadin		Arteri	II (Jalan Se	2/1 (2 Laj	Lurus	Baik	40		Jalan Propinsi
29	17167	DEPOK KC	24/10/2015 02:20		0	0	0	6.38775	106.746	Tabrakan	Redup / S	Cerah	jl parung ciputat		Arteri	II (Jalan Se	2/1 (2 Laj	Lurus	Baik	50		Jalan Kota / Kabupaten
30	17049	METRO JA	28/10/2015 09:00	Sedang	0	1	0	-6.23989	106.798	Di simpan	Terang / J	Cerah	Jalan Sisingamangar		Arteri	II (Jalan Se	4/1 (4 Laj	TL (Simpa	Baik	50		Jalan Propinsi
31	17040	DITLANTA	20/09/2015 23:00		0	0	0	-6.27177	106.873	Kendaraar	Terang / J	Cerah	Jalan Pendidikan Cit		Tol	I (Jalan Be	4/1 (4 Laj	Lurus	Baik	120		Jalan Propinsi
32	17039	DITLANTA	08/09/2015 07:05	Ringan	0	0	1	-6.25564	106.849	Tabrakan	Terang / J	Cerah	Jalan Pahlawan Kalil		Kolektor	III (Jalan K	2/1 (2 Laj	Lurus	Baik	60		Jalan Kota / Kabupaten
33	17035	DITLANTA	10/05/2015 09:00	Ringan	0	0	2	-6.2024	106.8	Tabrakan	Terang / J	Cerah	Jalan Jenderal Gatot		Arteri	I (Jalan Be	3/1 (3 Laj	Lurus	Baik	60		Jalan Propinsi
34	16952	METRO JA	26/10/2015 14:00	Ringan	0	0	1			Tabrakan	Terang / J	Cerah			Arteri	I (Jalan Be	2/1 (2 Laj	Lurus	Baik	50		Jalan Propinsi
35	16742	METRO JA	21/10/2015 12:00	Ringan	0	0	1	6.11329	106.893	Tabrakan	Terang / J	Cerah	Jalan Laksamana Yo		Arteri	I (Jalan Be	2/2 TB (2	Lurus	Baik	40		Jalan Propinsi
36	16273	METRO JA	16/10/2015 17:00	Ringan	0	0	1	6.24386	106.806	Tabrakan	Terang / J	Cerah	Jalan Tirtayasa No 6		Lokal / Lin	III (Jalan K	1/1 (1 Laj	Lurus	Baik	50		Jalan Kota / Kabupaten

2015

Figure 8.1 IRSMS data structure

The downloaded dataset contains 36,414 crashes recorded from January 2015 to December 2020 in the greater Jakarta area. The variables included in the dashboard development are:

1. District/area: crash location based on the police station’s jurisdiction area.
2. Date and time: time of the crash.
3. Severity: the severity of the crash (minor, severe, fatal).
4. Coordinates: latitude and longitude of crash location.
5. Road type: road type based on the number of lanes, directions, and the existence of a road separator.

B.2 Development method

The dashboard development adopted the Dynamic System Development Method (DSDM), introduced by Clegg and Barker in 1994 and refined to advocate for "just enough design up front" to ensure projects stay on track and meet deadlines. This method addresses software development challenges, such as meeting all requirements within constraints like time, scope, and budget, by employing the MoSCoW prioritisation technique and timeboxing. These strategies categorise requirements into must-haves, should-haves, could-haves, and will-not-haves, guiding focused and efficient project management. Due to time constraints, the dashboard prototype was limited in that it only incorporated "Must-have" features.

Suitable visualisations have been employed to enhance the accessibility of the traffic crash dataset. Visual representations give users a potent instrument to comprehend the data's trends, patterns, and connections, empowering them to render well-informed judgements regarding subsequent analyses (Carr and Tufte, 1987). Through the utilisation of visual representations, anomalies, correlations, and trends that might not be readily discernible in unprocessed data can be readily identified by users (Vartak *et al.*, 2017).

In addition to descriptive statistics and visualisations, a predictive statistical approach has been provided using a Random Forest (RF) model for forecasting future traffic crashes in Jakarta. The RF was chosen to provide a prediction example in the dashboard due to its widespread use in urban road safety studies (Ramya *et al.*, 2019; Atumo, Fang and Jiang, 2022). RF leverages a collection of multiple decision trees, dividing the data into training and testing datasets. It then employs bootstrapping to sample from the dataset, allowing for robust predictions repeatedly. Given that the traffic crash dataset contains timestamps and location data, the RF model can be extended to provide temporal and geographical forecasts, adding a valuable dimension to the analysis.

The RF model was prepared by first processing and cleaning the collected data. Then, a model was created and evaluated to predict crashes based on time and location data. The model was trained on 80% of the data and assessed using prediction accuracy and log loss metrics. The complete codes for the random forest model are provided at:

https://github.com/taufiqsyahrial/Jakarta_dashboard.

B.3 Validation

One standard method to ensure the dashboard is usable for users is by conducting a requirement validation session to allow a representative group of users to use the interface and analyse their ability to complete specific activities (Anas *et al.*, 2016; Pastushenko, Hynek and Hruška, 2021). Therefore, the prototype was presented to the participants to assess the degree to which the developed dashboard meets the information and feature requirements of the police. The validation sessions were part of the requirement elicitation phase. The sessions comprised presenting the dashboard prototype to fifteen Jakarta police leaders on five occasions, one for each station.

The dashboard prototype was presented to the participants, and a link was provided so they could try it. They were informed that the dashboard is in a prototype state and can be further modified for future actual usage. The participants stated that the dashboard adequately addressed their requirements. The feedback received from the participants was that it has a user-friendly interface, is understandable, and provides valuable insights. Only one request was received for entirely using the Indonesian language in the dashboard, which was implemented afterwards.

B.4 Dashboard prototype

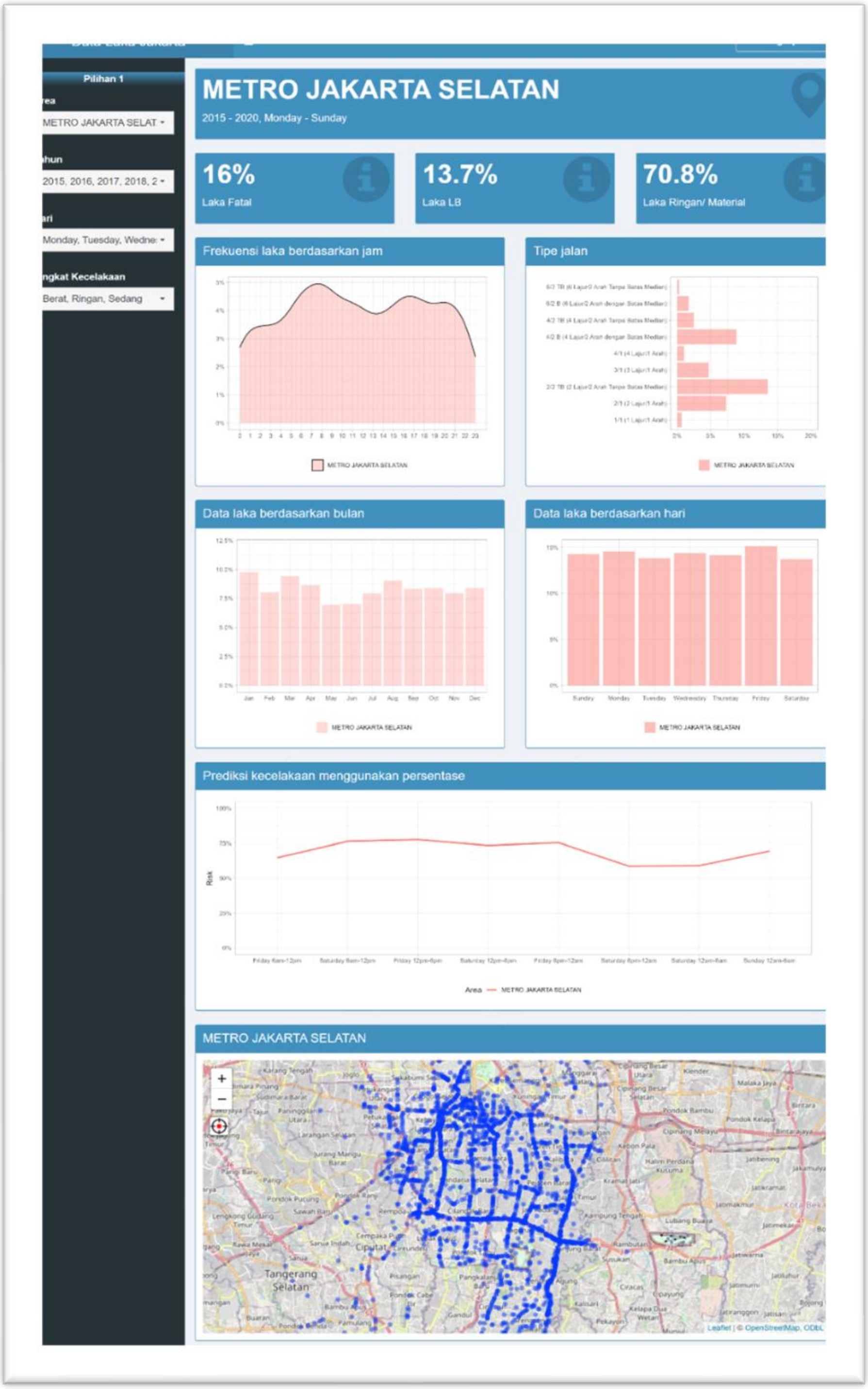

Figure 8.2 The dashboard full page

The dashboard prototype, illustrated in Figure 8.2, comprises twelve visualisation components. These components include one message box, two sidebars, and nine information boxes about traffic crashes. The ensuing sections provide concise descriptions of each of these components.

B.4.1 Location-tracking permission request

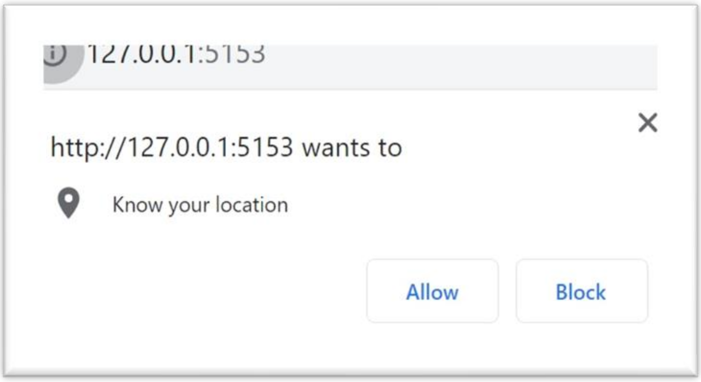

Figure 8.3 Location-tracking option

A pop-up location tracking request appears when the dashboard is accessed, which can be allowed or denied.

B.4.2 “About” pop-up message

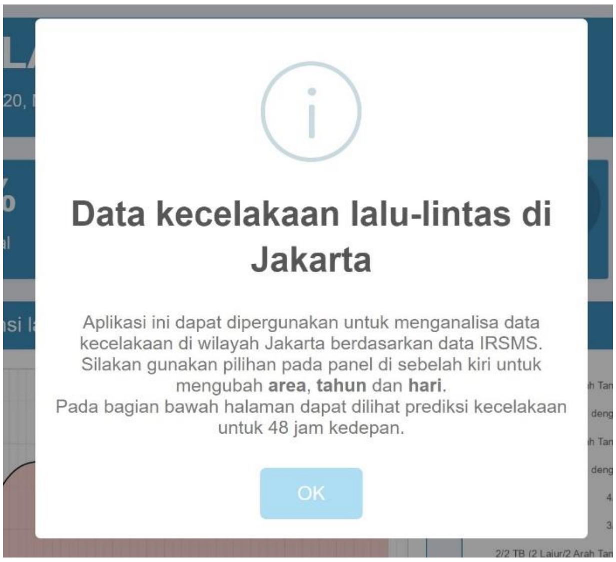

Figure 8.4 "About" feature

The pop-up box houses a message that conveys the following information: "This application is designed for the analysis of traffic crashes in Jakarta, utilising data from IRSMS. The left option panel is to alter the location, day, or year. For a 48-hour crash prediction, scroll down."

B.4.3 Sidebar picker for area, year, and day of week

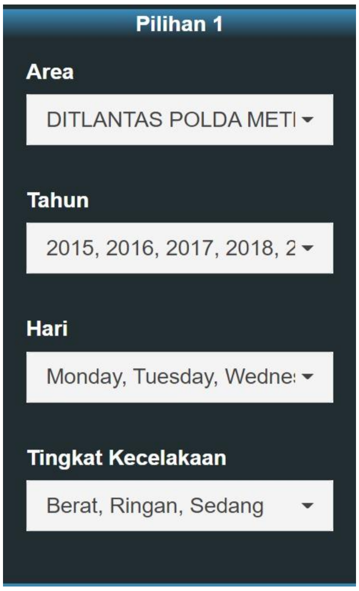

Figure 8.5 Area, year, and day of week selections

This sidebar picker provides selectable options for users to change the dashboard visualisation contents based on the following:

a. Area (traffic crash jurisdiction): Bandara Soekarno Hatta, Bekasi Kabupaten, Bekasi Kota, Depok Kota, Metro Tangerang, Pelabuhan Tanjong Priuk, Tangerang Kabupaten, Tangerang Selatan, Metro Jakarta Barat, Pusat, Selatan, Timur, Utara.

b. Tahun (year): 2015-2020.

c. Hari (day): Monday-Sunday.

d. Tingkat Kecelakaan (crash severity): Berat (heavy), Ringan (light), Sedang (Medium).

B.4.4 Casualty percentages

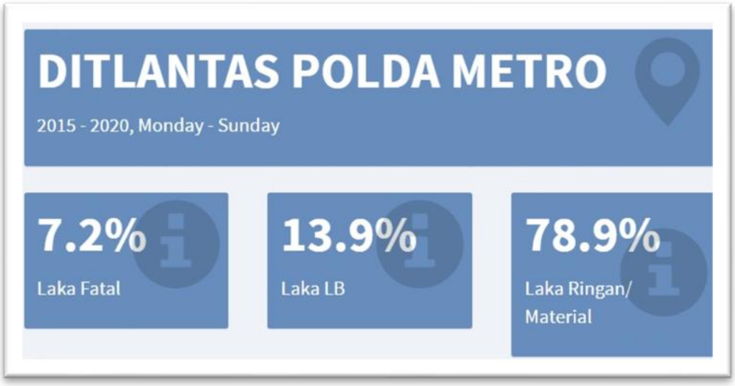

Figure 8.6 Casualty percentages

This information box displays the percentages of fatal crashes of the selected area, year, and day, with three indicators, namely: laka fatal (fatal crashes), laka LB-luka berat (heavy injury crashes), and laka ringan/ material (light/non-injury crashes). The percentages are calculated by dividing the crashes' severity types by the total number of crashes.

B.4.5 Hourly crash percentage

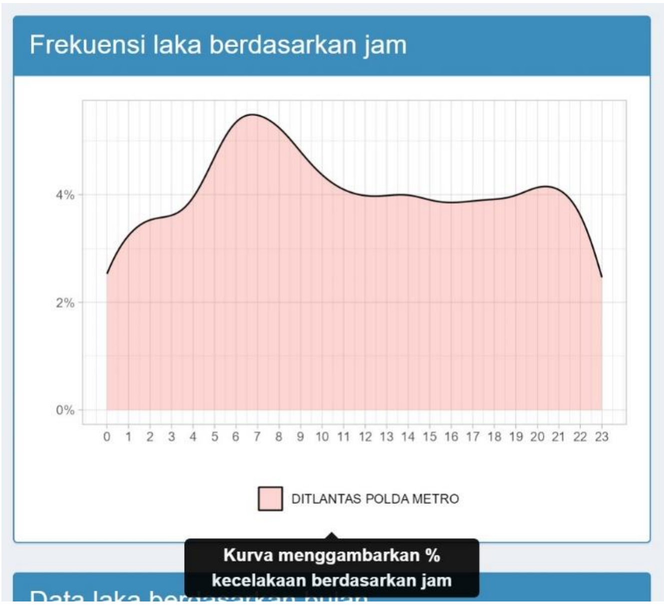

Figure 8.7 Crash by hour

A dual-line plot visualises the hourly crash percentage. The x-axis symbolises the time of day, and the y-axis represents the percentage of crashes, which is calculated by dividing the time of crashes by 24 hours.

B.4.6 Road type

Figure 8.8 Crash by road type

A dual bar chart visualises the road types where the crashes occurred. Due to the long names, the road type variable is plotted on the y-axis, whilst the percentage is on the x-axis.

B.4.7 Monthly crash distribution

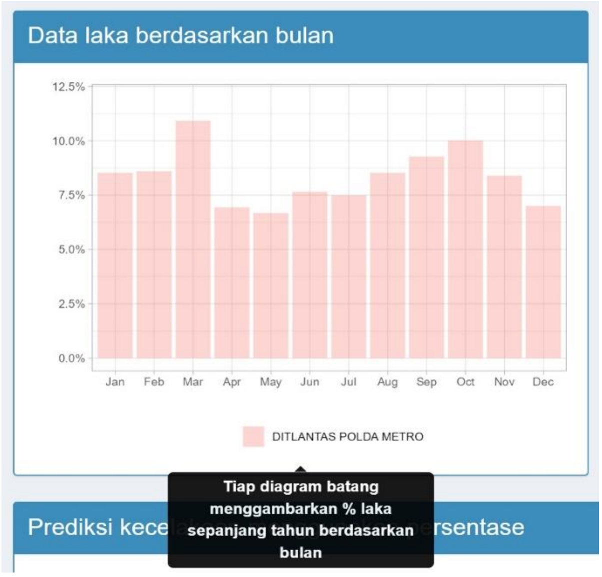

Figure 8.9 Crash by month

The “data laka berdasarkan bulan” box can be translated as the distribution of crashes across months. It employs a dual-bar chart representing the months on the X-axis and the crash percentage on the Y-axis.

B.4.8 Daily crash distribution

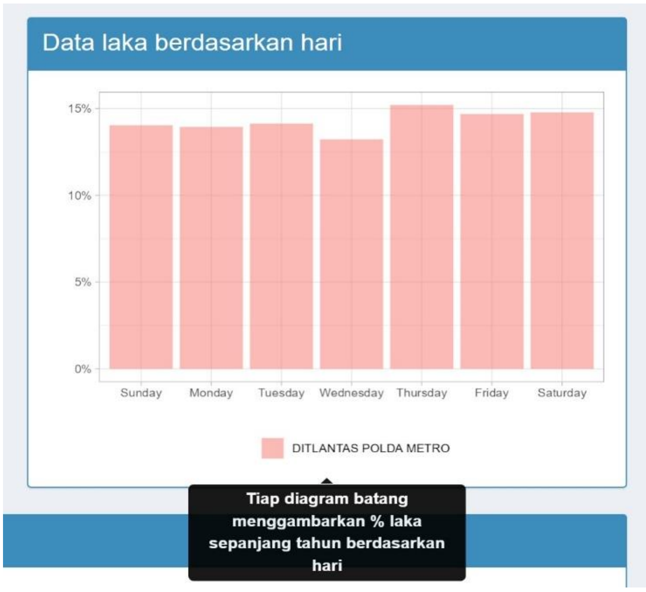

Figure 8.10 Crash by day

This bar chart is named "data laka berdasarkan hari", which translates as "crash distribution by weekday." The X-axis visualises the day's name, and the Y-axis shows the crash percentages.

B.4.9 Crash locations

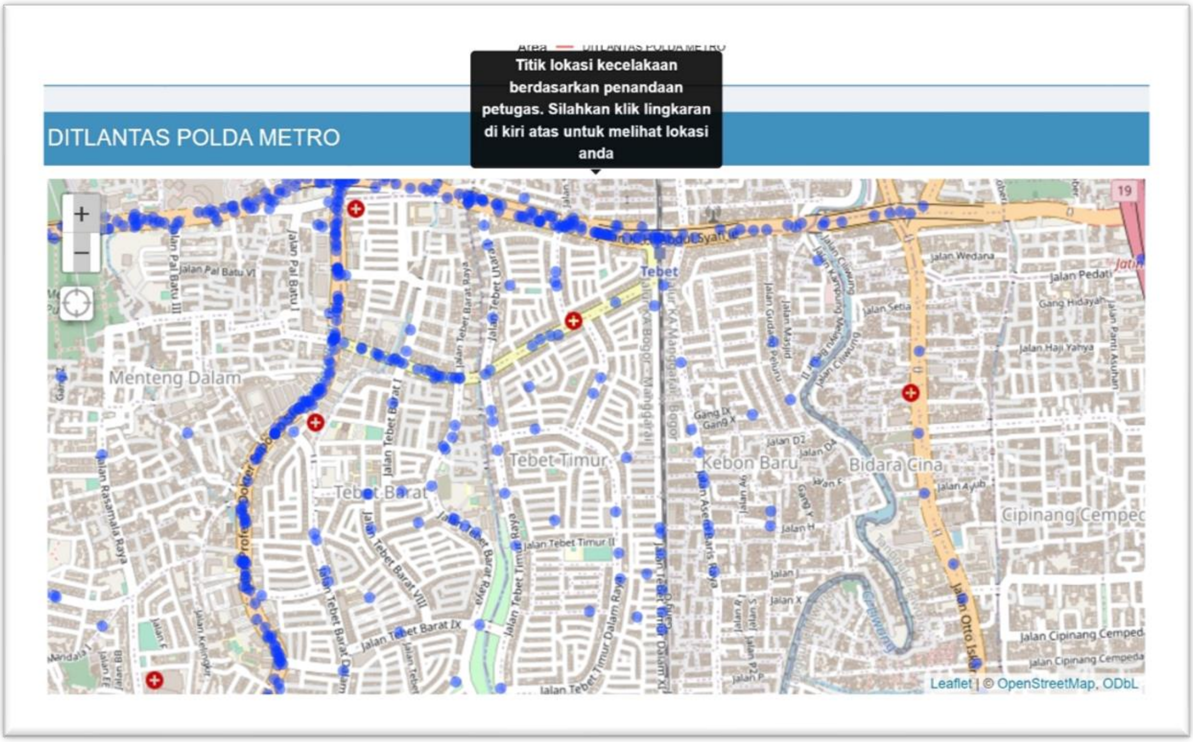

Figure 8.11 Crash locations

The crash location box plots with blue nodes (circles) the crash coordinates on an OSM license-free map (openstreetmap.org). The X-axis represents latitude, and the Y-axis represents longitude.

B.4.10 Crash prediction

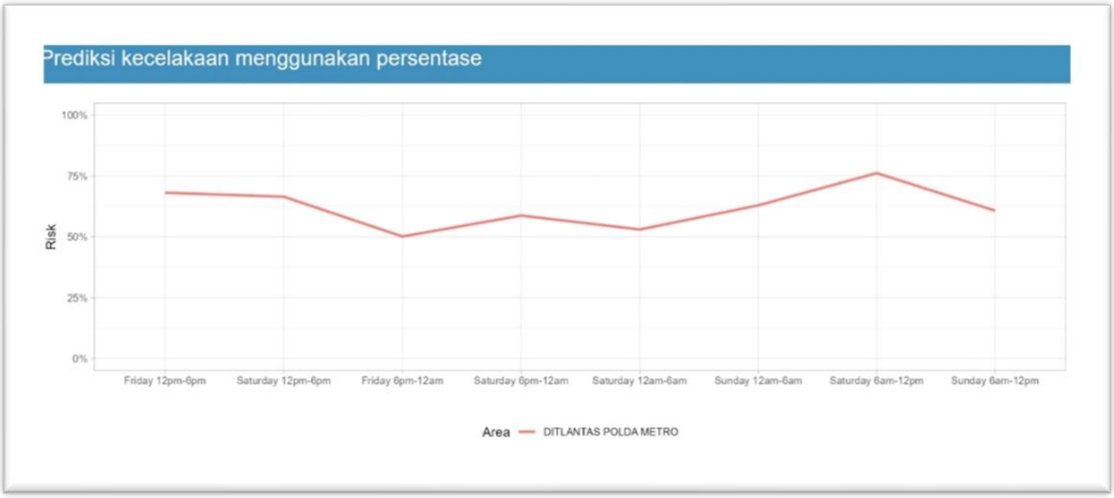

Figure 8.12 Crash prediction

A dual-line chart visually portrays traffic crash predictions at six-hour intervals, generated using a random forest algorithm. The X-axis delineates seven six-hour intervals, while the Y-axis quantifies crash probability percentages. To compute these predictions, the model incorporates variables encompassing time, day of the week, month, and area. Notably, there are a total of 786,744 possible permutations for these variables, which are divided into an 80% training dataset and a 20% test dataset. The model's outputs are configured as continuous variables, facilitating their representation through line chart visualisations.

Appendix C Survey questionnaires

Umur anda saat ini (tahun)/ Your current age (years)

Berapa lama anda telah bertugas menjadi anggota Polri? (tahun)/ How long have you served as a member of the National Police? (year)

Apa pendidikan umum terakhir anda?/ What is your last education?

o

1

. SMA sederajat/ highschool

o

2

. D4 s.d. S3/ Bachelor +

Mohon pilih sesuai pendapat anda terkait dasbor/ Please choose according to your opinion regarding the dashboard: (Seven-point Likert Scale: highly agree to highly disagree)

incen1 Jika saya menggunakan dasbor alokasi patroli, saya akan meningkatkan peluang saya untuk mendapatkan apresiasi di tempat kerja/ If I use the dashboard, I will increase my chances of being appreciated at work

incen2 Jika saya menggunakan dasbor alokasi patroli, saya akan meningkatkan peluang saya untuk mendapatkan pengakuan di tempat kerja/ If I use the dashboard, I will increase my chances of being recognised at work

influ1 Orang-orang yang penting bagi saya di tempat kerja berpendapat bahwa saya sebaiknya menggunakan dasbor alokasi patroli / People who are important to me at work think that I should use the dashboard

influ2 Orang-orang yang mempengaruhi perilaku saya di tempat kerja berpikir bahwa saya sebaiknya menggunakan dasbor alokasi patroli / People who influence my behaviour at work think that I should use the dashboard

influ3 Saya percaya, secara umum, kesatuan saya akan mendukung penggunaan dasbor alokasi patroli / In general, my organisation will support the use of the dashboard

bi1 saya berniat untuk menggunakan dasbor untuk alokasi patroli / I intend to use the dashboard for patrolling allocation

bi2 saya memprediksi saya akan menggunakan dasbor untuk alokasi patroli / I predict I would use the dashboard for patrolling allocation

bi3 saya berencana menggunakan dasbor untuk alokasi patroli / I plan to use the dashboard for patrolling allocation priv1 Saya khawatir apabila dasbor alokasi patroli akan terus menerus melacak lokasi saya/ I am concerned the dashboard may constantly track my location

priv2 Saya khawatir apabila dasbor alokasi patroli tidak menjamin privasi saya/ I am concerned the dashboard may not guarantee my privacy

inter1 Dasbor alokasi patroli mestinya bisa berkomunikasi dengan teknologi lain yang saya gunakan terkait pekerjaan/ The dashboard should be able to communicate with other work-related technologies I use

inter2 Dasbor alokasi patroli mestinya bisa berbagi data dengan teknologi lain yang saya gunakan terkait pekerjaan/ The dashboard should be able to share data with other work-related technologies I use

Mohon anda melakukan evaluasi atas dasbor yang telah anda coba. Silakan berikan penilaian secara spontan. Jangan berpikir terlalu lama tentang keputusan anda agar kesan yang anda dapat orisinal. Terkadang Anda bisa saja tidak terlalu yakin terkait atribut tertentu atau Anda melihat bahwa sebuah atribut tidak relevan. Kendatipun demikian, mohon putuskan evaluasi Anda atas setiap pertanyaan. Pendapat Anda sangat penting. Mohon diperhatikan: tidak ada jawaban salah atau benar!

Please evaluate the dashboard that you have tried. Please give a spontaneous assessment. Don't think too long about your decision so that the impression you get is genuine. Sometimes you are not very sure about a particular attribute or you see that an attribute is not relevant. Nevertheless, please decide your evaluation of each question. Your opinion is very important. Please note: there are no right or wrong answers!

Menurut saya dasbor adalah/ I think the dashboard is:

cepat/ fast (1)
lambat/ slow (7)

inovatif/ innovative(1)
konservatif/ conservative (7)

terdepan/ leading-edge (1)
lazim/ common (7)

mendukung/ supportive (1)

menghalangi/ obstructive (7)

Appendix D EFA results

D.1 EFA results

```
> print(fit_EFA_1)
Factor Analysis using method =  wls
Call: fa(r = polycor_matrix, nfactors = 1, rotate = "promax", 
    fm = "wls")
Standardized loadings (pattern matrix) based upon correlation matrix
     WLS1   h2   u2 com
sp   0.94 0.88 0.12   1
sup  0.93 0.86 0.14   1
inov 0.79 0.63 0.37   1
lead 0.93 0.87 0.13   1
it1  0.74 0.55 0.45   1
it2  0.76 0.58 0.42   1

               WLS1
SS loadings    4.37
Proportion Var 0.73

Mean item complexity =  1
Test of the hypothesis that 1 factor is sufficient.

df null model =  15  with the objective function =  8.08
df of  the model are 9  and the objective function was  2.37 

The root mean square of the residuals (RMSR) is  0.13 
The df corrected root mean square of the residuals is  0.17 

Fit based upon off diagonal values = 0.97
Measures of factor score adequacy             
                                                  WLS1
Correlation of (regression) scores with factors   0.98
Multiple R square of scores with factors          0.97
Minimum correlation of possible factor scores     0.93



> print(fit_EFA_2)
Factor Analysis using method =  wls
Call: fa(r = polycor_matrix, nfactors = 2, rotate = "promax", 
    fm = "wls")
Standardized loadings (pattern matrix) based upon correlation matrix
      WLS1  WLS2   h2    u2 com
sp    0.86  0.14 0.93 0.072 1.1
sup   0.89  0.11 0.92 0.078 1.0
inov  1.04 -0.22 0.83 0.174 1.1
lead  0.73  0.29 0.89 0.111 1.3
it1  -0.04  0.93 0.82 0.182 1.0
it2  -0.01  0.92 0.83 0.168 1.0

                      WLS1 WLS2
SS loadings           3.24 1.98
Proportion Var        0.54 0.33
Cumulative Var        0.54 0.87
Proportion Explained  0.62 0.38
Cumulative Proportion 0.62 1.00

 With factor correlations of 
     WLS1 WLS2
WLS1 1.00 0.65
WLS2 0.65 1.00

Mean item complexity =  1.1
Test of the hypothesis that 2 factors are sufficient.

df null model =  15  with the objective function =  8.08
df of  the model are 4  and the objective function was  0.72 
```

```
The root mean square of the residuals (RMSR) is  0.03
The df corrected root mean square of the residuals is  0.06

Fit based upon off diagonal values = 1
Measures of factor score adequacy
                                                  WLS1 WLS2
Correlation of (regression) scores with factors   0.99 0.95
Multiple R square of scores with factors          0.98 0.90
Minimum correlation of possible factor scores     0.96 0.8
```

Appendix E CFA-SEM results

```
lavaan 0.6.16 ended normally after 97 iterations

  Estimator                                       DWLS
  Optimization method                           NLMINB
  Number of model parameters                        66

  Number of observations                           714

Model Test User Model:
                                              Standard      Scaled
  Test Statistic                               497.178     444.116
  Degrees of freedom                               134         134
  P-value (Chi-square)                           0.000       0.000
  Scaling correction factor                                  1.386
  Shift parameter                                           85.456
    simple second-order correction

Model Test Baseline Model:

  Test statistic                            242854.111   69025.914
  Degrees of freedom                               120         120
  P-value                                        0.000       0.000
  Scaling correction factor                                  3.523

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.999       0.995
  Tucker-Lewis Index (TLI)                       0.999       0.996

  Robust Comparative Fit Index (CFI)                            NA
  Robust Tucker-Lewis Index (TLI)                               NA

Root Mean Square Error of Approximation:

  RMSEA                                          0.062       0.057
  90 Percent confidence interval - lower         0.056       0.051
  90 Percent confidence interval - upper         0.067       0.063
  P-value H_0: RMSEA <= 0.050                    0.000       0.025
  P-value H_0: RMSEA >= 0.080                    0.000       0.000

  Robust RMSEA                                                  NA
  90 Percent confidence interval - lower                        NA
  90 Percent confidence interval - upper                        NA
  P-value H_0: Robust RMSEA <= 0.050                            NA
  P-value H_0: Robust RMSEA >= 0.080                            NA

Standardized Root Mean Square Residual:

  SRMR                                           0.037       0.037

Parameter Estimates:

  Standard errors                           Robust.sem
  Information                                 Expected
  Information saturated (h1) model        Unstructured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std
.all
  IT =~
    it1               1.000                               0.914    0
.914
    it2               1.073    0.014   77.302    0.000    0.981    0
.981
  PC =~
    pc1               1.000                               0.995    0
.995
```

```
    pc2               0.866    0.048   17.973    0.000    0.861    0
.861
  SI =~
    si1               1.000                               0.959    0
.959
    si2               0.987    0.010   95.476    0.000    0.946    0
.946
    si3               1.011    0.009  112.613    0.000    0.969    0
.969
  IN =~
    in1               1.000                               0.980    0
.980
    in2               0.983    0.011   86.620    0.000    0.963    0
.963
  UX =~
    sp                1.000                               0.951    0
.951
    sup               1.054    0.032   33.226    0.000    1.002    1
.002
    inov              0.849    0.030   28.650    0.000    0.807    0
.807
    lead              0.999    0.033   29.926    0.000    0.950    0
.950
  BI =~
    bi1               1.000                               1.063    0
.990
    bi2               0.999    0.006  162.043    0.000    1.061    0
.988
    bi3               0.982    0.006  169.208    0.000    1.043    0
.974

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std
.all
  BI ~
    IT                0.577    0.057   10.094    0.000    0.496    0
.496
    PC               -0.069    0.032   -2.205    0.027   -0.065   -0
.065
    SI                0.230    0.072    3.191    0.001    0.207    0
.207
    IN                0.222    0.051    4.315    0.000    0.205    0
.205
    UX                0.090    0.038    2.368    0.018    0.080    0
.080
    edu               0.618    0.093    6.655    0.000    0.582    0
.291
    trf_exp           0.017    0.008    1.988    0.047    0.016    0
.119
    age              -0.036    0.008   -4.624    0.000   -0.034   -0
.281
```

Appendix F Researcher’s professional background

The researcher has over 15 years of experience working within the Indonesian National Traffic Police (INTP), specifically in traffic management and road safety operations. As a police commissioner in the Traffic Security and Safety Directorate, the researcher has supported policy implementation and operational planning, including using ICT tools to improve traffic management. This experience has given the researcher a practical understanding of the challenges and opportunities of adopting ICT in public sector contexts.

The researcher has had the opportunity to work with ICT systems designed to support traffic crash investigations. In their professional role, the researcher has collaborated with colleagues and external partners to explore how data can be used effectively in operational contexts. These experiences have helped the researcher better understand how technology can address real-world needs while recognising the barriers to successful implementation.

Through their role within the INTP, the researcher has developed working relationships with colleagues and stakeholders across different levels of the organisation. These relationships have made it possible to engage meaningfully with participants during the research process, ensuring open and candid discussions. Familiarity with organisational practices has also allowed the researcher to contextualise the data collected to reflect the realities of public sector operations.

The researcher’s professional background has helped inform the study’s approach, particularly ensuring the findings are grounded in practical realities. By drawing on their knowledge of the organisational context, the researcher has sought to align the study with the needs and challenges faced by government employees. This perspective has contributed to the study’s aim of providing actionable insights for ICT adoption in the public sector.

List of references

Ab Hamid, M.R., Sami, W. and Sidek, M.H.M. (2017) ‘Discriminant validity assessment: Use of Fornell & Larcker criterion versus HTMT criterion’, in *Journal of Physics: Conference Series*. IOP Publishing, p. 12163.

Abberley, L., Gould, N., Crockett, K. and Cheng, J. (2017) ‘Modelling road congestion using ontologies for big data analytics in smart cities’, in *2017 International Smart Cities Conference (ISC2)*. IEEE, pp. 1–6. Available at: https://doi.org/10.1109/ISC2.2017.8090795.

El Abdallaoui, H.E.A., El Fazziki, A., Ennaji, F.Z. and Sadgal, M. (2018) ‘Decision Support System for the Analysis of Traffic Accident Big Data’, in *2018 14th International Conference on Signal-Image Technology & Internet-Based Systems (SITIS)*. IEEE, pp. 514–521. Available at: https://doi.org/10.1109/SITIS.2018.00084.

Abdekhoda, M., Dehnad, A. and Zarei, J. (2022) ‘Factors influencing adoption of e-learning in healthcare: integration of UTAUT and TTF model’, *BMC Medical Informatics and Decision Making*, 22(1), p. 327. Available at: https://doi.org/10.1186/s12911-022-02060-9.

Abdulhafedh, A. (2017) ‘Road Crash Prediction Models: Different Statistical Modeling Approaches’, *Journal of Transportation Technologies*, 07(02), pp. 190–205. Available at: https://doi.org/10.4236/jtts.2017.72014.

Abdulkareem, A.K., Abdulkareem, Z.J., Ishola, A.A. and Akindele, I.T. (2022) ‘Does e-government impact e-participation? The influence of trust in e-government’, *International Review of Public Administration*, 27(2), pp. 91–110. Available at: https://doi.org/10.1080/12294659.2022.2071540.

Abdullah, M. (2023) ‘The cutting edge technologies in computer science: a review’, *International Journal of Advanced Research in Computer Science*, 14(01), pp. 13–22. Available at: https://doi.org/10.26483/ijarcs.v14i1.6945.

Abelein, U. and Paech, B. (2012) ‘A proposal for enhancing user-developer communication in large IT projects', in *2012 5th International Workshop on Co-operative and Human Aspects of Software Engineering (CHASE)*. IEEE, pp. 1-3. Available at: https://doi.org/10.1109/CHASE.2012.6223014.

Abelein, U., Sharp, H. and Paech, B. (2013) 'Does Involving Users in Software Development Really Influence System Success?', *IEEE Software*, 30(6), pp. 17–23. Available at: https://doi.org/10.1109/MS.2013.124.

Abraham, D. (2020) 'Data-Driven Decision Making and Community Indicators: Towards an Integration of DDDM in Community Development', in, pp. 199–210. Available at: https://doi.org/10.1007/978-3-030-48182-7_11.

Achmad, S. aditama Y., Suryadhi, S. and Subur, J. (2023) 'Rancang bangun alat pendeteksi kantuk pada kendaraan roda empat dengan metode haar cascade', *Journal Of Science and Engineering*, 6(2). Available at: https://doi.org/10.33387/josae.v6i2.6898.

Adeoye-Olatunde, O.A. and Olenik, N.L. (2021) 'Research and scholarly methods: Semi-structured interviews', *JACCP Journal of the American College of Clinical Pharmacy*, (September 2020), pp. 1–10. Available at: https://doi.org/10.1002/jac5.1441.

Adler, N., Hakkert, A.S., Raviv, T. and Sher, M. (2014) 'The Traffic Police Location and Schedule Assignment Problem', *Journal of Multi-Criteria Decision Analysis*, 21(5–6), pp. 315–333. Available at: https://doi.org/10.1002/mcda.1522.

Aftab, M. and Myeong, S. (2018) 'Challenges for Developing Countries to Adopt ICT in Government Services', in *2018 IEEE 9th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*. IEEE, pp. 1088–1093.

Afzaal, H.M. and Masood, S. (2019) 'Role of Inter-Organizational Information Integration in successful E-Governance', *International Journal of Innovations in Science and Technology* [Preprint], (02). Available at: https://doi.org/10.33411/ijist/2019010307.

Aggarwal, C.C. (2015) *Data mining: the textbook*. Springer.

Aggarwal, R., Kryscynski, D., Midha, V. and Singh, H. (2015) 'Early to Adopt and Early to Discontinue: The Impact of Self-Perceived and Actual IT Knowledge on Technology Use Behaviors of End Users', *Information Systems Research*, 26(1), pp. 127–144. Available at: https://doi.org/10.1287/isre.2014.0564.

Ahmed, D.A.A., Hundt, G.L. and Blackburn, C. (2011) 'Issues of gender, reflexivity and positionality in the field of disability: Researching visual impairment in an arab society', *Qualitative Social Work*, 10(4), pp. 467–484. Available at: https://doi.org/10.1177/1473325010370188.

Ahmed, S., Hossain, M.A., Ray, S.K., Bhuiyan, M.M.I. and Sabuj, S.R. (2023) 'A study on road accident prediction and contributing factors using explainable machine learning models: analysis and performance', *Transportation Research Interdisciplinary Perspectives*, 19, p. 100814. Available at: https://doi.org/10.1016/j.trip.2023.100814.

Ahmed, S.K., Mohamed, M.G., Abdulqadir, S.O., El-Kader, R.G.A., El-Shall, N.A., Chandran, D., Rehman, M.E.U. and Dhama, K. (2023) 'Road Traffic Accidental Injuries and Deaths: A Neglected Global Health Issue', *Health Science Reports* [Preprint]. Available at: https://doi.org/10.1002/hsr2.1240.

Ahn, J., Campos, F., Hays, M. and DiGiacomo, D.K. (2019) 'Designing in Context: Reaching Beyond Usability in Learning Analytics Dashboard Design', *Journal of Learning Analytics* [Preprint]. Available at: https://doi.org/10.18608/jla.2019.62.5.

Ajzen, I. (1991) 'The theory of planned behavior', *Handbook of Theories of Social Psychology: Volume 1*, pp. 438–459. Available at: https://doi.org/10.4135/9781446249215.n22.

Akgül, Y. (2016) 'Web Site Accessibility, Quality and Vulnerability Assessment: A Survey of Government Web Sites in the Turkish Republic', *Journal of Information Systems Engineering & Management* [Preprint]. Available at: https://doi.org/10.20897/lectito.201650.

Al-Harthei, H., Toth, V.T., Garib, A. and Mahmoud, S.A. (2017) 'Efficient real-time allocation of patrol cars in traffic management', *World Congress on Civil, Structural, and Environmental Engineering*, pp. 1–8. Available at: https://doi.org/10.11159/icte17.105.

Al-Hubaishi, H.S., Ahmad, S.Z. and Hussain, M. (2017) 'Exploring Mobile Government From the Service Quality Perspective', *Journal of Enterprise Information Management* [Preprint]. Available at: https://doi.org/10.1108/jeim-01-2016-0004.

Al-Kassab, J., Ouertani, Z.M., Schiuma, G. and Neely, A. (2014) 'Information visualization to support management decisions', *International Journal of Information Technology & Decision Making*, 13(02), pp. 407–428. Available at: https://doi.org/10.1142/S0219622014500497.

Al-Maskari, A. and Sanderson, M. (2010) 'A Review of Factors Influencing User Satisfaction in Information Retrieval', *Journal of the American Society for Information Science and Technology* [Preprint]. Available at: https://doi.org/10.1002/asi.21300.

Al-Rahmi, W.M., Uddin, M., Alkhalaf, S., Al-Dhlan, K.A., Cifuentes-Faura, J., Al-Rahmi, A.M. and Al-Adwan, A.S. (2022) 'Validation of an Integrated IS Success Model in the Study of E-Government', *Mobile Information Systems* [Preprint]. Available at: https://doi.org/10.1155/2022/8909724.

Al-Sultan, S., Al-Doori, M.M., Al-Bayatti, A.H. and Zedan, H. (2014) 'A comprehensive survey on vehicular Ad Hoc network', *Journal of Network and Computer Applications*, 37, pp. 380–392. Available at: https://doi.org/10.1016/j.jnca.2013.02.036.

Al-Yawer, H. and Ahmad, R. (2018) 'The Concept of User Participation in the Development Process of E-Government System', *International Journal of Scientific Research in Computer Science Engineering and Information Technology* [Preprint]. Available at: https://doi.org/10.32628/cseit1183790.

Alahi, M.E.E., Sukkuea, A., Tina, F.W., Nag, A., Kurdthongmee, W., Suwannarat,

K. and Mukhopadhyay, S.C. (2023) ‘Integration of IoT-Enabled Technologies and Artificial Intelligence (AI) for Smart City Scenario: Recent Advancements and Future Trends’, *Sensors*, 23(11), p. 5206. Available at: https://doi.org/10.3390/s23115206.

Alavi, M. and Joachimsthaler, E.A. (1992) ‘Revisiting DSS Implementation Research: A Meta-Analysis of the Literature and Suggestions for Researchers’, *MIS Quarterly*, 16(1), p. 95. Available at: https://doi.org/10.2307/249703.

Alawadhi, S. and Scholl, H.J. (2016) ‘Smart Governance: A Cross-Case Analysis of Smart City Initiatives’, in *2016 49th Hawaii International Conference on System Sciences (HICSS)*. IEEE, pp. 2953–2963. Available at: https://doi.org/10.1109/HICSS.2016.370.

Alay, S. and Koçak, M.S. (2002) ‘Validity and reliability of time management questionnaire’.

Albahlal, B. (2021) ‘An Examination of Factors Influencing Government Employees to Adopt and Use Social Media’, in, pp. 421–432. Available at: https://doi.org/10.1007/978-3-030-71292-1_32.

Albouq, S.S., Sen, A.A.A., Almashf, N., Yamin, M., Alshanqiti, A. and Bahbouh, N.M. (2022) ‘A Survey of Interoperability Challenges and Solutions for Dealing With Them in IoT Environment’, *Ieee Access* [Preprint]. Available at: https://doi.org/10.1109/access.2022.3162219.

Alderfer, C.P. and Simon, A.F. (2002) ‘Nonresponse Rates to Organic Questionnaire Items as Evidence of Parallel Processes during Organizational Diagnosis’, *The Journal of Applied Behavioral Science*, 38(4), pp. 416–435. Available at: https://doi.org/10.1177/002188602237790.

Alfiani, H., Kurnia Aditya, S., Lusa, S., Indra Sensuse, D., Wibowo Putro, P.A. and Indriasari, S. (2024) ‘E-Government Issues in Developing Countries Using TOE and UTAUT Frameworks: A Systematic Review’, *Policy & Governance Review*, 8(2), p. 169. Available at: https://doi.org/10.30589/PGR.V8I2.932.

Alhaderi, S. and Ahmed, F. (2015) ‘The effect of social characteristic in the acceptance and continue usage for information technology in the public sector’, *International Journal of Business and Social Science*, 6(7), pp. 186–192.

Alikhademi, K., Drobina, E., Prioleau, D., Richardson, B., Purves, D. and Gilbert, J.E. (2022) ‘A review of predictive policing from the perspective of fairness’, *Artificial Intelligence and Law*, 30(1), pp. 1–17. Available at: https://doi.org/10.1007/s10506-021-09286-4.

Aliyu, A.A., Bello, M.U., Kasim, R. and Martin, D. (2014) ‘Positivist and non-positivist paradigm in social science research: Conflicting paradigms or perfect partners’, *J. Mgmt. & Sustainability*, 4, p. 79.

Allen, M.S., Robson, D.A. and Iliescu, D. (2023) ‘Face Validity’, *European Journal of Psychological Assessment* [Preprint]. Available at: https://doi.org/10.1027/1015-5759/a000777.

Allio, M.K. (2012) ‘Strategic dashboards: Designing and deploying them to improve implementation’, *Strategy and Leadership*, 40(5), pp. 24–31. Available at: https://doi.org/10.1108/10878571211257159.

Almanasreh, E., Moles, R. and Chen, T.F. (2019) ‘Evaluation of methods used for estimating content validity’, *Research in social and administrative pharmacy*, 15(2), pp. 214–221.

Almeida, F. and Monteiro, J. (2017) ‘The Role of Responsive Design in Web Development.’, *Webology*, 14(2).

Almufti, M., Sellami, R. and Belguith, L.H. (2024) ‘Applying a Structural Model to Assess the Efficiency of E-Government Implementation in Developing Countries’, *3rd IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics, ICDCECE 2024* [Preprint]. Available at: https://doi.org/10.1109/ICDCECE60827.2024.10549437.

Almuqrin, A., Mutambik, I., Alomran, A., Gauthier, J. and Abusharhah, M. (2022) ‘Factors Influencing Public Trust in Open Government Data’, *Sustainability*, 14(15), p. 9765. Available at: https://doi.org/10.3390/su14159765.

Almuraqab, N.A.S. (2020) 'E & M-Government and smart city: A review of ICT strategies and plans in the United Arab Emirates', *International Journal of Management (IJM)*, 11(3).

Almutrafi, F. (2019) 'The What, Why and How of Conducting Focus-Group Research', *International Journal of Language and Linguistics*, 7(5), p. 235. Available at: https://doi.org/10.11648/J.IJLL.20190705.18.

Alshehri, A.H., Alanazi, F., Yosri, A.M. and Yasir, M. (2024) 'Comparing fatal crash risk factors by age and crash type by using machine learning techniques', *PLOS ONE*. Edited by S. Veerappampalayam Easwaramoorthy, 19(5), p. e0302171. Available at: https://doi.org/10.1371/journal.pone.0302171.

Alshira'h, M.H. (2020) 'The Effects of Usability and Accessibility for E-Government Services on the End-User Satisfaction', *International Journal of Interactive Mobile Technologies (Ijim)* [Preprint]. Available at: https://doi.org/10.3991/ijim.v14i13.14659.

Alwabel, A.S.A. and Zeng, X.-J. (2021) 'Data-driven modeling of technology acceptance: A machine learning perspective', *Expert Systems with Applications*, 185, p. 115584. Available at: https://doi.org/10.1016/j.eswa.2021.115584.

Amiri, A.M., Nadimi, N., Khalifeh, V. and Shams, M. (2021) 'GIS-based crash hotspot identification: a comparison among mapping clusters and spatial analysis techniques', *International Journal of Injury Control and Safety Promotion*, 28(3), pp. 325–338. Available at: https://doi.org/10.1080/17457300.2021.1925924.

Amoako-Gyampah, K. (2007) 'Perceived usefulness, user involvement and behavioral intention: an empirical study of ERP implementation', *Computers in Human Behavior*, 23(3), pp. 1232–1248. Available at: https://doi.org/10.1016/j.chb.2004.12.002.

Anas, H., Ilyas, M., Tariq, Q. and Hummayun, M. (2016) 'Requirements

Validation Techniques: An Empirical Study', *International Journal of Computer Applications*, 148(14), pp. 5–10. Available at: https://doi.org/10.5120/ijca2016910911.

Anas, M., Othman, I. and Fathey, M. (2018) 'E-government adoption: a systematic review in the context of developing nations', *International Journal of Innovation*, 8(1), pp. 59–76. Available at: https://pdfs.semanticscholar.org/c750/0ceb63ee39072cda14f5ff1155c22502d87d.pdf.

Anderson, D., Wu, R., Cho, J.-S. and Schroeder, K. (2015) *E-Government Strategy, ICT and Innovation for Citizen Engagement*. New York, NY: Springer New York (SpringerBriefs in Electrical and Computer Engineering). Available at: https://doi.org/10.1007/978-1-4939-3350-1.

Anderson, J.C. and Gerbing, D.W. (1988) 'Structural equation modeling in practice: A review and recommended two-step approach.', *Psychological Bulletin*, 103(3), pp. 411–423. Available at: https://doi.org/10.1037/0033-2909.103.3.411.

Anderson, N., Russ, S.A., Eisenberg, D. and Halfon, N. (2023) 'Dashboards as Mechanisms for Community Empowerment: Developing a Prototype for Child and Adolescent Well-Being in California', *Journal of Public Health Management and Practice* [Preprint]. Available at: https://doi.org/10.1097/phh.0000000000001746.

Anderson, T.K. (2009) 'Kernel density estimation and K-means clustering to profile road accident hotspots', *Accident Analysis & Prevention*, 41(3), pp. 359–364. Available at: https://doi.org/10.1016/j.aap.2008.12.014.

Andreasson, K. and Snaprud, M. (2014) 'The european e-government web accessibility divide', in *Proceedings of the 8th International Conference on Theory and Practice of Electronic Governance*. New York, NY, USA: ACM, pp. 391–394. Available at: https://doi.org/10.1145/2691195.2691287.

Anedda, M., Fadda, M., Girau, R., Pau, G. and Giusto, D. (2023) 'A social smart city for public and private mobility: A real case study', *Computer Networks*, 220, p. 109464. Available at: https://doi.org/10.1016/j.comnet.2022.109464.

Anjum, S. and Ismail, Z. (2022) 'Employee monitoring, productivity, privacy and harassment: Auditing technology training and adoption in public administration', in, p. 080002. Available at: https://doi.org/10.1063/5.0108484.

Anthopoulos, L.G. (2017) 'The Rise of the Smart City', in, pp. 5–45. Available at: https://doi.org/10.1007/978-3-319-57015-0_2.

Anthopoulos, L.G. and Reddick, C.G. (2016) 'Understanding electronic government research and smart city: A framework and empirical evidence', *Information Polity*, 21(1), pp. 99–117. Available at: https://doi.org/10.3233/IP-150371.

Antón, C., Camarero, C. and San José, R. (2014) 'Public Employee Acceptance of New Technological Processes: The case of an internal call centre', *Public Management Review*, 16(6), pp. 852–875. Available at: https://doi.org/10.1080/14719037.2012.758308.

Archmann, S. and Iglesias, C. (2010) 'eGovernment: A driving force for innovation and efficiency in public administration', *EIPAScope*, 2010(1), pp. 29–36.

Arduin, P.E., Rosenthal-Sabroux, C. and Grundstein, M. (2012) 'Considering tacit knowledge when bridging knowledge management and collaborative decision making', in *Proceedings of the EWG-DSS Liverpool-2012 Workshop on Decision Systems*, pp. 62–70.

Armour, M. (1984) 'Effect of Police Presence on Urban Driving Speeds.', *Australian road research*, 14(3), pp. 142–148.

Aronson, K.I., Ali, M., Reshetynak, E., Kaner, R.J., Martínez, F.J., Safford, M.M. and Pinheiro, L.C. (2021) 'Establishing Content-Validity of a Disease-Specific Health-Related Quality of Life Instrument for Patients With Chronic Hypersensitivity Pneumonitis', *Journal of Patient-Reported Outcomes* [Preprint].

Available at: https://doi.org/10.1186/s41687-020-00282-x.

Athmay, Al.A.A. Al, Fantazy, K. and Kumar, V. (2016) ‘E-Government Adoption and User’s Satisfaction: An Empirical Investigation’, *Euromed Journal of Business* [Preprint]. Available at: https://doi.org/10.1108/emjb-05-2014-0016.

Atumo, E.A., Fang, T. and Jiang, X. (2022) ‘Spatial statistics and random forest approaches for traffic crash hot spot identification and prediction’, *International Journal of Injury Control and Safety Promotion*, 29(2), pp. 207–216. Available at: https://doi.org/10.1080/17457300.2021.1983844.

Avila-Garcia, M.S., Bianchetti, M., Vazquez-De-la-Rosa, M.I., Avilés-Díaz, J.C., Franco-Gaona, E. and Tapia-Flores, J. (2022) ‘Using Think Aloud for Eliciting Requirements for a Reading Comprehension Software Tool’, in *2022 10th International Conference in Software Engineering Research and Innovation (CONISOFT)*. IEEE, pp. 168–173. Available at: https://doi.org/10.1109/CONISOFT55708.2022.00030.

Ayyıldız, T. (2020) ‘Business & Management Studies : an International Journal Analysing the Relationship Between Organisational’, *Bmij*, (3), pp. 3550–3581.

Azamela, J.C., Tang, Z., Ackah, O. and Awozum, S. (2022) ‘Assessing the Antecedents of E-Government Adoption: A Case of the Ghanaian Public Sector’, *SAGE Open*, 12(2), p. 215824402211010. Available at: https://doi.org/10.1177/21582440221101040.

Baalbaki, I., Malhotra, N.K. and Nasr, N. (2013) ‘Marketing Research: An Applied Orientation’. Pearson Education.

Bachner, J. (2013) *Predictive policing: preventing crime with data and analytics*. IBM Center for the Business of Government Washington, DC.

Badshah, I., Khan, Z.H., Gulliver, T.A., Khattak, K.S. and Saad, S. (2022) ‘Modeling Sustainable Traffic Behavior: Avoiding Congestion at a Stationary Bottleneck’, *Civil Engineering Journal*, 8(11), pp. 2378–2390. Available at: https://doi.org/10.28991/CEJ-2022-08-11-02.

Bagozzi, R.P. and Yi, Y. (1988) ‘On the Evaluation of Structural Equation Models’, *Journal of the Academy of Marketing Science* [Preprint]. Available at: https://doi.org/10.1177/009207038801600107.

Balaji, T.S., Arumugham, J., Cavrak, S., Knuycky, L. and Lutz, M. (2015) ‘Structural equation modeling in user experience research: Two case studies’, *Proceedings of the Human Factors and Ergonomics Society*, 2015-Janua, pp. 448-452. Available at: https://doi.org/10.1177/1541931215591095.

Baldini, M., Maso, L.D., Liberatore, G., Mazzi, F. and Terzani, S. (2018) ‘Role of Country- and Firm-Level Determinants in Environmental, Social, and Governance Disclosure’, *Journal of Business Ethics*, 150(1), pp. 79–98. Available at: https://doi.org/10.1007/s10551-016-3139-1.

Ballas, D. (2013) ‘What makes a “happy city”?’, *Cities*, 32(June 2013). Available at: https://doi.org/10.1016/j.cities.2013.04.009.

Bando, Y., Yoh, K., Sou, K., Chou, C.C. and Doi, K. (2023) ‘AI-Based Evaluation of Streets for People in Bangkok: Perspectives from Walkability and Lingerability’, *Sustainability*, 15(24). Available at: https://doi.org/10.3390/SU152416884.

Banerjee, A., Jha, A., Farooq, B., Mohan, D., Tiwari, G., Bhalla, K. and Goel, R. (2023) ‘Developing a National Database of Police-Reported Fatal Road Traffic Crashes for Road Safety Research and Management in India’, *SSRN Electronic Journal* [Preprint]. Available at: https://doi.org/10.2139/ssrn.4378219.

Bano, M. and Zowghi, D. (2015) ‘A systematic review on the relationship between user involvement and system success’, *Information and Software Technology*, 58, pp. 148–169. Available at: https://doi.org/10.1016/j.infsof.2014.06.011.

Barile, S., Orecchini, F., Saviano, M. and Farioli, F. (2018) ‘People, technology, and governance for sustainability: the contribution of systems and cyber-systemic thinking’, *Sustainability Science*, 13(5), pp. 1197–1208. Available at: https://doi.org/10.1007/s11625-018-0621-y.

Barki, H. and Hartwick, J. (1989) 'Rethinking the Concept of User Involvement', *MIS Quarterly*, 13(1), p. 53. Available at: https://doi.org/10.2307/248700.

Barki, H. and Hartwick, J. (1994) 'Measuring User Participation, User Involvement, and User Attitude', *MIS Quarterly*, 18(1), p. 59. Available at: https://doi.org/10.2307/249610.

Barki, H., Pare, G. and Sicotte, C. (2008) 'Linking IT Implementation and Acceptance via the Construct of Psychological Ownership of Information Technology', *Journal of Information Technology*, 23(4), pp. 269–280. Available at: https://doi.org/10.1057/jit.2008.12.

Barnette, J.J. (2000) 'Effects of Stem and Likert Response Option Reversals on Survey Internal Consistency: If You Feel the Need, There Is a Better Alternative to Using Those Negatively Worded Stems', *Educational and Psychological Measurement* [Preprint]. Available at: https://doi.org/10.1177/00131640021970592.

Baroudi, J.J., Olson, M.H. and Ives, B. (1986) 'An empirical study of the impact of user involvement on system usage and information satisfaction', *Communications of the ACM*, 29(3), pp. 232–238. Available at: https://doi.org/10.1145/5666.5669.

Barrett, P. (2007) 'Structural equation modelling: Adjudging model fit', *Personality and Individual Differences*, 42(5), pp. 815–824. Available at: https://doi.org/https://doi.org/10.1016/j.paid.2006.09.018.

Barua, M. (2012) 'E-Governance Adoption in Government Organization of India', *International Journal of Managing Public Sector Information and Communication Technologies*, 3(1), pp. 1–20. Available at: https://doi.org/10.5121/ijmpict.2012.3101.

Bates, L.J., Antrobus, E., Bennett, S. and Martin, P. (2015) 'Comparing Police and Public Perceptions of a Routine Traffic Encounter', *Police Quarterly*, 18(4), pp. 442–468. Available at: https://doi.org/10.1177/1098611115589290.

Batty, M., Axhausen, K.W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., Ouzounis, G.K. and Portugali, Y. (2012) ‘Smart Cities of the Future’, *The European Physical Journal Special Topics* [Preprint]. Available at: https://doi.org/10.1140/epjst/e2012-01703-3.

Baumgartner, J., Sonderegger, A. and Sauer, J. (2019) ‘No need to read: Developing a pictorial single-item scale for measuring perceived usability’, *International Journal of Human Computer Studies*, 122(August 2018), pp. 78–89. Available at: https://doi.org/10.1016/j.ijhcs.2018.08.008.

Bayaga, A. and du Plessis, A. (2024) ‘Ramifications of the Unified Theory of Acceptance and Use of Technology (UTAUT) among developing countries’ higher education staffs’, *Education and Information Technologies*, 29(8), pp. 9689–9714. Available at: https://doi.org/10.1007/s10639-023-12194-6.

Beatty, P.C. and Willis, G.B. (2007) ‘Research synthesis: The practice of cognitive interviewing’, *Public Opinion Quarterly*, 71(2), pp. 287–311. Available at: https://doi.org/10.1093/poq/nfm006.

Bedford, L., Mazerolle, L., Gilmour, J. and Martin, P. (2021) ‘The impact of mobile technology devices on street checks and crime incidents reported: results of a randomised controlled trial’, *Journal of Experimental Criminology*, 18(4), pp. 1–18. Available at: https://doi.org/10.1007/S11292-021-09470-1.

Behnood, H.R., Ayati, E., Brijs, T., Neghab, M.P. and Shen, Y. (2017) ‘A fuzzy decision-support system in road safety planning’, *Proceedings of the Institution of Civil Engineers - Transport*, 170(5), pp. 305–317. Available at: https://doi.org/10.1680/jtran.15.00062.

Bell, K., Fahmy, E. and Gordon, D. (2016) ‘Quantitative conversations: the importance of developing rapport in standardised interviewing’, *Quality & Quantity*, 50(1), pp. 193–212. Available at: https://doi.org/10.1007/s11135-014-0144-2.

Benfeldt Nielsen, O. (2017) ‘A comprehensive review of data governance literature’.

Bennett, R.H. (1998) ‘The importance of tacit knowledge in strategic deliberations and decisions’, *Management Decision*, 36(9), pp. 589–597. Available at: https://doi.org/10.1108/00251749810239478.

Bentler, P.M. (1990) ‘Comparative Fit Indexes in Structural Models.’, *Psychological Bulletin* [Preprint]. Available at: https://doi.org/10.1037/0033-2909.107.2.238.

Bentler, P.M. and Bonett, D.G. (1980) ‘Significance tests and goodness of fit in the analysis of covariance structures.’, *Psychological bulletin*, 88(3), p. 588.

Berg, A.C. van den, Giest, S. and Kraaij, W. (2022) ‘Assessing Inclusivity in Online Platforms Through Usability Evaluation With Google Analytics’, *Policy & Internet* [Preprint]. Available at: https://doi.org/10.1002/poi3.328.

Berkowsky, R.W., Sharit, J. and Czaja, S.J. (2017) ‘Factors Predicting Decisions About Technology Adoption Among Older Adults’, *Innovation in Aging*, 1(3). Available at: https://doi.org/10.1093/geroni/igy002.

Bernot, A., Trauth-Goik, A. and Trevaskes, S. (2021) ‘Handling COVID-19 With Big Data in China: Increasing “Governance Capacity” or “Function Creep”?’, *Australian Journal of International Affairs* [Preprint]. Available at: https://doi.org/10.1080/10357718.2021.1956430.

Bertot, J.C. and Jaeger, P.T. (2006) ‘User-Centered E-Government: Challenges and Benefits for Government Web Sites’, *Government Information Quarterly* [Preprint]. Available at: https://doi.org/10.1016/j.giq.2006.02.001.

Beuschel, W. (2008) ‘Dashboards for Management’, in *Encyclopedia of Decision Making and Decision Support Technologies*. IGI Global, pp. 116–123. Available at: https://doi.org/10.4018/978-1-59904-843-7.ch014.

Beyers, L.J.E. (2016) ‘Evaluation of Information Technology: The Case of Limpopo Legislature’, *Journal of Communication*, 7(2), pp. 331–336. Available at: https://doi.org/10.1080/0976691X.2016.11884915.

Bharosa, N., Lee, J. and Janssen, M. (2010) 'Challenges and obstacles in sharing and coordinating information during multi-agency disaster response: Propositions from field exercises', *Information systems frontiers*, 12, pp. 49–65.

Bhattacharjee, P., Baker, S. and Waycott, J. (2020) 'Older adults and their acquisition of digital skills: A review of current research evidence', in *32nd Australian Conference on Human-Computer Interaction*. New York, NY, USA: ACM, pp. 437–443. Available at: https://doi.org/10.1145/3441000.3441053.

Bhattacherjee, A. (2012) *Social Science Research: principles, methods, and practices, Book 3.* Available at: http://scholarcommons.usf.edu/cgi/viewcontent.cgi?article=1002&context=oa_textbooks.

Bhattacherjee and Sanford (2006) 'Influence Processes for Information Technology Acceptance: An Elaboration Likelihood Model', *MIS Quarterly*, 30(4), p. 805. Available at: https://doi.org/10.2307/25148755.

Bhattarai, K. and Budd, D. (2019) 'Effects of Rapid Urbanization on the Quality of Life', in *Multidimensional Approach to Quality of Life Issues*. Singapore: Springer Singapore, pp. 327–341. Available at: https://doi.org/10.1007/978-981-13-6958-2_21.

Bhave, D.P., Teo, L.H. and Dalal, R.S. (2019) 'Privacy at Work: A Review and a Research Agenda for a Contested Terrain', *Journal of Management* [Preprint]. Available at: https://doi.org/10.1177/0149206319878254.

Bhuiyan, H., Ara, J., Hasib, K.M., Sourav, M.I.H., Karim, F.B., Sik-Lanyi, C., Governatori, G., Rakotonirainy, A. and Yasmin, S. (2022) 'Crash severity analysis and risk factors identification based on an alternate data source: a case study of developing country', *Scientific Reports*, 12(1), p. 21243. Available at: https://doi.org/10.1038/s41598-022-25361-5.

Bibri, S.E. and Krogstie, J. (2017a) 'ICT of the New Wave of Computing for Sustainable Urban Forms: Their Big Data and Context-Aware Augmented Typologies and Design Concepts', *Sustainable Cities and Society* [Preprint].

Available at: https://doi.org/10.1016/j.scs.2017.04.012.

Bibri, S.E. and Krogstie, J. (2017b) ‘Smart Sustainable Cities of the Future: An Extensive Interdisciplinary Literature Review’, *Sustainable Cities and Society* [Preprint]. Available at: https://doi.org/10.1016/j.scs.2017.02.016.

Biesta, G. (2010) ‘Pragmatism and the philosophical foundations of mixed methods research’, *Sage handbook of mixed methods in social and behavioral research*, 2, pp. 95–118.

Biswas, A., Mahato, M., Ghosh, A., Haque, M.E., Ghoshal, S., Mazumder, D. and Acharya, S.K. (2020) ‘Production Orientation of KVK Adopted Farmers: The Socio-Ecological Estimation and Interpretation’, *Asian Journal of Agricultural Extension Economics & Sociology* [Preprint]. Available at: https://doi.org/10.9734/ajaees/2020/v38i1130458.

Black, W. and Babin, B.J. (2019) ‘Multivariate data analysis: Its approach, evolution, and impact’, in *The great facilitator: Reflections on the contributions of Joseph F. Hair, Jr. to marketing and business research*. Springer, pp. 121–130.

Blaikie, N. and Priest, J. (2017) *Social Research: Paradigms in Action*, *Rural Sociology*. Available at: https://books.google.co.uk/books?hl=en&lr=&id=6pXbDQAAQBAJ&oi=fnd&pg=PT11&dq=Blaikie,+N.+and+Priest,+J.+(2017)+Social+Research:+Paradigms+in+Action,+Cambridge,+Polity+Press.&ots=EqctB1B1AB&sig=LgL8Nh4M5VC0uNbbWWX63DWLsLM#v=onepage&q=Blaikie%2C N. and Prie.

Bliss, T., Guria, J., Jones, W. and Rockliffe, N. (1999) ‘A road safety resource allocation model’, *Transport Reviews*, 19(4), pp. 291–303. Available at: https://doi.org/10.1080/014416499295402.

Boateng and William (2018) ‘Validity issues in the application of selected qualitative social research methods’, *AFRREV IJAH: An International Journal of Arts and Humanities*, 7(2), pp. 1–7. Available at: https://doi.org/10.4314/IJAH.V7I2.1.

Bokhari, S.A.A. and Seunghwan, M. (2024) 'How Do Institutional and Technological Innovations Influence the Smart City Governance? Focused on Stakeholder Satisfaction and Crime Rate', *Sustainability*, 16(10), p. 4246. Available at: https://doi.org/10.3390/su16104246.

Bollen, K.A. (1990) 'Overall fit in covariance structure models: Two types of sample size effects.', *Psychological Bulletin*, 107(2), pp. 256–259. Available at: https://doi.org/10.1037/0033-2909.107.2.256.

Boomsma, A. (1982) 'Systems under indirect observation: Causality, structure, prediction', *The robustness of lisrel against small sample sizes in factor analysis models*, pp. 149–173.

Borsekova, K. and Nijkamp, P. (2018) 'Smart cities: A challenge to research and policy analysis', *Cities*, 78, pp. 1–3. Available at: https://doi.org/10.1016/j.cities.2018.03.015.

Boulton, L., Phythian, R., Kirby, S. and Dawson, I. (2021) 'Taking an Evidence-Based Approach to Evidence-Based Policing Research', *Policing: A Journal of Policy and Practice*, 15(2), pp. 1290–1305. Available at: https://doi.org/10.1093/police/paaa057.

Boyne, G.A. (2002) 'Public and Private Management: What's the Difference?', *Journal of Management Studies*, 39(1), pp. 97–122. Available at: https://doi.org/10.1111/1467-6486.00284.

Bradbury-Jones, C. (2007) 'Enhancing rigour in qualitative health research: Exploring subjectivity through Peshkin's I's', *Journal of Advanced Nursing*, 59(3), pp. 290–298. Available at: https://doi.org/10.1111/j.1365-2648.2007.04306.x.

Braun, V. and Clarke, V. (2006) 'Using thematic analysis in psychology', *Qualitative Research in Psychology*, 3(2), pp. 77–101. Available at: https://doi.org/10.1191/1478088706qp063oa.

Braun, V. and Clarke, V. (2013) 'Successful Qualitative Research: A Practical Guide for Beginners', p. 400. Available at:

https://books.google.com/books?id=EV_Q06CUsXsC&pgis=1.

Braun, V. and Clarke, V. (2019) 'Reflecting on reflexive thematic analysis', *Qualitative Research in Sport, Exercise and Health*, 11(4), pp. 589–597. Available at: https://doi.org/10.1080/2159676X.2019.1628806.

Braun, V., Clarke, V., Hayfield, N. and Terry, G. (2024) 'Thematic Analysis', in *Advanced Research Methods for Applied Psychology*. London: Routledge, pp. 238–248. Available at: https://doi.org/10.4324/9781003362715-21.

Bregni, S. (2018) 'Global communications newsletter', *IEEE Communications Magazine*, 49(1), pp. 1–4. Available at: https://doi.org/10.1109/MCOM.2015.7120009.

Brislin, R.W. (1970) 'Back-translation for cross-cultural research', *Journal of cross-cultural psychology*, 1(3), pp. 185–216.

Brockmann, E.N. and Anthony, W.P. (2002) 'Tacit Knowledge and Strategic Decision Making', *Group & Organization Management*, 27(4), pp. 436–455. Available at: https://doi.org/10.1177/1059601102238356.

Bröhl, C., Rasche, P., Jablonski, J., Theis, S., Wille, M. and Mertens, A. (2018) 'Desktop PC, Tablet PC, or Smartphone? An Analysis of Use Preferences in Daily Activities for Different Technology Generations of a Worldwide Sample', in, pp. 3–20. Available at: https://doi.org/10.1007/978-3-319-92034-4_1.

Brous, P. and Janssen, M. (2020) 'Trusted Decision-Making: Data Governance for Creating Trust in Data Science Decision Outcomes', *Administrative Sciences*, 10(4), p. 81. Available at: https://doi.org/10.3390/admsci10040081.

Brown, T.A. (2015) *Confirmatory factor analysis for applied research*. Guilford publications.

Browne, M.W. and Cudeck, R. (1992) 'Alternative Ways of Assessing Model Fit', *Sociological Methods & Research*, 21(2), pp. 230–258. Available at: https://doi.org/10.1177/0049124192021002005.

Browning, M. and Arrigo, B. (2021) ‘Stop and Risk: Policing, Data, and the Digital Age of Discrimination’, *American Journal of Criminal Justice*, 46(2), pp. 298–316. Available at: https://doi.org/10.1007/s12103-020-09557-x.

Brożek, B., Furman, M., Jakubiec, M. and Kucharzyk, B. (2024) ‘The black box problem revisited. Real and imaginary challenges for automated legal decision making’, *Artificial Intelligence and Law*, 32(2), pp. 427–440. Available at: https://doi.org/10.1007/s10506-023-09356-9.

de Bruijn, H., Warnier, M. and Janssen, M. (2022) ‘The perils and pitfalls of explainable AI: Strategies for explaining algorithmic decision-making’, *Government Information Quarterly*, 39(2), p. 101666. Available at: https://doi.org/10.1016/j.giq.2021.101666.

Bryant, F.B. and Satorra, A. (2012) ‘Principles and Practice of Scaled Difference Chi-Square Testing’, *Structural Equation Modeling a Multidisciplinary Journal* [Preprint]. Available at: https://doi.org/10.1080/10705511.2012.687671.

Bryman, A. (2012) *Social Research Methods, 4th Edition*.

Brynjolfsson, E., Hitt, L. and Kim, H. (2011) ‘Strength in numbers: How does data-driven decision-making affect firm performance?’, *International Conference on Information Systems 2011, ICIS 2011*, 1, pp. 541–558. Available at: https://doi.org/10.2139/ssrn.1819486.

Brynjolfsson, E. and McElheran, K. (2016) ‘The Rapid Adoption of Data-Driven Decision-Making’, *American Economic Review*, 106(5), pp. 133–139. Available at: https://doi.org/10.1257/aer.p20161016.

Budding, T., Faber, B. and Gradus, R. (2018) ‘Assessing electronic service delivery in municipalities: determinants and financial consequences of e-government implementation’, *Local Government Studies*, 44(5), pp. 697–718. Available at: https://doi.org/10.1080/03003930.2018.1473768.

Burgard, T., Bošnjak, M. and Wedderhoff, N. (2020) ‘Response Rates in Online Surveys With Affective Disorder Participants’, *Zeitschrift für Psychologie*, 228(1), pp. 14–24. Available at: https://doi.org/10.1027/2151-2604/a000394.

Burns, R.B. (2000) *Introduction to research methods*.

Butsenko, E. (2022) 'How Data Mining Can Improve Road Safety in Cities', *Social Sciences*, 11(3), p. 130. Available at: https://doi.org/10.3390/socsci11030130.

Button, K.S., Ioannidis, J.P.A., Mokrysz, C., Nosek, B.A., Flint, J., Robinson, E.S.J. and Munafò, M.R. (2013) 'Power failure: why small sample size undermines the reliability of neuroscience', *Nature Reviews Neuroscience*, 14(5), pp. 365–376. Available at: https://doi.org/10.1038/nrn3475.

Buxton, B. (2010) *Sketching user experiences: getting the design right and the right design*. Morgan kaufmann.

Byrne, B.M. (2005) 'Factor analytic models: Viewing the structure of an assessment instrument from three perspectives', *Journal of personality assessment*, 85(1), pp. 17–32.

Byrne, B.M. (2013) *Structural Equation Modeling With Lisrel, Prelis, and Simplis*. Psychology Press. Available at: https://doi.org/https://doi.org/10.4324/9780203774762.

Byrne, B.M. (2016) *Structural Equation Modeling With AMOS*. Routledge. Available at: https://doi.org/10.4324/9781315757421.

Cafiso, S. and Di Silvestro, G. (2011) 'Performance of Safety Indicators in Identification of Black Spots on Two-Lane Rural Roads', *Transportation Research Record: Journal of the Transportation Research Board*, 2237(1), pp. 78–87. Available at: https://doi.org/10.3141/2237-09.

Caird, S. and Hallett, S.R. (2018) 'Towards Evaluation Design for Smart City Development', *Journal of Urban Design* [Preprint]. Available at: https://doi.org/10.1080/13574809.2018.1469402.

Callens, C. (2023) 'User Involvement as a Catalyst for Collaborative Public Service Innovation', *Journal of Public Administration Research and Theory*, 33(2), pp. 329–341. Available at: https://doi.org/10.1093/jopart/muac030.

Camarena, L. and Fusi, F. (2022) ‘Always Connected: Technology Use Increases Technostress Among Public Managers’, *The American Review of Public Administration*, 52(2), pp. 154–168. Available at: https://doi.org/10.1177/02750740211050387.

Caragliu, A., del Bo, C. and Nijkamp, P. (2011) ‘Smart cities in Europe’, *Journal of Urban Technology*, 18(2), pp. 65–82. Available at: https://doi.org/10.1080/10630732.2011.601117.

Cardullo, P. and Kitchin, R. (2019) ‘Smart urbanism and smart citizenship: The neoliberal logic of ‘citizen-focused’smart cities in Europe’, *Environment and planning C: politics and space*, 37(5), pp. 813–830.

Carmichael, I. and Marron, J.S. (2018) ‘Data science vs. statistics: two cultures?’, *Japanese Journal of Statistics and Data Science*, 1(1), pp. 117–138. Available at: https://doi.org/10.1007/s42081-018-0009-3.

Carr, D.B. and Tufte, E.R. (1987) ‘The Visual Display of Quantitative Information’, *Technometrics* [Preprint]. Available at: https://doi.org/10.2307/1269894.

Carter, D. (2017) ‘Smart cities: terrain for “epic struggle” or new urban utopias?’, *Town Planning Review*, 88(1), pp. 1–7. Available at: https://doi.org/10.3828/tpr.2017.2.

Cascaes Cardoso, M. (2017) ‘The Onboarding Effect’, in *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems*. New York, NY, USA: ACM, pp. 263–267. Available at: https://doi.org/10.1145/3027063.3027128.

Castelnovo, W., Misuraca, G. and Savoldelli, A. (2016) ‘Smart Cities Governance: The Need for a Holistic Approach to Assessing Urban Participatory Policy Making’, *Social Science Computer Review*, 34(6), pp. 724–739. Available at: https://doi.org/10.1177/0894439315611103.

Castro, M. and De Santos-Berbel, C. (2015) ‘Spatial analysis of geometric design consistency and road sight distance’, *International Journal of Geographical Information Science*, 29(12), pp. 2061–2074. Available at: https://doi.org/10.1080/13658816.2015.1037304.

Castro, S.L.-D. (2016) ‘Technology Helps, People Make: A Smart City Governance Framework Grounded in Deliberative Democracy’, in *Computer Law & Security Review*, pp. 0–392.

Cattell, R.B. (1966) ‘The scree test for the number of factors’, *Multivariate behavioral research*, 1(2), pp. 245–276.

Caudle, S.L., Gorr, W.L. and Newcomer, K.E. (1991) ‘Key Information Systems Management Issues for the Public Sector’, *MIS Quarterly*, 15(2), p. 171. Available at: https://doi.org/10.2307/249378.

Cavallo, F.L. (2022) ‘Who and What Connects the Dots? Emma Kunz’s Method as Infographics and the Politics of Probability’, *Parallax*, 28(4), pp. 426–441. Available at: https://doi.org/10.1080/13534645.2023.2206241.

Cavaye, A.L.M. (1995) ‘User participation in system development revisited’, *Information & Management*, 28(5), pp. 311–323.

Cepeda-Carrion, G., Cegarra-Navarro, J.-G. and Cillo, V. (2019) ‘Tips to use partial least squares structural equation modelling (PLS-SEM) in knowledge management’, *Journal of Knowledge Management*, 23(1), pp. 67–89.

Chagas, B.A., Ferreguetti, K., Ferreira, T.C., Marcolino, M.S., Ribeiro, L., Pagano, A., Reis, Z.S.N., Prates, R.O., Meira, W. and Ribeiro, A.B. (2021) ‘Chatbot as a Telehealth Intervention Strategy in the COVID-19 Pandemic’, *Clei Electronic Journal* [Preprint]. Available at: https://doi.org/10.19153/cleiej.24.3.6.

Chaiken, J.M. and Dormont, P. (1978) ‘A Patrol Car Allocation Model: Capabilities and Algorithms’, *Management Science*, 24(12), pp. 1291–1300. Available at: https://doi.org/10.1287/mnsc.24.12.1291.

Chan, E.Y. and Saqib, N. (2021) 'Privacy Concerns Can Explain Unwillingness to Download and Use Contact Tracing Apps When COVID-19 Concerns Are High', *Computers in Human Behavior* [Preprint]. Available at: https://doi.org/10.1016/j.chb.2021.106718.

Chandra, A.W., Silalahi, B.P. and Guritman, S. (2023) 'Optimasi Vehicle Routing Problem with Time Windows pada Rute Patroli Polisi di Kecamatan Dramaga, Kabupaten Bogor'. Available at: http://repository.ipb.ac.id/handle/123456789/131974.

Chang, C.M., Vavrova, M. and Mahnaz, S.L. (2022) 'Integrating Vulnerable Road User Safety Criteria into Transportation Asset Management to Prioritize Budget Allocation at the Network Level', *Sustainability*, 14(14), p. 8317. Available at: https://doi.org/10.3390/su14148317.

Chang, W. and Borges Ribeiro, B. (2018) 'shinydashboard: create dashboards with "Shiny"', *R package version 0.7*, 1.

Charmsaz, S., Prencipe, M., Kiely, M., Pidgeon, G.P. and Collins, D.M. (2018) 'Innovative Technologies Changing Cancer Treatment', *Cancers*, 10(6), p. 208. Available at: https://doi.org/10.3390/cancers10060208.

Chelst, K. (1978) 'An Algorithm for Deploying a Crime Directed (Tactical) Patrol Force', *Management Science*, 24(12), pp. 1314–1327. Available at: https://doi.org/10.1287/mnsc.24.12.1314.

Chen, C.C., Liu, J.Y.-C. and Chen, H.-G. (2011) 'Discriminative effect of user influence and user responsibility on information system development processes and project management', *Information and Software Technology*, 53(2), pp. 149–158. Available at: https://doi.org/10.1016/j.infsof.2010.10.001.

Chen, F., Chen, S. and Ma, X. (2018) 'Analysis of hourly crash likelihood using unbalanced panel data mixed logit model and real-time driving environmental big data', *Journal of Safety Research*, 65, pp. 153–159. Available at: https://doi.org/10.1016/j.jsr.2018.02.010.

Chen, H., Cheng, T. and Wise, S. (2017) ‘Developing an online cooperative police patrol routing strategy’, *Computers, Environment and Urban Systems*, 62, pp. 19–29. Available at: https://doi.org/10.1016/j.compenvurbsys.2016.10.013.

Chen, H., Cheng, T. and Ye, X. (2019) ‘Designing efficient and balanced police patrol districts on an urban street network’, *International Journal of Geographical Information Science*, 33(2), pp. 269–290. Available at: https://doi.org/10.1080/13658816.2018.1525493.

Chen, L. and Mohamed, S.A.M. (2010) ‘The Strategic Importance of Tacit Knowledge Management Activities in Construction’, *Construction Innovation* [Preprint]. Available at: https://doi.org/10.1108/14714171011037165.

Chen, R., Meng, Q. and Yu, J.J. (2023) ‘Optimal government incentives to improve the new technology adoption: Subsidizing infrastructure investment or usage?’, *Omega*, 114, p. 102740. Available at: https://doi.org/10.1016/j.omega.2022.102740.

Chen, X. and Liu, W. (2018) ‘Psychometric Properties of the Dental Activities Test: An Exploratory Factor Analysis in Older Adults With Cognitive Impairment’, *Behavioural Neurology* [Preprint]. Available at: https://doi.org/10.1155/2018/8625916.

Chen, Y.-W., Chien, S.-Y. and Yu, F. (2023) ‘An overview of XAI Algorithms’, in *2023 International Automatic Control Conference (CACS)*. IEEE, pp. 1–5. Available at: https://doi.org/10.1109/CACS60074.2023.10326174.

Cheney, P.H., Mann, R.I. and Amoroso, D.L. (1986) ‘Organizational factors affecting the success of end-user computing’, *Journal of Management Information Systems*, 3(1), pp. 65–80.

Cheng, Z., Zu, Z., Lü, J. and Lu, J. (2018) ‘Traffic Crash Evolution Characteristic Analysis and Spatiotemporal Hotspot Identification of Urban Road Intersections’, *Sustainability*, 11(1), p. 160. Available at: https://doi.org/10.3390/su11010160.

Chillakuri, B. (2020) ‘Understanding Generation Z Expectations for Effective

Onboarding', *Journal of Organizational Change Management* [Preprint]. Available at: https://doi.org/10.1108/jocm-02-2020-0058.

Chimtengo, S.A., Hanif, R. and Mvonye, C. (2016) 'Factors Hindering the Adoption of Electronic Procurement System in Public Sector Organisations in Malawi', *Strategic Journal of Business & Change Management*, 3(4), pp. 1544–1554.

Chohan, S.R. and Hu, G. (2020) 'Success Factors Influencing Citizens' Adoption of IoT Service Orchestration for Public Value Creation in Smart Government', *IEEE Access*, 8, pp. 208427–208448. Available at: https://doi.org/10.1109/ACCESS.2020.3036054.

Chohan, S.R. and Hu, G. (2022) 'Strengthening digital inclusion through e-government: cohesive ICT training programs to intensify digital competency', *Information Technology for Development*, 28(1), pp. 16–38. Available at: https://doi.org/10.1080/02681102.2020.1841713.

Chohan, S.R., Hu, G., Khan, A., Pasha, A.T., Saleem, F. and Sheikh, M.A. (2021) 'IoT as Societal Transformer: Improving Citizens' Continuous Usage Intention in Digital Society Through Perceived Public Value', *Library Hi Tech* [Preprint]. Available at: https://doi.org/10.1108/lht-05-2021-0156.

Choi, B.C.K., Pang, T., Lin, V., Puska, P., Sherman, G., Goddard, M., Ackland, M., Sainsbury, P., Stachenko, S., Morrison, H. and Clottey, C. (2005) 'Can Scientists and Policy Makers Work Together?', *Journal of Epidemiology & Community Health* [Preprint]. Available at: https://doi.org/10.1136/jech.2004.031765.

Choi, Y., Gil-Garcia, J.R., Burke, G.B., Costello, J., Werthmuller, D. and Aranay, O. (2021) 'Towards data-driven decision-making in government: Identifying opportunities and challenges for data use and analytics', *Proceedings of the Annual Hawaii International Conference on System Sciences*, 2020-Janua(February), pp. 2183–2192. Available at: https://doi.org/10.24251/hicss.2021.268.

Choroszewicz, M. and Alastalo, M. (2021) ‘Organisational and Professional Hierarchies in a Data Management System: Public–private Collaborative Building of Public Healthcare and Social Services in Finland’, *Information Communication & Society* [Preprint]. Available at: https://doi.org/10.1080/1369118x.2021.1942952.

Chourabi, H., Nam, T., Walker, S., Gil-Garcia, J.R., Mellouli, S., Nahon, K., Pardo, T.A. and Scholl, H.J. (2012) ‘Understanding smart cities: An integrative framework’, *Proceedings of the Annual Hawaii International Conference on System Sciences*, pp. 2289–2297. Available at: https://doi.org/10.1109/HICSS.2012.615.

Chung, H.-Y., Lee, G.-G. and Kuo, R.-Z. (2016) ‘Determinants of Public Servants’ Intention to Adopt E-Government Learning’, *Review of Public Personnel Administration*, 36(4), pp. 396–411. Available at: https://doi.org/10.1177/0734371X15590482.

Churchill Jr, G.A. (1979) ‘A paradigm for developing better measures of marketing constructs’, *Journal of marketing research*, 16(1), pp. 64–73.

Cialdini, R.B. and Goldstein, N.J. (2004) ‘Social Influence: Compliance and Conformity’, *Annual Review of Psychology* [Preprint]. Available at: https://doi.org/10.1146/annurev.psych.55.090902.142015.

Clare, P., Slade, T., Courtney, R.J., Martire, K. and Mattick, R.P. (2014) ‘The Difference Between Rigor and Specificity in Examining Methodologies for Analyzing Survey Data: Response to Commentary’, *Nicotine & Tobacco Research*, 16(12), pp. 1539–1540. Available at: https://doi.org/10.1093/ntr/ntu189.

Clark, P., Clark, P., Tashakkori, A., Creswell, J.W., Clark, P. and Clark, P. (2007) ‘Exploring the Nature of Research Questions in Mixed Methods Research’, *Journal of Mixed Methods Research*, 1(3), pp. 207–211. Available at: https://doi.org/10.1177/1558689807302814.

Clarke, D.D., Ward, P., Truman, W. and Bartle, C. (2010) ‘A poor way to die: social deprivation and road traffic fatalities’, *Behavioural Research in Road*

Safety 2008 Eighteenth Seminar, (1997), pp. 81–93. Available at: http://www.dft.gov.uk/pgr/roadsafety/research/rsrr/theme5/poorwaytodie.pdf.

Claussen, J., Kretschmer, T. and Mayrhofer, P. (2013) 'The effects of rewarding user engagement: The case of Facebook apps', *Information Systems Research*, 24(1), pp. 186–200. Available at: https://doi.org/10.1287/isre.1120.0467.

Clavadetscher, C. (1998) 'User involvement: key to success', *IEEE software*, 15(2), p. 30.

Clayton, J. and Sibbald, S. (2020) 'Privacy and Ethics Are Fundamental to Tech Development', *The International Review of Information Ethics*, 28. Available at: https://doi.org/10.29173/irie379.

Cohen, J. (1988) 'Statistical power analysis for the behavioral sciences (revised ed.)'. New York: Academic Press.

Cohen, J. (1992) 'A power primer.', *Psychological bulletin*, 112(1), pp. 155–159. Available at: https://doi.org/10.1037//0033-2909.112.1.155.

Cohen, J.B.T.-S.P.A. for the B.S. (ed.) (1977) 'Front Matter', in. Academic Press, p. iii. Available at: https://doi.org/https://doi.org/10.1016/B978-0-12-179060-8.50001-3.

Colquitt, J.A., Sabey, T.B., Rodell, J.B. and Hill, E.T. (2019) 'Content Validation Guidelines: Evaluation Criteria for Definitional Correspondence and Definitional Distinctiveness.', *Journal of Applied Psychology* [Preprint]. Available at: https://doi.org/10.1037/apl0000406.

Compeau, D., Higgins, C.A. and Huff, S. (1999) 'Social Cognitive Theory and Individual Reactions to Computing Technology: A Longitudinal Study', *MIS Quarterly*, 23(2), p. 145. Available at: https://doi.org/10.2307/249749.

Compeau, D.R. and Higgins, C.A. (1995) 'Computer Self-Efficacy: Development of a Measure and Initial Test', *MIS Quarterly*, 19(2), p. 189. Available at:

https://doi.org/10.2307/249688.

Conroy, M.M. and Evans-Cowley, J. (2005) ‘Informing and interacting: The use of E-government for citizen participation in planning’, *Journal of E-Government*, 1(3), pp. 73–92. Available at: https://doi.org/10.1300/J399v01n03_05.

Consia Consultants (2021) ‘Consia Consultants _ Devex’.

Contreras-Figueroa, V., Montane-Jimenez, L.G., Cepero, T., Benitez-Guerrero, E., Mezura-Godoy, C., Montané-Jiménez, L.G., Cepero, T., Benítez-Guerrero, E. and Mezura-Godoy, C. (2021) ‘Information Visualization in Adaptable Dashboards for Smart Cities: A Systematic Review’, *Proceedings - 2021 9th International Conference in Software Engineering Research and Innovation, CONISOFT 2021*, pp. 34–43. Available at: https://doi.org/10.1109/CONISOFT52520.2021.00017.

Cook, C., Heath, F. and Thompson, R.L. (2000) ‘A meta-analysis of response rates in web-or internet-based surveys’, *Educational and psychological measurement*, 60(6), pp. 821–836.

Cook, R., Jones-Chick, R., Roulin, N. and O’Rourke, K. (2020) ‘Job Seekers’ Attitudes Toward Cybervetting: Scale Development, Validation, and Platform Comparison’, *International Journal of Selection and Assessment* [Preprint]. Available at: https://doi.org/10.1111/ijsa.12300.

Cook, T.D. and Campbell, D.T. (1979) ‘Quasi-experimentation: design and analysis issues for field settings’.

Cooperstein, S.E. and Kocevar-Weidinger, E. (2004) ‘Beyond active learning: a constructivist approach to learning’, *Reference Services Review*, 32(2), pp. 141–148. Available at: https://doi.org/10.1108/00907320410537658.

Cordella, A. and Bonina, C. (2012) ‘A Public Value Perspective for ICT Enabled Public Sector Reforms: A Theoretical Reflection’, *Government Information Quarterly* [Preprint]. Available at: https://doi.org/10.1016/j.giq.2012.03.004.

Costello, A.B. and Osborne, J. (2019) ‘Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis', *Practical assessment, research, and evaluation*, 10(1), p. 7.

Costello, P., Jackson, M.L. and Moreton, R. (2013) 'Education as a Determining Factor in ICT Adoption: A Case Study of ICT SMEs', *International Journal of Management Practice* [Preprint]. Available at: https://doi.org/10.1504/ijmp.2013.055827.

Craddock, A., Roberts, B., Godwin, J., Tudor, D. and Richards, K. (2012) 'The DSDM Agile Project Framework for Scrum', *Dynamic Systems Development Method (DSDM) Consortium*, p. 22. Available at: https://cdn.ymaws.com/www.agilebusiness.org/resource/resmgr/documents/whitepaper/the_dsdm_agile_project_frame.pdf.

Craig, S.G., Hoang, E.C. and Kohlhase, J.E. (2023) 'Adoption of Technological Change in the Public Sector: Evidence From US States', *International Regional Science Review*, 46(3), pp. 299–327. Available at: https://doi.org/10.1177/01600176221125692.

Cranefield, J. and Pries-Heje, J. (2020) 'Moving beyond showcasing: The five faces of leadership in smart city transformation'.

Crawford, J.L., Yee, D., Hallenbeck, H.W., Naumann, A.A., Shapiro, K., Thompson, R.J. and Braver, T.S. (2020) 'Dissociable Effects of Monetary, Liquid, and Social Incentives on Motivation and Cognitive Control', *Frontiers in Psychology* [Preprint]. Available at: https://doi.org/10.3389/fpsyg.2020.02212.

Creswell, J.W. (2009) 'Mapping the field of mixed methods research', *Journal of mixed methods research*. SAGE publications Sage CA: Los Angeles, CA, pp. 95-108.

Creswell, J.W. and Tashakkori, A. (2007) 'Differing perspectives on mixed research methods', *Journal of Mixed Research Methods*, 1(4), pp. 303–308.

Cribb, R. and Ford, M. (2009) '1 Indonesia as an Archipelago: Managing Islands, Managing the Seas'. Available at: https://doi.org/10.1355/9789812309815-005.

Cruz, C.O. and Sarmento, J.M. (2017) ‘Reforming Traditional PPP Models to Cope With the Challenges of Smart Cities’, *Competition and Regulation in Network Industries* [Preprint]. Available at: https://doi.org/10.1177/1783591717734794.

Cui, H., Dong, J., Zhu, M., Li, X. and Wang, Q. (2022) ‘Identifying accident black spots based on the accident spacing distribution’, *Journal of Traffic and Transportation Engineering (English Edition)*, 9(6), pp. 1017–1026. Available at: https://doi.org/10.1016/j.jtte.2021.02.006.

Cui, P., Yang, X., Abdel-Aty, M., Zhang, J. and Yan, X. (2024) ‘Advancing urban traffic accident forecasting through sparse spatio-temporal dynamic learning’, *Accident Analysis & Prevention*, 200, p. 107564. Available at: https://doi.org/10.1016/j.aap.2024.107564.

Curtin, K.M., Hayslett-McCall, K. and Qiu, F. (2010) ‘Determining Optimal Police Patrol Areas with Maximal Covering and Backup Covering Location Models’, *Networks and Spatial Economics*, 10(1), pp. 125–145. Available at: https://doi.org/10.1007/s11067-007-9035-6.

D’Ignazio, C., Graeff, E., Harrington, C.N. and Rosner, D.K. (2020) ‘Toward Equitable Participatory Design’, in *Companion Publication of the 2020 Conference on Computer Supported Cooperative Work and Social Computing*. New York, NY, USA: ACM, pp. 437–445. Available at: https://doi.org/10.1145/3406865.3418588.

Dachler, H.P. and Wilpert, B. (1978) ‘Conceptual Dimensions and Boundaries of Participation in Organizations: A Critical Evaluation’, *Administrative Science Quarterly*, 23(1), p. 1. Available at: https://doi.org/10.2307/2392432.

Dai, J., Guo, S., Tian, Y. and Yang, T. (2024) ‘Enhancing the Governance Capabilities through Smart Technology: Scenario Application of Image Recognition and Its Effects in Chinese Local Governance’, *IEEE Access*, pp. 1–1. Available at: https://doi.org/10.1109/ACCESS.2020.3021912.

Damanpour, F. and Schneider, M. (2006) ‘Phases of the Adoption of Innovation in Organizations: Effects of Environment, Organization and Top Managers 1’, *British*

Journal of Management, 17(3), pp. 215–236. Available at: https://doi.org/10.1111/j.1467-8551.2006.00498.x.

Damanpour, F. and Schneider, M. (2009) 'Characteristics of Innovation and Innovation Adoption in Public Organizations: Assessing the Role of Managers', *Journal of Public Administration Research and Theory*, 19(3), pp. 495–522. Available at: https://doi.org/10.1093/jopart/mun021.

Dameri, R.P. (2013) 'Searching for Smart City definition: a comprehensive proposal', *INTERNATIONAL JOURNAL OF COMPUTERS & TECHNOLOGY*, 11(5), pp. 2544–2551. Available at: https://doi.org/10.24297/ijct.v11i5.1142.

Damoah, I.S. and Kumi, D.K. (2018) 'Causes of government construction projects failure in an emerging economy', *International Journal of Managing Projects in Business*, 11(3), pp. 558–582. Available at: https://doi.org/10.1108/IJMPB-04-2017-0042.

Daniel, C.J.Y., Wahid, N.A. and Tan, C.L. (2020) 'Why smart leaders are important in smart city development – a conceptual framework', *International Journal of Industrial Management*, 5, pp. 1–9. Available at: https://doi.org/10.15282/ijim.5.0.2020.5617.

Dargay, J., Gately, D. and Sommer, M. (2007) 'Vehicle ownership and income growth, worldwide: 1960-2030', *Energy Journal*, 28(4), pp. 143–170. Available at: https://doi.org/10.5547/ISSN0195-6574-EJ-Vol28-No4-7.

Darioshi, R. and Lahav, E. (2021) 'The impact of technology on the human decision-making process', *Human Behavior and Emerging Technologies* [Preprint]. Available at: https://doi.org/10.1002/hbe2.257.

Dasgupta, N. and Kapadia, F. (2022) 'The Future of the Public Health Data Dashboard', *American Journal of Public Health*, 112(6), pp. 886–888. Available at: https://doi.org/10.2105/AJPH.2022.306871.

David, B., Chalon, R. and Delomier, F. (2013) 'Supportive User Interfaces for MOCOCO (Mobile, Contextualized and Collaborative) Applications', in, pp. 29–38.

Available at: https://doi.org/10.1007/978-3-642-39342-6_4.

Davis, F. (1986) ‘Technology Acceptance Model for empirically testing end-user information systems: theory and results’, *PhDThesis - Massachussetts Institute of technology* [Preprint].

Davis, F.D. (1989) ‘Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology’, *MIS Quarterly*, 13(3), p. 319. Available at: https://doi.org/10.2307/249008.

Davis, F.D. and Venkatesh, V. (1996) ‘A critical assessment of potential measurement biases in the technology acceptance model: three experiments’, *International Journal of Human-Computer Studies*, 45(1), pp. 19–45. Available at: https://doi.org/10.1006/ijhc.1996.0040.

Davis, K., Minckas, N., Bond, V., Clark, C.J., Colbourn, T., Drabble, S.J., Hesketh, T., Hill, Z., Morrison, J., Mweemba, O., Osrin, D., Prost, A., Seeley, J., Shahmanesh, M., Spindler, E.J., Stern, E., Turner, K.M. and Mannell, J. (2019) ‘Beyond interviews and focus groups: a framework for integrating innovative qualitative methods into randomised controlled trials of complex public health interventions’, *Trials*, 20(1), pp. 329–329. Available at: https://doi.org/10.1186/S13063-019-3439-8.

Dawes, S.S., Cresswell, A.M. and Pardo, T.A. (2009) ‘From “Need to Know” to “Need to Share”: Tangled Problems, Information Boundaries, and the Building of Public Sector Knowledge Networks’, *Public Administration Review*, 69(3), pp. 392–402. Available at: https://doi.org/10.1111/j.1540-6210.2009.01987_2.x.

Deakin, H. and Wakefield, K. (2014) ‘Skype interviewing: reflections of two PhD researchers’, *Qualitative Research*, 14(5), pp. 603–616. Available at: https://doi.org/10.1177/1468794113488126.

Deangelo, B.G. and Hansen, B. (2014) ‘Life and Death in the Fast Lane: Police Enforcement and Traffic Fatalities’, *American Economic Journal : Economic Policy*, 6(2), pp. 231–257.

Dearing, J.W. and Cox, J.G. (2018) ‘Diffusion of innovations theory, principles, and practice’, *Health Affairs*, 37(2), pp. 183–190. Available at: https://doi.org/10.1377/hlthaff.2017.1104.

Debnath, S. and Subramanian, S. (2022) ‘AnnoteREI! A Tool for Transcribing and Annotating Requirements Elicitation Interviews’, in *2022 IEEE 30th International Requirements Engineering Conference (RE)*. IEEE, pp. 255–256. Available at: https://doi.org/10.1109/RE54965.2022.00031.

Dedehayir, O., Mäkinen, S.J. and Ortt, J.R. (2018) ‘Roles during innovation ecosystem genesis: A literature review’, *Technological Forecasting and Social Change*, 136, pp. 18–29.

Dekker, R., Koot, P., Birbil, S.I. and van Embden Andres, M. (2022) ‘Co-designing algorithms for governance: Ensuring responsible and accountable algorithmic management of refugee camp supplies’, *Big Data & Society*, 9(1). Available at: https://doi.org/10.1177/20539517221087855.

Deligiannis, A.P. and Anagnostopoulos, D. (2017) ‘Towards Open Justice: ICT Acceptance in the Greek Justice System the Case of the Integrated Court Management System for Penal and Civil Procedures (OSDDY/PP)’, in *2017 Conference for E-Democracy and Open Government (CeDEM)*. IEEE, pp. 82–91.

Dell’Acqua, G., De Luca, M. and Mauro, R. (2011) ‘Road Safety Knowledge-Based Decision Support System’, *Procedia - Social and Behavioral Sciences*, 20, pp. 973–983. Available at: https://doi.org/10.1016/j.sbspro.2011.08.106.

Delmastro, F., Arnaboldi, V. and Conti, M. (2016) ‘People-centric computing and communications in smart cities’, *IEEE Communications Magazine*, 54(7), pp. 122–128. Available at: https://doi.org/10.1109/MCOM.2016.7509389.

DeLone, W.H. and McLean, E.R. (2003) ‘The DeLone and McLean model of information systems success: A ten-year update’, *Journal of Management Information Systems*, 19(4), pp. 9–30. Available at: https://doi.org/10.1080/07421222.2003.11045748.

DeNardis, L. (2010) ‘E-Governance Policies for Interoperability and Open Standards’, *Policy & Internet*, 2(3), pp. 129–164. Available at: https://doi.org/10.2202/1944-2866.1060.

Deng, L., Turner, D.E., Gehling, R. and Prince, B. (2010) ‘User experience, satisfaction, and continual usage intention of IT’, *European Journal of Information Systems*, 19(1), pp. 60–75. Available at: https://doi.org/10.1057/ejis.2009.50.

Denscombe, M. (2010) ‘The good research guide for small social research projects’. Glasgow, McGraw-Hill House.

Denzin, N.K. (2010) ‘Moments, mixed methods, and paradigm dialogs’, *Qualitative Inquiry*, 16(6), pp. 419–427. Available at: https://doi.org/10.1177/1077800410364608.

Department for Transport UK (2021) ‘Road Safety Data’, *Data.Gov.Uk* [Preprint]. Available at: http://data.gov.uk/dataset/road-accidents-safety-data/.

Desjardins, F. and Lavallière, M. (2023) ‘Evaluation of a Road Safety Awareness Campaign Deployed along the Roadside in Saguenay (Québec, Canada)’, *International Journal of Environmental Research and Public Health*, 20(11), p. 6012. Available at: https://doi.org/10.3390/ijerph20116012.

Dewinter, M., Vandeviver, C., Vander Beken, T., Witlox, F., Beken, T. Vander and Witlox, F. (2020) ‘Analysing the Police Patrol Routing Problem: A Review’, *Isprs International Journal of Geo-Information*, 9(3). Available at: https://doi.org/10.3390/ijgi9030157.

Dhagarra, D., Goswami, M. and Kumar, G. (2020) ‘Impact of Trust and Privacy Concerns on Technology Acceptance in Healthcare: An Indian Perspective’, *International Journal of Medical Informatics*, 141(February), p. 104164. Available at: https://doi.org/10.1016/j.ijmedinf.2020.104164.

Dhanoa, V., Walchshofer, C., Hinterreiter, A., Stitz, H., Groeller, E. and Streit, M. (2022) ‘A Process Model for Dashboard Onboarding’, *Computer Graphics*

Forum, 41(3), pp. 501–513. Available at: https://doi.org/10.1111/cgf.14558.

Diáz-Oreiro, I., López, G., Quesada, L. and Guerrero, L.A. (2021) ‘UX Evaluation with Standardized Questionnaires in Ubiquitous Computing and Ambient Intelligence: A Systematic Literature Review’, *Advances in Human-Computer Interaction*, 2021. Available at: https://doi.org/10.1155/2021/5518722.

Díaz-oreiro, I., López, G., Quesada, L. and Guerrero, L.A. (2019) ‘Standardized Questionnaires for User Experience Evaluation : A Systematic Literature Review †’, (October 2018), pp. 1–12. Available at: https://doi.org/10.3390/proceedings2019031014.

Díez, E. and McIntosh, B.S. (2009) ‘A review of the factors which influence the use and usefulness of information systems’, *Environmental Modelling & Software*, 24(5), pp. 588–602.

Van Dijk, J.A.G.M. (2006) ‘Digital divide research, achievements and shortcomings’, *Poetics*, 34(4–5), pp. 221–235.

Van Dijk, J.A.G.M. (2017) ‘Digital Divide: Impact of Access’, in *The International Encyclopedia of Media Effects*. Wiley, pp. 1–11. Available at: https://doi.org/10.1002/9781118783764.wbieme0043.

Dillman, D.A. (2007) ‘Mail and internet surveys: The tailored design method, 2nd ed.’, *Mail and internet surveys: The tailored design method, 2nd ed.* Hoboken, NJ, US: John Wiley & Sons Inc, pp. xviii, 523–xviii, 523.

Dinev, T., Hart, P. and Mullen, M.R. (2008) ‘Internet privacy concerns and beliefs about government surveillance - An empirical investigation’, *Journal of Strategic Information Systems*, 17(3), pp. 214–233. Available at: https://doi.org/10.1016/j.jsis.2007.09.002.

Dingelstad, J., Borst, R.T. and Meijer, A. (2022) ‘Hybrid Data Competencies for Municipal Civil Servants: An Empirical Analysis of the Required Competencies for Data-Driven Decision-Making’, *Public Personnel Management*, 51(4), pp. 458–490. Available at: https://doi.org/10.1177/00910260221111744.

DiStefano, C. and Hess, B.T. (2005) ‘Using Confirmatory Factor Analysis for Construct Validation: An Empirical Review’, *Journal of Psychoeducational Assessment* [Preprint]. Available at: https://doi.org/10.1177/073428290502300303.

DiStefano, C., Liu, J., Jiang, N. and Shi, D. (2018) ‘Examination of the Weighted Root Mean Square Residual: Evidence for Trustworthiness?’, *Structural Equation Modeling*, 25(3), pp. 453–466. Available at: https://doi.org/10.1080/10705511.2017.1390394.

Dmitrieva, E., Pathani, A., Pushkarna, G., Acharya, P., Rana, M. and Surekha, P. (2024) ‘Real-Time Traffic Management in Smart Cities: Insights from the Traffic Management Simulation and Impact Analysis’, *BIO Web of Conferences*. Edited by P.K. Prabhakar, 86, p. 01098. Available at: https://doi.org/10.1051/bioconf/20248601098.

Doğan, İ. (2022) ‘A simulation study comparing model fit measures of structural equation modeling with multivariate contaminated normal distribution’, *Communications in Statistics - Simulation and Computation*, 51(5), pp. 2526–2536. Available at: https://doi.org/10.1080/03610918.2019.1698745.

Dong, C.-D., Shao, C., Li, J. and Xiong, Z. (2018) ‘An Improved Deep Learning Model for Traffic Crash Prediction’, *Journal of Advanced Transportation* [Preprint]. Available at: https://doi.org/10.1155/2018/3869106.

Dong, J., Zhang, H., Cui, M., Lin, Y., Wu, H.Y. and Bi, C. (2023) ‘TCEVis: Visual analytics of traffic congestion influencing factors based on explainable machine learning’, *Visual Informatics*, 8(1), pp. 56–66. Available at: https://doi.org/10.1016/J.VISINF.2023.11.003.

Donne, J.D. and Fortin, F. (2020) ‘Innovation and Policing: Factors Influencing the Adoption of Social Medias by Members of Quebec Police Organizations’, *Policing: A Journal of Policy and Practice*, 14(3), pp. 726–739. Available at: https://doi.org/10.1093/police/pay079.

Dow, S., Fortuna, J., Schwartz, Dan, Altringer, B., Schwartz, Daniel and

Klemmer, S. (2011) 'Prototyping dynamics: sharing multiple designs improves exploration, group rapport, and results', in *Proceedings of the SIGCHI conference on human factors in computing systems*, pp. 2807–2816.

Drennan, J. (2003) 'Cognitive Interviewing: Verbal Data in the Design and Pretesting of Questionnaires', *Journal of Advanced Nursing* [Preprint]. Available at: https://doi.org/10.1046/j.1365-2648.2003.02579.x.

van Duivenboden, H. and Thaens, M. (2008) 'ICT-driven innovation and the culture of public administration: A contradiction in terms?', *Information Polity*, 13(3,4), pp. 213–232. Available at: https://doi.org/10.3233/IP-2008-0157.

Dukić, D., Dukić, G. and Bertović, N. (2017) 'Public administration employees' readiness and acceptance of e-government', *Information Development*, 33(5), pp. 525–539. Available at: https://doi.org/10.1177/0266666916671773.

Dwivedi, M., Upadhyay, M.S. and Tripathi, A. (2012) 'A working framework for the user-centered design approach and a survey of the available methods', *International Journal of Scientific and Research Publications*, 2(4), pp. 12–19.

Dwivedi, Y.K., Rana, N.P., Jeyaraj, A., Clement, M. and Williams, M.D. (2019) 'Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a Revised Theoretical Model', *Information Systems Frontiers*, 21(3), pp. 719–734. Available at: https://doi.org/10.1007/s10796-017-9774-y.

Eccles, K., Fiedler, R., Persaud, B., Lyon, C. and Hansen, G. (2012) *NCHRP Report 729: Automated Enforcement for Speeding and Red Light Running*, *Transportation Research Board* …. Available at: http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:REPORT+729+Automated+Enforcement+for+Speeding+and+Red+Light+Running#0.

Eckert, S. and Kohler, S. (2014) 'Urbanization and health in developing countries: a systematic review', *World Health Popul*, 15(1), pp. 7–20.

Economou-Zavlanos, N.J. *et al.* (2024) 'Translating ethical and quality principles for the effective, safe and fair development, deployment and use of artificial intelligence technologies in healthcare', *Journal of the American Medical Informatics Association*, 31(3), pp. 705–713. Available at: https://doi.org/10.1093/jamia/ocad221.

Efe, A. and Özdamarlar, Ş. (2021) 'Security Controls Against Mobile Application Threats', *International Journal of Engineering and Innovative Research* [Preprint]. Available at: https://doi.org/10.47933/ijeir.838873.

El-Haddadeh, R., Weerakkody, V., Osmani, M., Thakker, D. and Kapoor, K.K. (2019) 'Examining Citizens' Perceived Value of Internet of Things Technologies in Facilitating Public Sector Services Engagement', *Government Information Quarterly* [Preprint]. Available at: https://doi.org/10.1016/j.giq.2018.09.009.

Elamrani Abou Elassad, Z., Mousannif, H. and Al Moatassime, H. (2020) 'A proactive decision support system for predicting traffic crash events: A critical analysis of imbalanced class distribution', *Knowledge-Based Systems*, 205, p. 106314. Available at: https://doi.org/10.1016/j.knosys.2020.106314.

Elise Carreker, L. and Bachman, W. (2000) 'Geographic Information System Procedures to Improve Speed and Accuracy in Locating Crashes', *Transportation Research Record: Journal of the Transportation Research Board*, 1719(1), pp. 215–218. Available at: https://doi.org/10.3141/1719-28.

Engellant, K.A.., Holland, D.D.. and Piper, R.T. (2016) 'Assessing convergent and discriminant validity of the motivation construct for the technology integration education model', *Journal of Higher Education Theory & Practice*, 16(1), pp. 37–50.

Engin, Z. and Treleaven, P. (2019) 'Algorithmic Government: Automating Public Services and Supporting Civil Servants in using Data Science Technologies', *The Computer Journal*, 62(3), pp. 448–460. Available at: https://doi.org/10.1093/comjnl/bxy082.

Espoir, D.K., Sunge, R. and Bannor, F. (2023) 'Exploring the dynamic effect of economic growth on carbon dioxide emissions in Africa: evidence from panel PMG estimator', *Environmental Science and Pollution Research*, 30(52), pp.

112959–112976. Available at: https://doi.org/10.1007/s11356-023-30108-4.

Estevez, E. and Janowski, T. (2013) ‘Electronic Governance for Sustainable Development - Conceptual framework and state of research’, *Government Information Quarterly*, 30(SUPPL. 1), pp. 94–109. Available at: https://doi.org/10.1016/j.giq.2012.11.001.

Fabrigar, L.R. and Wegener, D.T. (2011) *Exploratory factor analysis*. Oxford University Press.

Fabrigar, L.R., Wegener, D.T., MacCallum, R.C. and Strahan, E.J. (1999) ‘Evaluating the Use of Exploratory Factor Analysis in Psychological Research.’, *Psychological Methods* [Preprint]. Available at: https://doi.org/10.1037/1082-989x.4.3.272.

Falk, C.F. and Muthukrishna, M. (2023) ‘Parsimony in model selection: Tools for assessing fit propensity.’, *Psychological Methods*, 28(1), pp. 123–136. Available at: https://doi.org/10.1037/met0000422.

Fan, J. and Yang, W. (2015) ‘Study on E-Government Services Quality: The Integration of Online and Offline Services’, *Journal of Industrial Engineering and Management* [Preprint]. Available at: https://doi.org/10.3926/jiem.1405.

Fang, Y. and Shan, Z. (2024) ‘Optimising smart city evaluation: A people-oriented analysis method’, *IET Smart Cities*, 6(1), pp. 41–53. Available at: https://doi.org/10.1049/smc2.12073.

Farmanbar, M. and Rong, C. (2020) ‘Triangulum City Dashboard: An Interactive Data Analytic Platform for Visualizing Smart City Performance’, *Processes*, 8(2), p. 250. Available at: https://doi.org/10.3390/pr8020250.

Farmer, C., Miller, P. and Kennedy, S. (2024) ‘“A little bit of a toothless tiger … ” Police banning powers in Western Australia: key informant perspectives and implications for the administration of justice’, *Police Practice and Research*, 25(5), pp. 594–611. Available at: https://doi.org/10.1080/15614263.2024.2329283.

Farmer, C.M. (2017) ‘Automated Traffic Enforcement: Responding to the Critics’, *Journal of Traffic and Transportation Engineering*, 5(1), pp. 1–7. Available at: https://doi.org/10.17265/2328-2142/2017.01.001.

Feilzer, M.Y., Yvonne Feilzer, M., Feilzer, M.Y. and Yvonne Feilzer, M. (2010) ‘Doing mixed methods research pragmatically: Implications for the rediscovery of pragmatism as a research paradigm’, *Journal of Mixed Methods Research*, 4(1), pp. 6–16. Available at: https://doi.org/10.1177/1558689809349691.

Feizizadeh, B., Omarzadeh, D., Sharifi, A., Rahmani, A., Lakes, T. and Blaschke, T. (2022) ‘A GIS-Based Spatiotemporal Modelling of Urban Traffic Accidents in Tabriz City during the COVID-19 Pandemic’, *Sustainability*, 14(12), p. 7468. Available at: https://doi.org/10.3390/su14127468.

Feng, M., Wang, X. and Quddus, M. (2020) ‘Developing multivariate time series models to examine the interrelations between police enforcement, traffic violations, and traffic crashes’, *Analytic Methods in Accident Research*, 28. Available at: https://doi.org/10.1016/j.amar.2020.100139.

Few, A.L., Stephens, D.P. and Rouse-Arnett, M. (2004) ‘Sister-to-Sister Talk: Transcending Boundaries and Challenges in Qualitative Research With Black Women’, *innovative strategies & techniques*, 52(3), pp. 147–155. Available at: https://doi.org/10.1017/cbo9780511543937.014.

Few, S. (2013) *Information dashboard design: Displaying data for at-a-glance monitoring*. Analytics Press Burlingame.

Field, A. (2013) *Discovering statistics using IBM SPSS statistics*. sage.

Finch, H. (2006) ‘Comparison of the Performance of Varimax and Promax Rotations: Factor Structure Recovery for Dichotomous Items’, *Journal of Educational Measurement*, 43(1), pp. 39–52. Available at: https://doi.org/10.1111/j.1745-3984.2006.00003.x.

Fishbein, M. (1979) ‘A theory of reasoned action: Some applications and implications.’, *Nebraska Symposium on Motivation*, 27, pp. 65–116.

Fishbein, M. and Ajzen, I. (1975) ‘Belief, attitude, intention, and behavior: An introduction to theory and research’.

Fisher, R.A. (1936) ‘Statistical methods for research workers.’, *Statistical methods for research workers*. [Preprint], (6th Ed).

Flora, D.B. (2020) ‘Your Coefficient Alpha Is Probably Wrong, but Which Coefficient Omega Is Right? A Tutorial on Using R to Obtain Better Reliability Estimates’, *Advances in Methods and Practices in Psychological Science*, 3(4), pp. 484–501. Available at: https://doi.org/10.1177/2515245920951747.

Fornell, C. and Larcker, D.F. (1981) ‘Evaluating Structural Equation Models with Unobservable Variables and Measurement Error’, *Journal of Marketing Research*, 18(1), p. 39. Available at: https://doi.org/10.2307/3151312.

Forster, Y., Forster, Y., Hergeth, S., Hergeth, S., Naujoks, F., Naujoks, F., Krems, J.F. and Krems, J.F. (2018) ‘How Usability Can Save the Day - Methodological Considerations for Making Automated Driving a Success Story’, in *Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*. New York, NY, USA: ACM, pp. 278–290. Available at: https://doi.org/10.1145/3239060.3239076.

Foth, M. (2018) ‘Participatory Urban Informatics: Towards Citizen-ability’, *Smart and Sustainable Built Environment* [Preprint]. Available at: https://doi.org/10.1108/sasbe-10-2017-0051.

Foth, M., Choi, J.H. and Satchell, C. (2011) ‘Urban informatics’, in *Proceedings of the ACM 2011 conference on Computer supported cooperative work*, pp. 1–8.

Franch, X., Mendez, D., Vogelsang, A., Heldal, R., Knauss, E., Oriol, M., Travassos, G.H., Carver, J.C. and Zimmermann, T. (2022) ‘How do Practitioners Perceive the Relevance of Requirements Engineering Research?’, *IEEE Transactions on Software Engineering*, 48(6), pp. 1947–1964. Available at: https://doi.org/10.1109/TSE.2020.3042747.

Fuad, A. and Hsu, C.-Y. (2018) ‘UTAUT for HSS: initial framework to study health

IT adoption in the developing countries', *F1000Research*, 7, p. 101. Available at: https://doi.org/10.12688/f1000research.13798.1.

Fyfe, N.R. (2019) 'Evidence-based policing: translating research into practice', *Policing and Society*, 29(9), pp. 1126–1127. Available at: https://doi.org/10.1080/10439463.2019.1678621.

Gallagher, M.W. and Brown, T.M. (2013) 'Introduction to Confirmatory Factor Analysis and Structural Equation Modeling'. Available at: https://doi.org/10.1007/978-94-6209-404-8_14.

Ganapati, S. (2009) 'Use of Dashboards in Government', pp. 92–96. Available at: www.businessofgovernment.org.

Ganapati, S. (2011) 'Key features for designing a dashboard', *Government Finance Review*, pp. 883–7856.

Ganguly, A., Talukdar, A. and Chatterjee, D. (2019) 'Evaluating the role of social capital, tacit knowledge sharing, knowledge quality and reciprocity in determining innovation capability of an organization', *Journal of Knowledge Management*, 23(6), pp. 1105–1135. Available at: https://doi.org/10.1108/JKM-03-2018-0190.

García-Arteaga, J.D. and Lotero, L. (2023) 'A Network-Based Analysis to Assess COVID-19 Disruptions in the Bogotá BRT System', *Environment and Planning B Urban Analytics and City Science* [Preprint]. Available at: https://doi.org/10.1177/23998083221150646.

Garcia Alonso, R. and Lippez-De Castro, S. (2016) 'Technology Helps, People Make: A Smart City Governance Framework Grounded in Deliberative Democracy BT - Smarter as the New Urban Agenda: A Comprehensive View of the 21st Century City', in J.R. Gil-Garcia, T.A. Pardo, and T. Nam (eds). Cham: Springer International Publishing, pp. 333–347. Available at: https://doi.org/10.1007/978-3-319-17620-8_18.

Garrick, J. and Chan, A. (2017) 'Knowledge management and professional experience: the uneasy dynamics between tacit knowledge and performativity in organizations', *Journal of Knowledge Management*, 21(4), pp. 872–884. Available at: https://doi.org/10.1108/JKM-02-2017-0058.

Gates, C. and Matthews, P. (2014) 'DATA is the new currency', pp. 105–116.

Van Der Geest, T. and Velleman, E. (2014) 'Easy-to-read meets accessible web in the e-government context', *Procedia Computer Science*, 27(Dsai 2013), pp. 327–333. Available at: https://doi.org/10.1016/j.procs.2014.02.036.

Geroliminis, N., Karlaftis, M.G. and Skabardonis, A. (2009) 'A spatial queuing model for the emergency vehicle districting and location problem', *Transportation Research Part B: Methodological*, 43(7), pp. 798–811. Available at: https://doi.org/10.1016/j.trb.2009.01.006.

Gerstl-Pepin, C. and Patrizio, K. (2009) 'Learning from Dumbledore's Pensieve: Metaphor as an aid in teaching reflexivity in qualitative research', *Qualitative Research*, 9(3), pp. 299–308. Available at: https://doi.org/10.1177/1468794109105029.

Al Ghazzawi, W., Al Subayi, H. and Yaghi, K. (2018) 'Decision Support System as an Intermediate Variable to Enhance the Influence of Tacit knowledge on The Quality of Strategic Decisions', in. شبكة المؤتمرات العربية. Available at: https://doi.org/10.24897/acn.64.68.235.

Ghorbanian, A., Aiello, B. and Staples, J. (2022) 'Under-Representation of Transgender Identities in Research: The Limitations of Traditional Quantitative Survey Data', *Transgender Health*, 7(3), pp. 261–269. Available at: https://doi.org/10.1089/trgh.2020.0107.

Giffinger, R. and Gudrun, H. (2010) 'Smart cities ranking: an effective instrument for the positioning of the cities?', *ACE: Architecture, City and Environment* [Preprint], (June). Available at: https://doi.org/10.5821/ace.v4i12.2483.

Gigerenzer, G. and Gaissmaier, W. (2011) 'Heuristic Decision Making', *Annual*

Review of Psychology, 62(1), pp. 451–482. Available at: https://doi.org/10.1146/annurev-psych-120709-145346.

Gil-Garcia, J.R., Helbig, N. and Ojo, A. (2014) ‘Being smart: Emerging technologies and innovation in the public sector’, *Government Information Quarterly*, 31(S1), pp. I1–I8. Available at: https://doi.org/10.1016/j.giq.2014.09.001.

Gil-Garcia, J.R. and Pardo, T.A. (2006) ‘Multi-Method Approaches to Digital Government Research: Value Lessons and Implementation Challenges’, in *Proceedings of the 39th Annual Hawaii International Conference on System Sciences (HICSS’06)*. IEEE, pp. 67a-67a. Available at: https://doi.org/10.1109/HICSS.2006.356.

Gilbert, C. (2023) ‘Data driven decisions: a practical toolkit for library and information professionals Data driven decisions: a practical toolkit for library and information professionals , by Amy Stubbing, London, Facet Publishing, 2022, 196 pp., $125.25(soft cover), ISBN’, *Journal of the Australian Library and Information Association*, 72(2), pp. 209–209. Available at: https://doi.org/10.1080/24750158.2023.2205560.

Ginters, E. (2020) ‘Digital Technologies Acceptance/Adoption Modeling Respecting Age Factor’, in, pp. 621–630. Available at: https://doi.org/10.1007/978-3-030-45691-7_58.

Girardi, D., Ferrari, A., Novielli, N., Spoletini, P., Fucci, D. and Huichapa, T. (2020) ‘The Way it Makes you Feel Predicting Users’ Engagement during Interviews with Biofeedback and Supervised Learning’, in *2020 IEEE 28th International Requirements Engineering Conference (RE)*. IEEE, pp. 32–43. Available at: https://doi.org/10.1109/RE48521.2020.00016.

Di Giulio, M. and Vecchi, G. (2023) ‘Implementing digitalization in the public sector. Technologies, agency, and governance’, *Public Policy and Administration*, 38(2), pp. 133–158. Available at: https://doi.org/10.1177/09520767211023283.

Giunipero, L., Dawley, D. and Anthony, W.P. (1999) 'The Impact of Tacit Knowledge on Purchasing Decisions', *Journal of Supply Chain Management*, 35(4), pp. 42–49. Available at: https://doi.org/10.1111/j.1745-493X.1999.tb00055.x.

Given, L. (2008) 'Purposive Sample', pp. 645–647. Available at: https://doi.org/10.4135/9781412963909 NV - 0.

Glasersfeld, E. von (1989) 'Facts and the self from a constructivist point of view', *Poetics*, 18(4), pp. 435–448. Available at: https://doi.org/https://doi.org/10.1016/0304-422X(89)90041-7.

Gleeson, J., Kitchin, R. and McCarthy, E. (2022) 'Dashboards and Public Health: The Development, Impacts, and Lessons From the Irish Government COVID-19 Dashboards', *American Journal of Public Health*, 112(6), pp. 896–899. Available at: https://doi.org/10.2105/AJPH.2022.306848.

Gmach, D., Rolia, J., Cherkasova, L. and Kemper, A. (2009) 'Resource pool management: Reactive versus proactive or let's be friends', *Computer Networks*, 53(17), pp. 2905–2922. Available at: https://doi.org/10.1016/j.comnet.2009.08.011.

Goeke, R.J., Faley, R.H., Brandyberry, A.A. and Dow, K.E. (2016) 'How Experience and Expertise Affect the Use of a Complex Technology', *Information Resources Management Journal*, 29(2), pp. 59–80. Available at: https://doi.org/10.4018/IRMJ.2016040104.

Goette, L., Huffman, D. and Meier, S. (2006) 'The Impact of Group Membership on Cooperation and Norm Enforcement: Evidence Using Random Assignment to Real Social Groups', *American Economic Review*, 96(2), pp. 212–216. Available at: https://doi.org/10.1257/000282806777211658.

Goguen, J.A. and Linde, C. (1993) 'Techniques for requirements elicitation', in *[1993] Proceedings of the IEEE International Symposium on Requirements Engineering*. IEEE, pp. 152–164.

Goldenhar, L.M., Schwatka, N. V and Johnson, S.K. (2019) 'Leadership Skills for Strengthening Jobsite Safety Climate', *Journal of Safety Research* [Preprint]. Available at: https://doi.org/10.1016/j.jsr.2019.04.011.

Goldkuhl, G. and Röstlinger, A. (2014) 'Intentions for simplicity and consequences of complexity: A diagnostic case study of an e-government portal and its back-office processes', in *The 11th Scandinavian workshop on e-government*, pp. 1–17.

Gómez, L.F. and Heeks, R. (2016) 'Measuring the Barriers to Big Data for Development: Design-Reality Gap Analysis in Colombia's Public Sector', *SSRN Electronic Journal* [Preprint]. Available at: https://doi.org/10.2139/ssrn.3431745.

Goodhue, D.L. and Thompson, R.L. (1995) 'Task-Technology Fit and Individual', 19(2), pp. 213–236.

Gorsuch, R.L. (1997) 'Exploratory Factor Analysis: Its Role in Item Analysis', *Journal of Personality Assessment*, 68(3), pp. 532–560. Available at: https://doi.org/10.1207/s15327752jpa6803_5.

Gortmaker, S.L., Hosmer, D.W. and Lemeshow, S. (1994) 'Applied Logistic Regression.', *Contemporary Sociology a Journal of Reviews* [Preprint]. Available at: https://doi.org/10.2307/2074954.

Gracia, T.J.H. and García, A.C. (2018) 'Sustainable Smart Cities. Creating Spaces for Technological, Social and Business Development', in.

Gracias, J.S., Parnell, G.S., Specking, E., Pohl, E.A. and Buchanan, R. (2023) 'Smart Cities—A Structured Literature Review', *Smart Cities*, 6(4), pp. 1719–1743. Available at: https://doi.org/10.3390/smartcities6040080.

Graeber, J., Warmerdam, E., Aufenberg, S., Bull, C., Davies, K., Dixon, J., Emmert, K., Judd, C., Maetzler, C., Reilmann, R., Ng, W.-F., Macrae, V., Maetzler, W. and Kaduszkiewicz, H. (2023) 'Technology acceptance of digital devices for home use: Qualitative results of a mixed methods study', *DIGITAL*

HEALTH, 9. Available at: https://doi.org/10.1177/20552076231181239.

Graf-Vlachy, L., Buhtz, K. and König, A. (2018) ‘Social influence in technology adoption: taking stock and moving forward’, *Management Review Quarterly*, 68(1), pp. 37–76. Available at: https://doi.org/10.1007/s11301-017-0133-3.

Granic, A. (2017) ‘Technology in use: The importance of good interface design’, in *2017 International Conference on Infocom Technologies and Unmanned Systems (Trends and Future Directions) (ICTUS)*. IEEE, pp. 43–49. Available at: https://doi.org/10.1109/ICTUS.2017.8285972.

Grant, A.K., Felner, J.K., Castañeda, Y., Pratap, P. and Hebert-Beirne, J. (2024) ‘Leveraging Key Informant Interviews to Inform Intervention Development: The Greater Lawndale Healthy Work Project’, *Community Health Equity Research & Policy*, 44(4), pp. 429–438. Available at: https://doi.org/10.1177/2752535X231196395.

Green, L. and Kolesar, P. (1984) ‘A Comparison of the Multiple Dispatch and M / M / c Priority Queueing Models of Police Patrol’, *Management Science*, 30(6), pp. 665–670. Available at: https://doi.org/10.1287/mnsc.30.6.665.

Greener, S. (2022) ‘Digging for acceptance theory’, *Interactive Learning Environments*, 30(4), pp. 587–588. Available at: https://doi.org/10.1080/10494820.2022.2062170.

Gregoriades, A. and Chrystodoulides, A. (2018) ‘Extracting traffic safety knowledge from historical accident data’, in *Adjunct Proceedings of the 14th International Conference on Location Based Services*. ETH Zurich, pp. 109–114.

Grimm, P. (2010) ‘Social Desirability Bias’, in *Wiley International Encyclopedia of Marketing*. Wiley. Available at: https://doi.org/10.1002/9781444316568.wiem02057.

Grimshaw, J.M., Eccles, M.P., Lavis, J.N., Hill, S.J. and Squires, J.E. (2012) ‘Knowledge translation of research findings’, *Implementation Science*, 7(1), p. 50. Available at: https://doi.org/10.1186/1748-5908-7-50.

Gru, K. (2021) 'Dashboards – new tools of cartographic communication', 13, pp. 7–12.

Guillemin, M. and Gillam, L. (2004) 'Ethics, reflexivity, and "Ethically important moments" in research', *Qualitative Inquiry*, 10(2), pp. 261–280. Available at: https://doi.org/10.1177/1077800403262360.

Guo, F., Zhang, D., Dong, Y. and Guo, Z. (2019) 'Urban link travel speed dataset from a megacity road network', *Scientific Data*, 6(1), p. 61. Available at: https://doi.org/10.1038/s41597-019-0060-3.

Guo, X., Zhou, Z., Zhao, Y., Zhang, M., Zhikang, L., Wei, L. and Zhang, J. (2017) 'Research on Tacit Knowledge Acquisition Based on Gray Theory and RBF Neural Network', *Matec Web of Conferences* [Preprint]. Available at: https://doi.org/10.1051/matecconf/201710005016.

Gupta, H. (2021) 'What do we talk about when we talk about heat?', *City and Society*, 33(1), pp. 682–692. Available at: https://doi.org/10.1111/ciso.12381.

Gupta, B., Dasgupta, S. and Gupta, A. (2008) 'Adoption of ICT in a government organization in a developing country: An empirical study', *The Journal of Strategic Information Systems*, 17(2), pp. 140–154. Available at: https://doi.org/10.1016/j.jsis.2007.12.004.

Gupta, S., Abbas, A.F. and Srivastava, R. (2022) 'Technology Acceptance Model (TAM): A Bibliometric Analysis from Inception', *Journal of Telecommunications and the Digital Economy*, 10(3), pp. 77–106. Available at: https://doi.org/10.18080/jtde.v10n3.598.

Gurstein, M.B. (2011) 'Open data: Empowering the empowered or effective data use for everyone?', *First Monday* [Preprint]. Available at: https://doi.org/10.5210/fm.v16i2.3316.

Guthrie, S. (1996) 'The Role of Tacit Knowledge in Judgement and Decision Making.'

Hadjimatheou, K. and Nathan, C. (2022) ‘The Ethics of Predictive Policing’, in *Oxford Handbook of Digital Ethics*. Oxford University Press, pp. 433–448. Available at: https://doi.org/10.1093/oxfordhb/9780198857815.013.22.

Hair, J.F., Ringle, C.M. and Sarstedt, M. (2013) ‘Partial Least Squares Structural Equation Modeling: Rigorous Applications, Better Results and Higher Acceptance’, *Long Range Planning*, 46(1–2), pp. 1–12. Available at: https://doi.org/10.1016/j.lrp.2013.01.001.

Hamad, K., Al-Ruzouq, R., Zeiada, W., Abu Dabous, S. and Khalil, M.A. (2020) ‘Predicting incident duration using random forests’, *Transportmetrica A: Transport Science*, 16(3), pp. 1269–1293. Available at: https://doi.org/10.1080/23249935.2020.1733132.

Handley, H.A.H. (2013) ‘A Network Model for Human Interoperability’, *Human Factors the Journal of the Human Factors and Ergonomics Society* [Preprint]. Available at: https://doi.org/10.1177/0018720813493640.

Hanea, A.M., Christophersen, A. and Alday, S. (2022) ‘Bayesian networks for risk analysis and decision support’, *Risk Analysis*, 42(6), pp. 1149–1154. Available at: https://doi.org/10.1111/risa.13938.

Hanea, A.M., Hemming, V. and Nane, G.F. (2022) ‘Uncertainty Quantification with Experts: Present Status and Research Needs’, *Risk Analysis*, 42(2), pp. 254–263. Available at: https://doi.org/10.1111/risa.13718.

Hanif, S., Ahsan, A. and Wise, G. (2020) ‘Icebergs of Expertise-Based Leadership: The Role of Expert Leaders in Public Administration’, *Sustainability* [Preprint]. Available at: https://doi.org/10.3390/su12114544.

Hanna, N.K. (2010) ‘An ICT-Transformed Government and Society’, in, pp. 1–25. Available at: https://doi.org/10.1007/978-1-4419-1506-1_1.

Hao, R. and Ruan, T. (2024) ‘Advancing Traffic Simulation Precision and Scalability: A Data-Driven Approach Utilizing Deep Neural Networks’, *Sustainability*, 16(7), p. 2666. Available at:

https://doi.org/10.3390/su16072666.

Hardesty, D.M. and Bearden, W.O. (2004) ‘The use of expert judges in scale development. Implications for improving face validity of measures of unobservable constructs’, *Journal of Business Research*, 57(2), pp. 98–107. Available at: https://doi.org/10.1016/S0148-2963(01)00295-8.

Hardi, R. and Gohwong, S. (2020) ‘E-Government Based Urban Governance on the Smart City Program in Makassar, Indonesia’, *Journal of Contemporary Governance and Public Policy*, 1(1), pp. 12–17. Available at: https://doi.org/10.46507/jcgpp.v1i1.10.

Hartmann, M.R.K., Hestehave, N.K., Høgh, L. and Rønn, K.V. (2018) ‘Knowing from Within’, *Nordisk politiforskning*, 5(1), pp. 7–27. Available at: https://doi.org/10.18261/issn.1894-8693-2018-01-03.

Hashim, R. (2010) ‘Economic issues in information systems implementation in local government’, *International Review of Business Research Papers*, 6(1), pp. 562–573.

Hassenzahl, M., Burmester, M. and Koller, F. (2003) ‘Construction and Evaluation of a User Experience Questionnaire’, *Mensch & Computer Interaktion in Bewegung*, pp. 187–196. Available at: http://attrakdiff.de/files/mc2003_hassenzahl_review.pdf.

Hassenzahl, M., Diefenbach, S. and Göritz, A. (2010) ‘Interacting with Computers Needs , affect , and interactive products – Facets of user experience’, *Interacting with Computers*, 22(5), pp. 353–362. Available at: https://doi.org/10.1016/j.intcom.2010.04.002.

Hassenzahl, M. and Tractinsky, N. (2006) ‘User experience - a research agenda’, *Behaviour & Information Technology*, 25(2), pp. 91–97. Available at: https://doi.org/10.1080/01449290500330331.

Hayotte, M., Thérouanne, P., Gray, L., Corrion, K. and d’Arripe-Longueville, F. (2020) ‘The French eHealth acceptability scale using the unified theory of acceptance and use of technology 2 model: instrument validation study', *Journal of medical Internet research*, 22(4), p. e16520.

He, J. and King, W.R. (2008) 'The role of user participation in information systems development: implications from a meta-analysis', *Journal of management information systems*, 25(1), pp. 301–331.

Heeks, R. (2006) 'Understanding and measuring eGovernment: international benchmarking studies', in *UNDESA workshop,"E-participation and E-government: Understanding the present and creating the future", Budapest, Hungary*, pp. 27–28.

Heene, M., Hilbert, S., Draxler, C., Ziegler, M. and Bühner, M. (2011) 'Masking Misfit in Confirmatory Factor Analysis by Increasing Unique Variances: A Cautionary Note on the Usefulness of Cutoff Values of Fit Indices.', *Psychological Methods* [Preprint]. Available at: https://doi.org/10.1037/a0024917.

Helin, K., Kuula, T., Vizzi, C., Karjalainen, J. and Vovk, A. (2018) 'User Experience of Augmented Reality System for Astronaut's Manual Work Support', *Frontiers in Robotics and Ai* [Preprint]. Available at: https://doi.org/10.3389/frobt.2018.00106.

Heller, F., Pusic, E., Strauss, G. and Wilpert, B. (1998) *Organizational participation: Myth and reality*. Oxford University Press.

Helm, S. (2013) 'A Matter of Reputation and Pride: Associations between Perceived External Reputation, Pride in Membership, Job Satisfaction and Turnover Intentions', *British Journal of Management*, 24(4), pp. 542–556. Available at: https://doi.org/10.1111/j.1467-8551.2012.00827.x.

Henseler, J., Ringle, C.M. and Sarstedt, M. (2014) 'A New Criterion for Assessing Discriminant Validity in Variance-Based Structural Equation Modeling', *Journal of the Academy of Marketing Science* [Preprint]. Available at: https://doi.org/10.1007/s11747-014-0403-8.

Henson, R.K. and Roberts, J.K. (2006) 'Use of exploratory factor analysis in published research: Common errors and some comment on improved practice', *Educational and Psychological measurement*, 66(3), pp. 393–416.

Hidayat, R. and Wulandari, N.D. (2022) 'Data Analysis Procedures With Structural Equation Modelling (SEM): Narrative Literature Review', *Open Access Indonesia Journal of Social Sciences* [Preprint]. Available at: https://doi.org/10.37275/oaijss.v5i6.142.

Hiller, K. (2022) 'Predictive Policing and the Charter', *Manitoba Law Journal*, 44(6), pp. 224–245. Available at: https://doi.org/10.29173/mlj1303.

Hinkin, T.R. (1995) 'A Review of Scale Development Practices in the Study of Organizations', *Journal of Management* [Preprint]. Available at: https://doi.org/10.1177/014920639502100509.

Hino, M., Benami, E. and Brooks, N. (2018) 'Machine learning for environmental monitoring', *Nature Sustainability*, 1(10), pp. 583–588. Available at: https://doi.org/10.1038/s41893-018-0142-9.

Hinton, J., Watson, B. and Oviedo-Trespalacios, O. (2022) 'A novel conceptual framework investigating the relationship between roadside advertising and road safety: The driver behaviour and roadside advertising conceptual framework', *Transportation Research Part F: Traffic Psychology and Behaviour*, 85, pp. 221–235. Available at: https://doi.org/10.1016/j.trf.2021.12.002.

Hjeij, M. and Vilks, A. (2023) 'A brief history of heuristics: how did research on heuristics evolve?', *Humanities and Social Sciences Communications*, 10(1), p. 64. Available at: https://doi.org/10.1057/s41599-023-01542-z.

Ho, A., Silvers, A. and Stainton, T. (2014) 'Continuous surveillance of persons with disabilities: Conflicts and compatibilities of personal and public goods', *Journal of Social Philosophy*, 45(3), pp. 348–368. Available at: https://doi.org/10.1111/JOSP.12067/ABSTRACT.

Hogarth, R.M. and Soyer, E. (2014) 'Using simulated experience to make sense of big data', *MIT Sloan Management Review* [Preprint].

Holbrook, A.L. and Krosnick, J.A. (2010) ‘Social desirability bias in voter turnout reports: Tests using the item count technique’, *Public Opinion Quarterly*, 74(1), pp. 37–67. Available at: https://doi.org/10.1093/poq/nfp065.

Hollands, R.G. (2008) ‘Will the real smart city please stand up? Intelligent, progressive or entrepreneurial?’, *City*, 12(3), pp. 303–320. Available at: https://doi.org/10.1080/13604810802479126.

Hooper, D., Coughlan, J. and Mullen, M.R. (2008) ‘Structural equation modelling: Guidelines for determining model fit’, *Electronic Journal of Business Research Methods*, 6(1), pp. 53–60.

Horani, O.M., Al-Adwan, A.S., Yaseen, H., Hmoud, H., Al-Rahmi, W.M. and Alkhalifah, A. (2023) ‘The critical determinants impacting artificial intelligence adoption at the organizational level’, *Information Development*, p. 026666692311668. Available at: https://doi.org/10.1177/02666669231166889.

Hornbæk, K. and Hertzum, M. (2017) ‘Technology Acceptance and User Experience’, *ACM Transactions on Computer-Human Interaction*, 24(5), pp. 1–30. Available at: https://doi.org/10.1145/3127358.

Horng, T.T., Assim, M.I.S.B.A., Mee, C.K. and Kuan, L.H. (2021) ‘Identifying the Determinants for Developing of Smart City Initiatives in Delivering Convenience and Safety to Local Community’, *International Journal of Academic Research in Business and Social Sciences* [Preprint]. Available at: https://doi.org/10.6007/ijarbss/v11-i17/11404.

Hossain, M., Abdel-Aty, M., Quddus, M., Muromachi, Y. and Sadeek, S.N. (2019) ‘Real-Time Crash Prediction Models: State-of-the-Art, Design Pathways and Ubiquitous Requirements’, *Accident Analysis & Prevention* [Preprint]. Available at: https://doi.org/10.1016/j.aap.2018.12.022.

Hossin, M.A., Du, J., Mu, L. and Asante, I.O. (2023) ‘Big Data-Driven Public Policy Decisions: Transformation Toward Smart Governance’, *SAGE Open*, 13(4), p. 21582440231215124.

Hu, L. and Bentler, P.M. (1999) ‘Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives’, *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), pp. 1–55. Available at: https://doi.org/10.1080/10705519909540118.

Hu, P.J.-H., Clark, T.H.K. and Ma, W.W. (2003) ‘Examining technology acceptance by school teachers: a longitudinal study’, *Information & Management*, 41(2), pp. 227–241. Available at: https://doi.org/10.1016/S0378-7206(03)00050-8.

Hu, Q., Zhou, Z. and Sun, X. (2014) ‘A Study on Urban Road Traffic Safety Based on Matter Element Analysis’, *Computational Intelligence and Neuroscience* [Preprint]. Available at: https://doi.org/10.1155/2014/458483.

Huang, H. and Abdel-Aty, M. (2010) ‘Multilevel data and Bayesian analysis in traffic safety’, *Accident Analysis & Prevention*, 42(6), pp. 1556–1565. Available at: https://doi.org/10.1016/j.aap.2010.03.013.

Huang, Z. and Loo, B.P.Y. (2022) ‘Urban traffic congestion in twelve large metropolitan cities: A thematic analysis of local news contents, 2009–2018’, *International Journal of Sustainable Transportation*, 17(6), pp. 592–614. Available at: https://doi.org/10.1080/15568318.2022.2076633.

Huda, M.N., Kurniasari, E.N. and Ruroh, S.M. (2022) ‘Journal of Local Government Issues (LOGOS) A Systematic Literature Review of E-Government Evaluation’, 5(1), pp. 32–48.

Hung, S.-Y.Y., Tang, K.-Z.Z., Chang, C.-M.M. and Ke, C.-D. De (2009) ‘User acceptance of intergovernmental services: An example of electronic document management system’, *Government Information Quarterly*, 26(2), pp. 387–397. Available at: https://doi.org/10.1016/j.giq.2008.07.003.

Hung, T.-W. and Yen, C.-P. (2023) ‘Predictive policing and algorithmic fairness’, *Synthese*, 201(6), p. 206. Available at: https://doi.org/10.1007/s11229-023-04189-0.

Hung, T.W. and Yen, C.P. (2021) ‘On the person-based predictive policing of AI’, *Ethics and Information Technology*, 23(3), pp. 1–12. Available at: https://doi.org/10.1007/S10676-020-09539-X.

Hussain, A. and Mkpojiogu, E.O.C. (2015) ‘The Effect of Responsive Web Design on the User Experience With Laptop and Smartphone Devices’, *Jurnal Teknologi* [Preprint]. Available at: https://doi.org/10.11113/jt.v77.6041.

Idkhan, A.M. and Idris, M.M. (2023) ‘The Impact of User Satisfaction in the Use of E-Learning Systems in Higher Education: A CB-SEM Approach’, *International Journal of Environment, Engineering and Education*, 5(3), pp. 100–110. Available at: https://doi.org/10.55151/ijeedu.v5i3.91.

Idoughi, D. and Abdelhakim, D. (2018) ‘Developing Countries E-Government Services Evaluation Identifying and Testing Antecedents of Satisfaction Case of Algeria’, 14(1), pp. 63–65. Available at: https://doi.org/10.4018/IJEGR.2018010104.

Indonesian Government (2002) *Laws of the republic Indonesia number 2 of 2002 about state police of the republic of Indonesia*.

Indonesian Government (2009) *Laws of the Republic Indonesia number 22 of 2009 about traffic and road transport*. Available at: https://korlantas.polri.go.id/wp-content/uploads/2021/03/uu_no_22_tahun_2009.pdf.

Indonesian National Police (2011) ‘Berita Negara’, *Peraturan Kapolri* [Preprint].

Indonesian National Police (2018) ‘IRSMS’.

Iqbal, A., Rehman, Z.U., Ali, S., Ullah, K. and Ghani, U. (2020) ‘Road traffic accident analysis and identification of black spot locations on highway’, *Civil Engineering Journal (Iran)*, 6(12), pp. 2448–2456. Available at: https://doi.org/10.28991/cej-2020-03091629.

IRTAD (2019) ‘Road safety annual report’, *International Transport Forum*, p. 60.

Available at: https://barnard.edu/sites/default/files/inline/student_user_guide_for_spss.pdf%0Ahttp://www.ibm.com/support%0Ahttp://www.spss.com/sites/dm-book/legacy/ProgDataMgmt_SPSS17.pdf%0Ahttps://www.neps-data.de/Portals/0/Working Papers/WP_XLV.pdf%0Ahttp://www2.psy.

Isaac, O., Abdullah, Z., Aldholay, A.H. and Abdulbaqi Ameen, A. (2019) ‘Antecedents and outcomes of internet usage within organisations in Yemen: An extension of the Unified Theory of Acceptance and Use of Technology (UTAUT) model’, *Asia Pacific Management Review*, 24(4), pp. 335–354. Available at: https://doi.org/10.1016/j.apmrv.2018.12.003.

Isaac, O. and Mutahar, A.M. (2017) ‘Internet Usage within Government Institutions in Yemen: An Extended Technology Acceptance Model (TAM) with Internet Self-Efficacy and Performance Impact Information System Strategic Planning View project SMART-Government View project’, (August). Available at: https://www.researchgate.net/publication/318866085.

Ishkineeva, G., Ishkineeva, F. and Akhmetova, S. (2015) ‘Major Approaches towards Understanding Smart Cities Concept’, *Asian Social Science*, 11(5). Available at: https://doi.org/10.5539/ass.v11n5p70.

Islam, M.N., Bouwman, H. and Islam, A.K.M.N. (2020) ‘Evaluating Web and Mobile User Interfaces With Semiotics: An Empirical Study’, *Ieee Access* [Preprint]. Available at: https://doi.org/10.1109/access.2020.2991840.

Ismagilova, E., Hughes, L., Rana, N.P. and Dwivedi, Y.K. (2022) ‘Security, Privacy and Risks Within Smart Cities: Literature Review and Development of a Smart City Interaction Framework’, *Information Systems Frontiers*, 24(2), pp. 393–414. Available at: https://doi.org/10.1007/s10796-020-10044-1.

Isnayanti, I. and Abdurakhman, A. (2019) ‘Model persamaan struktural dengan metode diagonally weighted least square (dwls) untuk data ordinal’, *MEDIA STATISTIKA*, 12(1), p. 100. Available at: https://doi.org/10.14710/medstat.12.1.100-116.

Ivankova, N. and Wingo, N. (2018) ‘Applying Mixed Methods in Action Research: Methodological Potentials and Advantages’, *American Behavioral Scientist*, 62(7), pp. 978–997. Available at: https://doi.org/10.1177/0002764218772673.

Ives, B. and Olson, M.H. (1984) ‘User involvement and MIS success: A review of research’, *Management science*, 30(5), pp. 586–603.

Jackson, C.M., Chow, S. and Leitch, R.A. (1997) ‘Toward an Understanding of the Behavioral Intention to Use an Information System’, *Decision Sciences*, 28(2), pp. 357–389. Available at: https://doi.org/10.1111/j.1540-5915.1997.tb01315.x.

Janssen, M., Charalabidis, Y. and Zuiderwijk, A. (2012) ‘Benefits, Adoption Barriers and Myths of Open Data and Open Government’, *Information Systems Management* [Preprint]. Available at: https://doi.org/10.1080/10580530.2012.716740.

Jedwab, R., Loungani, P. and Yezer, A. (2021) ‘Comparing cities in developed and developing countries: Population, land area, building height and crowding’, *Regional Science and Urban Economics*, 86, p. 103609. Available at: https://doi.org/10.1016/j.regsciurbeco.2020.103609.

Jetzek, T., Avital, M. and Bjorn-Andersen, N. (2014) ‘Data-Driven Innovation through Open Government Data’, *Journal of theoretical and applied electronic commerce research*, 9(2), pp. 15–16. Available at: https://doi.org/10.4067/S0718-18762014000200008.

Jing, C., Du, M., Li, S. and Liu, S. (2019) ‘Geospatial dashboards for monitoring smart city performance’, *Sustainability (Switzerland)*, 11(20). Available at: https://doi.org/10.3390/su11205648.

Jiwani, F.N. and Krawchenko, T. (2014) ‘Public Policy, Access to Government, and Qualitative Research Practices: Conducting Research within a Culture of Information Control’, *Canadian Public Policy*, 40(1), pp. 57–66. Available at: https://doi.org/10.3138/cpp.2012-051.

Joewono, T.B. and Susilo, Y.O. (2017) ‘Traffic violations by young motorcyclists on Indonesian urban roads', *Journal of Transportation Safety & Security*, 9(sup1), pp. 236–261. Available at: https://doi.org/10.1080/19439962.2016.1247123.

Johnson, R.B. and Onwuegbuzie, A.J. (2004) 'Mixed Methods Research: A Research Paradigm Whose Time Has Come', *Educational Researcher*, 33(7), pp. 14–26. Available at: https://doi.org/10.3102/0013189X033007014.

Joinson, A. (1999) 'Social desirability, anonymity, and internet-based questionnaires', *Behavior Research Methods, Instruments, & Computers*, 31(3), pp. 433–438. Available at: https://doi.org/10.3758/BF03200723.

Joinson, A., Reips, U., Buchanan, T. and Schofield, C.P. (2010) 'Privacy, Trust, and Self-Disclosure Online', *Human-Computer Interaction* [Preprint]. Available at: https://doi.org/10.1080/07370020903586662.

Jones, N.B. and Mahon, J.F. (2012) 'Nimble Knowledge Transfer in High Velocity/Turbulent Environments', *Journal of Knowledge Management* [Preprint]. Available at: https://doi.org/10.1108/13673271211262808.

De Jong, M.G., Pieters, R. and Fox, J.-P. (2010) 'Reducing Social Desirability Bias through Item Randomized Response: An Application to Measure Underreported Desires', *Journal of Marketing Research*, 47(1), pp. 14–27. Available at: https://doi.org/10.1509/jmkr.47.1.14.

Jöreskog, K.G., Sörbom, D. and Magidson, J. (1979) 'Advances in factor analysis and structural equation models', *(No Title)* [Preprint].

Joseph, B.K. (2017) 'Determining Factors Influencing E-Government Development in the Developing World: A Case Study of Zambia', *Journal of e-Government Studies and Best Practices*, 2017, pp. 1–16. Available at: https://doi.org/10.5171/2017.143795.

Kachwamba, M. and Hussein, A. (2009) 'Determinants of e-government maturity: Do organizational specific factors matter?', *Journal of US-China public administration*, 6, pp. 1–7.

Kadkhodaei, Masoud, Shad, R., Ziaee, S.A. and Kadkhodaei, Mohsen (2023) ‘Prediction model for drivers’ tendency to perpetrate a double parking violation on urban trips’, *Transport Policy*, 141, pp. 331–339. Available at: https://doi.org/10.1016/J.TRANPOL.2023.08.001.

Kadoic, N. and Kedmenec, I. (2016) ‘Using ICT tools for decision making support in local government units’, in *2016 39th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO)*. IEEE, pp. 1533–1538. Available at: https://doi.org/10.1109/MIPRO.2016.7522382.

Kaiser, H.F. (1960) ‘The application of electronic computers to factor analysis’, *Educational and psychological measurement*, 20(1), pp. 141–151.

Kalamaras, I., Zamichos, A., Salamanis, A., Drosou, A., Kehagias, D.D., Margaritis, G., Papadopoulos, S. and Tzovaras, D. (2018) ‘An Interactive Visual Analytics Platform for Smart Intelligent Transportation Systems Management’, *IEEE Transactions on Intelligent Transportation Systems*, 19(2), pp. 487–496. Available at: https://doi.org/10.1109/TITS.2017.2727143.

Kaluarachchi, Y. (2022) ‘Implementing Data-Driven Smart City Applications for Future Cities’, *Smart Cities*, 5(2), pp. 455–474. Available at: https://doi.org/10.3390/smartcities5020025.

Kamal, M.M. (2006) ‘IT Innovation Adoption in the Government Sector: Identifying the Critical Success Factors’, *Journal of Enterprise Information Management* [Preprint]. Available at: https://doi.org/10.1108/17410390610645085.

Kamnik, R., Nekrep Perc, M. and Topolšek, D. (2020) ‘Using the scanners and drone for comparison of point cloud accuracy at traffic accident analysis’, *Accident Analysis and Prevention*, 135(December 2019). Available at: https://doi.org/10.1016/j.aap.2019.105391.

Kant, R. and Jaiswal, D. (2017) ‘The Impact of Perceived Service Quality Dimensions on Customer Satisfaction’, *The International Journal of Bank Marketing* [Preprint]. Available at: https://doi.org/10.1108/ijbm-04-2016-0051.

Kaplan, J.L., Wright, M.J., Lazarus, L., Congemi, N., Arnold, R., Mercante, D., Diaz, J.H., Vrahas, M. and Hunt, J.P. (2000) 'Use of an unmanned police car to reduce traffic speed', *Journal of Trauma and Acute Care Surgery*, 49(1), pp. 43–46.

Karavasilis, I., Zafiropoulos, K. and Vrana, V. (2010) 'Extending TAM to Understand E-Governance Adoption by Teachers in Greece', in, pp. 57–68. Available at: https://doi.org/10.1007/978-3-642-16324-1_7.

Karuri, J., Waiganjo, P. and Orwa, D. (2014) 'Determinants of Acceptance and Use of DHIS2: Survey Instrument Validation and Preliminary Findings using PLS-SEM', *Journal of Emerging Trends in Computing and Information Sciences*, 5(8), pp. 647–660.

Kattel, R., Lember, V. and Tõnurist, P. (2020) 'Collaborative innovation and human-machine networks', *Public Management Review*, 22(11), pp. 1652–1673. Available at: https://doi.org/10.1080/14719037.2019.1645873.

Kaushik, K. and Mishra, R. (2019) 'Predictors of E-government adoption in India: direct and indirect effects of technology anxiety and information quality', *International Journal of Business Information Systems*, 31(3), p. 305. Available at: https://doi.org/10.1504/IJBIS.2019.10022639.

Keddie, A. (2023) 'Gender equality reform and police organizations: A social justice approach', *Gender, Work & Organization*, 30(3), pp. 810–825. Available at: https://doi.org/10.1111/gwao.12918.

Kennedy, L.W., Caplan, J.M. and Piza, E. (2011) 'Risk Clusters, Hotspots, and Spatial Intelligence: Risk Terrain Modeling as an Algorithm for Police Resource Allocation Strategies', *Journal of Quantitative Criminology*, 27(3), pp. 339–362. Available at: https://doi.org/10.1007/s10940-010-9126-2.

Khan, M., Raya, R.P. and Viswanathan, R. (2022) 'Enhancing employee innovativeness and job performance through a culture of workplace innovation', *International Journal of Productivity and Performance Management*, 71(8), pp. 3179–3204. Available at: https://doi.org/10.1108/IJPPM-09-2020-0466.

Khan, S.U., Shah, A. and Rizwan, M.F. (2021) ‘Do Financing Constraints Matter for Technological and Non-technological Innovation? A (Re)examination of Developing Markets’, *Emerging Markets Finance and Trade*, 57(9), pp. 2739–2766. Available at: https://doi.org/10.1080/1540496X.2019.1695593.

Khan, Z., Dambruch, J., Peters-Anders, J., Sackl, A., Strasser, A., Fröhlich, P., Templer, S. and Soomro, K. (2017) ‘Developing knowledge-based citizen participation platform to support smart city decision making: The smarticipate case study’, *Information (Switzerland)*, 8(2), pp. 1–24. Available at: https://doi.org/10.3390/info8020047.

Khanal, B., Zahertar, A. and Lavrenz, S. (2024) ‘Heterogeneity in crash data: A cross comparison between ordered probability model and its variant using crashes at suburban type arterial’, *Accident Analysis & Prevention*, 200, p. 107524. Available at: https://doi.org/10.1016/j.aap.2024.107524.

Khatri, N. and Ng, H.A. (2000) ‘The Role of Intuition in Strategic Decision Making’, *Human Relations*, 53(1), pp. 57–86. Available at: https://doi.org/10.1177/0018726700531004.

Khrais, L.T. and Mahmoud, M.A. (2019) ‘A Readiness Evaluation of Applying e-Government in the Society : Shall Citizens begin to Use it ?’, 10(9), pp. 55–59.

Kilicer, K., Bardakci, S. and Arpaci, I. (2018) ‘Investigation of Emerging Technology Usage Characteristics as Predictors of Innovativeness’, *Contemporary Educational Technology*, 9(3), pp. 225–245. Available at: https://doi.org/10.30935/cet.444100.

Kim, M.D. and Lee, K.S. (2023) ‘Mapping participation in ICT4D: A meta-analytic review of development communication research’, *International Communication Gazette*, 85(2), pp. 141–163. Available at: https://doi.org/10.1177/17480485221111308.

Kim, S.H., Won, J., Kim, J.-Y. and Lee, S. (2018) ‘The Review on MaaS Application Methods for Smart Cities’, *International Journal of Transportation* [Preprint]. Available at: https://doi.org/10.14257/ijt.2018.6.2.04.

Kim, Y., Reinecke, K. and Hullman, J. (2018) ‘Data Through Others ’ Eyes : The Impact of Visualizing Others ’ Expectations on Visualization Interpretation’, 24(1), pp. 760–769.

King, N. and Brooks, J. (2018) ‘Thematic Analysis in Organisational Research’, *The SAGE Handbook of Qualitative Business and Management Research Methods: Methods and Challenges*, pp. 219–236. Available at: https://doi.org/10.4135/9781526430236.n14.

King, N. and Horrocks, C. (2010) *Interviews in Qualitative Research*.

Kintz, M., Kochanowski, M. and Koetter, F. (2017) ‘Creating User-specific Business Process Monitoring Dashboards with a Model-driven Approach’, (Modelsward), pp. 353–361. Available at: https://doi.org/10.5220/0006135203530361.

Király, G. and Miskolczi, P. (2019) ‘Dynamics of participation: System dynamics and participation—An empirical review’, *Systems Research and Behavioral Science*, 36(2), pp. 199–210. Available at: https://doi.org/10.1002/sres.2580.

Kisiała, W. and Kudłak, R. (2024) ‘Local car markets in an emerging economy: exploring the dichotomous nature of car ownership growth’, *European Transport Research Review*, 16(1), p. 22. Available at: https://doi.org/10.1186/s12544-024-00645-1.

Kitamura, Y., Hayashi, M. and Yagi, E. (2018) ‘Traffic problems in Southeast Asia featuring the case of Cambodia’s traffic accidents involving motorcycles’, *IATSS Research*, 42(4), pp. 163–170. Available at: https://doi.org/10.1016/j.iatssr.2018.11.001.

Kitchin, R. (2014) ‘The real-time city? Big data and smart urbanism’, *GeoJournal*, 79(1), pp. 1–14. Available at: http://www.jstor.org/stable/24432611.

Kitchin, R. (2015) ‘Making sense of smart cities: Addressing present shortcomings’, *Cambridge Journal of Regions, Economy and Society*, 8(1), pp.

131–136. Available at: https://doi.org/10.1093/cjres/rsu027.

Kitchin, R. (2016) ‘The ethics of smart cities and urban science’, *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 374(2083). Available at: https://doi.org/10.1098/rsta.2016.0115.

Kitchin, R. and McArdle, G. (2016) ‘Urban data and city dashboards: Six key issues’, *Data and the City*, pp. 1–21.

Kliemann, N., Wardle, J., Johnson, F. and Croker, H. (2016) ‘Reliability and Validity of a Revised Version of the General Nutrition Knowledge Questionnaire’, *European Journal of Clinical Nutrition* [Preprint]. Available at: https://doi.org/10.1038/ejcn.2016.87.

Klievink, B., Bharosa, N. and Tan, Y.-H. (2016) ‘The collaborative realization of public values and business goals: Governance and infrastructure of public-private information platforms’, *Government Information Quarterly*, 33(1), pp. 67–79. Available at: https://doi.org/10.1016/j.giq.2015.12.002.

Kline, R.B. (2023) *Principles and practice of structural equation modeling*. Guilford publications.

Kobayashi, A. (2003) ‘GPC ten years on: Is self-reflexivity enough?’, *Gender, Place and Culture*, 10(4), pp. 345–349. Available at: https://doi.org/10.1080/0966369032000153313.

Kogan, N. and Lee, K.J. (2014) ‘Exploratory Research on the Success Factors and Challenges of Smart City Projects’, *Asia Pacific Journal of Information Systems*, 24(2), pp. 141–189. Available at: https://doi.org/10.14329/apjis.2014.24.2.141.

Kolisnyk, M., Kwiatkowski, M.R., Leung, C.K. and Zacharias, B. (2022) ‘Analysis of Multi-Dimensional Road Accident Data for Disaster Management in Smart Cities’, in *2022 IEEE 23rd International Conference on Information Reuse and Integration for Data Science (IRI)*. IEEE, pp. 43–48. Available at: https://doi.org/10.1109/IRI54793.2022.00022.

Komninos, N., Pallot, M. and Schaffers, H. (2013) ‘Special Issue on Smart Cities and the Future Internet in Europe’, *Journal of the Knowledge Economy*, 4(2), pp. 119–134. Available at: https://doi.org/10.1007/s13132-012-0083-x.

Koops, B.-J. (2021) ‘The concept of function creep’, *Law, Innovation and Technology*, 13(1), pp. 29–56. Available at: https://doi.org/10.1080/17579961.2021.1898299.

Korlantas Polri (2018) *Vademikum Polantas No. 20/2018*. Available at: https://wapi.k3i-korlantas.id/uploads/regulation_doc/VADEMIKUM POLANTAS TAHUN 2018.pdf.

Korlantas Polri (2022) ‘Korlantas Polri - Informasi Lalu Lintas Indonesia’. Available at: https://korlantas.polri.go.id/.

Korstjens, I. and Moser, A. (2018) ‘Series: Practical guidance to qualitative research. Part 4: Trustworthiness and publishing’, *European Journal of General Practice*, 24(1), pp. 120–124. Available at: https://doi.org/10.1080/13814788.2017.1375092.

Kozanoglu, D.C. and Abedin, B. (2021) ‘Understanding the role of employees in digital transformation: conceptualization of digital literacy of employees as a multi-dimensional organizational affordance’, *Journal of Enterprise Information Management*, 34(6), pp. 1649–1672. Available at: https://doi.org/10.1108/JEIM-01-2020-0010.

Krasnykov, Y. (2023) ‘Change Management for Improving the Quality of Public Services’, *Theory and Practice of Public Administration*, (2), pp. 22–37. Available at: https://doi.org/10.26565/1727-6667-2023-2-02.

Krausmann, F., Gingrich, S., Eisenmenger, N., Erb, K.H., Haberl, H. and Fischer-Kowalski, M. (2009) ‘Growth in global materials use, GDP and population during the 20th century’, *Ecological Economics*, 68(10), pp. 2696–2705. Available at: https://doi.org/10.1016/j.ecolecon.2009.05.007.

Kreuter, F., Presser, S. and Tourangeau, R. (2008) ‘Social Desirability Bias in

CATI, IVR, and Web Surveys: The Effects of Mode and Question Sensitivity', *Public Opinion Quarterly*, 72(5), pp. 847–865. Available at: https://doi.org/10.1093/poq/nfn063.

Krosnick, J.A., Holbrook, A.L., Berent, M.K., Carson, R.T., Hanemann, W.M., Kopp, R.J., Mitchell, R.C., Presser, S., Ruud, P.A., Smith, V.K., Moody, W.R., Green, M.C. and Conaway, M. (2001) 'The Impact of "No Opinion" Response Options on Data Quality', *Public Opinion Quarterly*, 66(3), pp. 371–403. Available at: https://doi.org/10.1086/341394.

Krueger, R.A. (2014) *Focus groups: A practical guide for applied research*. Sage publications.

Krutova, O., Turja, T., Koistinen, P., Melin, H. and Särkikoski, T. (2022) 'Job insecurity and technology acceptance: an asymmetric dependence', *Journal of Information, Communication and Ethics in Society*, 20(1), pp. 110–133. Available at: https://doi.org/10.1108/JICES-03-2021-0036.

Kucera, J. and Chlapek, D. (2014) 'Benefits and Risks of Open Government Data', *Journal of Systems Integration*, pp. 30–41. Available at: https://doi.org/10.20470/jsi.v5i1.185.

Kujala, S. (2003) 'User involvement: a review of the benefits and challenges', *Behaviour & information technology*, 22(1), pp. 1–16.

Kumar, P., Kumar Rathaur, A., Ahmad, R., Sinha, M.K. and Sangal, R. (2010) 'Dashboard: An integration and testing platform based on backboard architecture for NLP applications', in *Proceedings of the 6th International Conference on Natural Language Processing and Knowledge Engineering(NLPKE-2010)*. IEEE, pp. 1–8. Available at: https://doi.org/10.1109/NLPKE.2010.5587779.

Kumar, S. and Toshniwal, D. (2016) 'Analysis of hourly road accident counts using hierarchical clustering and cophenetic correlation coefficient (CPCC)', *Journal of Big Data*, 3(1), p. 13. Available at: https://doi.org/10.1186/s40537-016-0046-3.

Kumar, S.P. and Saha, S. (2017) ‘Influence of Trust and Participation in Decision Making on Employee Attitudes in Indian Public Sector Undertakings’, *SAGE Open*, 7(3), p. 215824401773303. Available at: https://doi.org/10.1177/2158244017733030.

Kumekpor, T.K.B. (2002) *Research methods and techniques of social research*. SonLife Press & Services.

Kummitha, R.K.R. (2020) ‘Smart Technologies for Fighting Pandemics: The Techno- And Human- Driven Approaches in Controlling the Virus Transmission’, *Government Information Quarterly* [Preprint]. Available at: https://doi.org/10.1016/j.giq.2020.101481.

Kuo, P.-F., Lord, D. and Walden, T.D. (2013) ‘Using geographical information systems to organize police patrol routes effectively by grouping hotspots of crash and crime data’, *Journal of Transport Geography*, 30, pp. 138–148. Available at: https://doi.org/10.1016/j.jtrangeo.2013.04.006.

Kurilovas, E. (2020) ‘On data-driven decision-making for quality education’, *Computers in Human Behavior*, 107, p. 105774. Available at: https://doi.org/10.1016/j.chb.2018.11.003.

Kvale, S. (2011) ‘Interview Variations’, *Doing Interviews*, pp. 68–77. Available at: https://doi.org/10.4135/9781849208963.n6.

Kwak, N.K. and Leavitt, M.B. (1984) ‘Police patrol beat design: efforts allocation and expected performance evaluation’, *Decision Sciences*, 15(3), pp. 421–433. Available at: https://doi.org/10.1111/j.1540-5915.1984.tb01227.x.

Kyriakou, K. and Otterbacher, J. (2024) ‘Modular oversight methodology: a framework to aid ethical alignment of algorithmic creations’, *Design Science*, 10, p. e32. Available at: https://doi.org/10.1017/dsj.2024.23.

Lai, H.-J. (2017) ‘Examining civil servants’ decisions to use Web 2.0 tools for learning, based on the decomposed theory of planned behavior’, *Interactive Learning Environments*, 25(3), pp. 295–305. Available at:

https://doi.org/10.1080/10494820.2015.1121879.

Laine, M., Santala, S., Jokinen, J. and Oulasvirta, A. (2021) ‘Responsive and Personalized Web Layouts With Integer Programming’, *Proceedings of the Acm on Human-Computer Interaction* [Preprint]. Available at: https://doi.org/10.1145/3461735.

Lallemand, C. and Koenig, V. (2017) ‘“How could an intranet be like a friend to me?” - Why standardized UX scales don’t always fit’, in *ACM International Conference Proceeding Series*, pp. 9–16. Available at: https://doi.org/10.1145/3121283.3121288.

Langford, R. (2012) ‘Qualitative research methods, by Monique Hennink, Inge Hutter and Ajay Bailey’. Taylor & Francis.

Larson, R.C. (1972) *Urban police patrol analysis*. MIT Press Cambridge, MA.

Larson, R.C. (1974) ‘A hypercube queuing model for facility location and redistricting in urban emergency services’, *Computers & Operations Research*, 1(1), pp. 67–95. Available at: https://doi.org/10.1016/0305-0548(74)90076-8.

Larson, R.C. (1975) ‘Approximating the Performance of Urban Emergency Service Systems’, *Operations Research*, 23(5), pp. 845–868. Available at: https://doi.org/10.1287/opre.23.5.845.

Larson, R.C. and Stevenson, K.A. (1972) ‘On Insensitivities in Urban Redistricting and Facility Location’, *Operations Research*, 20(3), pp. 595–612. Available at: https://doi.org/10.1287/opre.20.3.595.

Laugwitz, B., Held, T. and Schrepp, M. (2007) ‘Construction and Evaluation of a User Experience Questionnaire’, *Lncs*, 5298, p. 2007. Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.472.3719&rep=rep1&type=pdf.

Laugwitz, B., Held, T. and Schrepp, M. (2008) ‘Construction and Evaluation of a User Experience Questionnaire BT - HCI and Usability for Education and Work’, in A. Holzinger (ed.). Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 63–76.

Lawson-Body, A., Lawson-Body, L. and Illia, A. (2023) ‘Data Visualization: Developing and Validating Dashboard Measurement Instruments’, *Journal of Computer Information Systems*, 63(3), pp. 479–491. Available at: https://doi.org/10.1080/08874417.2022.2073295.

Lee, C., Hellinga, B. and Saccomanno, F. (2006) ‘Evaluation of variable speed limits to improve traffic safety’, *Transportation Research Part C: Emerging Technologies*, 14(3), pp. 213–228. Available at: https://doi.org/10.1016/j.trc.2006.06.002.

Lee, G. and Xia, W. (2010) ‘Toward agile: an integrated analysis of quantitative and qualitative field data on software development agility’, *MIS quarterly*, 34(1), pp. 87–114.

Lee, J. and Lee, H. (2014) ‘Developing and validating a citizen-centric typology for smart city services’, *Government Information Quarterly*, 31(SUPPL.1). Available at: https://doi.org/10.1016/j.giq.2014.01.010.

Leigh, J., Dunnett, S. and Jackson, L. (2019) ‘Predictive police patrolling to target hotspots and cover response demand’, *Annals of Operations Research*, 283(1–2), pp. 395–410. Available at: https://doi.org/10.1007/s10479-017-2528-x.

Lemke, F., Ehrhardt, K. and Popelyshyn, O. (2021) ‘Support and Resistance of Public Officials Towards Current eGovernment Initiatives – A Case Study on Ukraine and Germany’, *der moderne staat – Zeitschrift für Public Policy, Recht und Management*, 14(1–2021), pp. 61–80. Available at: https://doi.org/10.3224/dms.v14i1.08.

Leonard-Barton, D. and Deschamps, I. (1988) ‘Managerial influence in the implementation of new technology’, *Management science*, 34(10), pp. 1252–1265.

Leu, J.-H., Lin, B.-C., Liao, Y.-Y. and Gan, D.-Y. (2021) ‘Smart City Development in Taiwan’, *Iet Smart Cities* [Preprint]. Available at:

https://doi.org/10.1049/smc2.12008.

Levenson, A. and Fink, A.A. (2017) ‘Human Capital Analytics: Too Much Data and Analysis, Not Enough Models and Business Insights’, *Journal of Organizational Effectiveness People and Performance* [Preprint]. Available at: https://doi.org/10.1108/joepp-03-2017-0029.

Li, C.H. (2015) ‘Confirmatory Factor Analysis With Ordinal Data: Comparing Robust Maximum Likelihood and Diagonally Weighted Least Squares’, *Behavior Research Methods*, 48(3), pp. 936–949. Available at: https://doi.org/10.3758/s13428-015-0619-7.

Li, X., Dadashova, B., Yu, S. and Zhang, Z. (2020) ‘Rethinking Highway Safety Analysis by Leveraging Crowdsourced Waze Data’, *Sustainability*, 12(23), p. 10127. Available at: https://doi.org/10.3390/su122310127.

Liang, H., Xue, Y. and Wu, L. (2013) ‘Ensuring Employees’ IT Compliance: Carrot or Stick?’, *Information Systems Research*, 24(2), pp. 279–294. Available at: https://doi.org/10.1287/isre.1120.0427.

Liddle, B. (2012) ‘The systemic, long-run relation among gasoline demand, gasoline price, income, and vehicle ownership in OECD countries: Evidence from panel cointegration and causality modeling’, *Transportation Research Part D: Transport and Environment*, 17(4), pp. 327–331. Available at: https://doi.org/10.1016/j.trd.2012.01.007.

Lilhore, U.K., Imoize, A.L., Li, C.-T., Simaiya, S., Pani, S.K., Goyal, N., Kumar, A. and Lee, C.-C. (2022) ‘Design and Implementation of an ML and IoT Based Adaptive Traffic-Management System for Smart Cities’, *Sensors*, 22(8), p. 2908. Available at: https://doi.org/10.3390/s22082908.

Lincoln, Y.S. and Guba, E.G. (1982) ‘Establishing Dependability and Confirmability in Naturalistic Inquiry Through an Audit’, *American Educational Research Association Annual Meeting* [Preprint].

Lincoln, Y.S. and Guba, E.G. (1986) ‘But is it rigorous? Trustworthiness and authenticity in naturalistic evaluation', *new directions for program evaluation*, 1986(30), pp. 73–84. Available at: https://doi.org/10.1002/EV.1427.

Lincoln, Y.S., Lynham, S.A. and Guba, E.G. (2011) 'Paradigmatic controversies, contradictions, and emerging confluences, revisited', *The Sage handbook of qualitative research*, 4(2), pp. 97–128.

Liu, J. and Khattak, A. (2020) 'Informed decision-making by integrating historical on-road driving performance data in high-resolution maps for connected and automated vehicles', *Journal of Intelligent Transportation Systems*, 24(1), pp. 11–23. Available at: https://doi.org/10.1080/15472450.2019.1699076.

Liu, Q. (2022) 'Beyond Technology Use: A People-Centred Approach to Reconceptualising the Adoption of Learning Technologies'. Available at: https://doi.org/10.59197/asrhe.v3i1.6539.

Liu, T., Mostafa, S., Mohamed, S.A.M. and Nguyen, T. (2020) 'Emerging Themes of Public-Private Partnership Application in Developing Smart City Projects: A Conceptual Framework', *Built Environment Project and Asset Management* [Preprint]. Available at: https://doi.org/10.1108/bepam-12-2019-0142.

Liu, Y., Safavi, T., Dighe, A. and Koutra, D. (2018) 'Graph summarization methods and applications: A survey', *ACM computing surveys (CSUR)*, 51(3), pp. 1–34.

Liu, Y., Zhang, Q. and Lv, Z. (2022) 'Real-Time Intelligent Automatic Transportation Safety Based on Big Data Management', *IEEE Transactions on Intelligent Transportation Systems*, 23(7), pp. 9702–9711. Available at: https://doi.org/10.1109/TITS.2021.3106388.

Lock, O., Bednarz, T., Leao, S.Z. and Pettit, C. (2020) 'A review and reframing of participatory urban dashboards', *City, Culture and Society*, 20, p. 100294. Available at: https://doi.org/10.1016/j.ccs.2019.100294.

Longhurst, R. (2003) 'Semi-structured interviews and focus groups', *Key methods in geography*, 3(2), pp. 143–156.

Lopes, A.V. and Farias, J.S. (2022) ‘How can governance support collaborative innovation in the public sector? A systematic review of the literature’, *International Review of Administrative Sciences*, 88(1), pp. 114–130. Available at: https://doi.org/10.1177/0020852319893444.

Lopes, N.V. (2017) ‘Smart governance: A key factor for smart cities implementation’, *2017 IEEE International Conference on Smart Grid and Smart Cities, ICSGSC 2017*, pp. 277–282. Available at: https://doi.org/10.1109/ICSGSC.2017.8038591.

Lord, D. and Mannering, F. (2010) ‘The statistical analysis of crash-frequency data: A review and assessment of methodological alternatives’, *Transportation Research Part A: Policy and Practice*, 44(5), pp. 291–305. Available at: https://doi.org/10.1016/j.tra.2010.02.001.

Lou, L., Li, L., Yang, S.-B. and Koh, J. (2021) ‘Promoting User Participation of Shared Mobility in the Sharing Economy: Evidence from Chinese Bike Sharing Services’, *Sustainability*, 13(3), p. 1533. Available at: https://doi.org/10.3390/su13031533.

Louati, A., Louati, H., Kariri, E., Neifar, W., Hassan, M.K., Khairi, M.H.H., Farahat, M.A. and El-Hoseny, H.M. (2024) ‘Sustainable Smart Cities through Multi-Agent Reinforcement Learning-Based Cooperative Autonomous Vehicles’, *Sustainability*, 16(5), p. 1779. Available at: https://doi.org/10.3390/su16051779.

Lowry, P.B. and Gaskin, J. (2014) ‘Partial Least Squares (PLS) Structural Equation Modeling (SEM) for Building and Testing Behavioral Causal Theory: When to Choose It and How to Use It’, *IEEE Transactions on Professional Communication*, 57(2), pp. 123–146. Available at: https://doi.org/10.1109/TPC.2014.2312452.

Lucena, F. de O. and Popadiuk, S. (2019) ‘Tacit knowledge in unstructured decision process’, *RAUSP Management Journal*, 55(1), pp. 22–39. Available at: https://doi.org/10.1108/RAUSP-05-2018-0021.

Von Lucke, J. (2016) ‘Smart Government – The Potential of Intelligent Networking in Government and Public Administration’, in *2016 Conference for E-Democracy and Open Government (CeDEM)*. IEEE, pp. 137–144. Available at: https://doi.org/10.1109/CeDEM.2016.22.

Luna-Reyes, L.F. and Gil-Garcia, J.R. (2014) ‘Digital government transformation and internet portals: The co-evolution of technology, organizations, and institutions’, *Government information quarterly*, 31(4), pp. 545–555.

Lyytinen, K. and Hirschheim, R. (1988) ‘Information systems as rational discourse: an application of Habermas’s theory of communicative action’, *Scandinavian Journal of Management*, 4(1–2), pp. 19–30. Available at: https://doi.org/10.1016/0956-5221(88)90013-9.

Ma, J., Kockelman, K.M. and Damien, P. (2008) ‘A Multivariate Poisson-Lognormal Regression Model for Prediction of Crash Counts by Severity, Using Bayesian Methods’, *Accident Analysis & Prevention* [Preprint]. Available at: https://doi.org/10.1016/j.aap.2007.11.002.

Ma, Y., Wu, C., Kang, P., Hong, C. and Jiang, C. (2018) ‘Internet of Things Applications in Public Safety Management: A Survey’, *Library Hi Tech* [Preprint]. Available at: https://doi.org/10.1108/lht-12-2017-0275.

MacCallum, R.C., Browne, M.W. and Sugawara, H.M. (1996) ‘Power analysis and determination of sample size for covariance structure modeling.’, *Psychological Methods*. US: American Psychological Association, pp. 130–149. Available at: https://doi.org/10.1037/1082-989X.1.2.130.

MacCallum, R.C. and Hong, S. (1997) ‘Power Analysis in Covariance Structure Modeling Using GFI and AGFI’, *Multivariate Behavioral Research*, 32(2), pp. 193–210. Available at: https://doi.org/10.1207/s15327906mbr3202_5.

MacDermid, J.C. (2021) ‘ICF Linking and Cognitive Interviewing Are Complementary Methods for Optimizing Content Validity of Outcome Measures: An Integrated Methods Review’, *Frontiers in Rehabilitation Sciences* [Preprint]. Available at: https://doi.org/10.3389/fresc.2021.702596.

Machluf, Y., Tal, O., Navon, A. and Chaiter, Y. (2017) ‘From Population Databases to Research and Informed Health Decisions and Policy’, *Frontiers in Public Health* [Preprint]. Available at: https://doi.org/10.3389/fpubh.2017.00230.

Mackun, T. and Żukowska, Joanna (2017) ‘The safety issue of roadside advertising – comparison of polish and abu dhabi regulations’, *MATEC Web of Conferences*. Edited by K. Jamroz and J. Żukowska, 122, p. 03005. Available at: https://doi.org/10.1051/matecconf/201712203005.

Madaki, A.S., Ahmad, K. and Singh, D. (2024) ‘Information technology integration implementation in public sector organizations: Exploring challenges, opportunities, and future trends’, *Information Development* [Preprint]. Available at: https://doi.org/10.1177/02666669241255661.

Madushani, J.P.S.S., Sandamal, R.M.K., Meddage, D.P.P., Pasindu, H.R. and Gomes, P.I.A. (2023) ‘Evaluating expressway traffic crash severity by using logistic regression and explainable & supervised machine learning classifiers’, *Transportation Engineering*, 13, p. 100190. Available at: https://doi.org/10.1016/j.treng.2023.100190.

Madyatmadja, E.D. and Prabowo, H. (2016) ‘Participation to public e-service development: A systematic literature review’, *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, 8(3), pp. 139–143.

Magdalena, R., Ruldeviyani, Y., Sensuse, D.I. and Bernando, C. (2019) ‘Methods to Enhance the Utilization of Business Intelligence Dashboard by Integration of Evaluation and User Testing’, in *2019 3rd International Conference on Informatics and Computational Sciences (ICICoS)*. IEEE, pp. 1–6. Available at: https://doi.org/10.1109/ICICoS48119.2019.8982481.

Maheshwari, D. and Janssen, M. (2013) ‘Measurement and benchmarking foundations: Providing support to organizations in their development and growth using dashboards’, *Government Information Quarterly*, 30(SUPPL. 1). Available at: https://doi.org/10.1016/j.giq.2012.11.002.

Maheshwari, D. and Janssen, M. (2014) ‘Dashboards for supporting organizational development: Principles for the design and development of public sector performance dashboards’, *ACM International Conference Proceeding Series*, 2014-Janua, pp. 178–185. Available at: https://doi.org/10.1145/2691195.2691224.

Mahmoodi, R.K. and Nojedeh, S.H. (2016) ‘Investigating the Effectiveness of E-government Establishment in Government Organizations’, *Procedia - Social and Behavioral Sciences*, 230, pp. 136–141. Available at: https://doi.org/10.1016/j.sbspro.2016.09.017.

Mahmoud, A. (2015) ‘An information theoretic approach for extracting and tracing non-functional requirements’, in *2015 IEEE 23rd International Requirements Engineering Conference (RE)*. IEEE, pp. 36–45. Available at: https://doi.org/10.1109/RE.2015.7320406.

Majumdar, S. and Chatterjee, U. (2020) ‘Modelling Urban Growth Using Urban Growth Deterministic Model in Kolkata Metropolitan Area: A Geo-Statistical Approach’, *Modeling Earth Systems and Environment* [Preprint]. Available at: https://doi.org/10.1007/s40808-020-00985-6.

Malhotra, N., Hall, J., Shaw, M. and Oppenheim, P. (2006) *Marketing research: An applied orientation*. Deakin University.

Manaf, H.A., Armstrong, S., Lawton, A. and Harvey, W.S. (2017) ‘Managerial Tacit Knowledge, Individual Performance, and the Moderating Role of Employee Personality’, *International Journal of Public Administration* [Preprint]. Available at: https://doi.org/10.1080/01900692.2017.1386676.

Mandinach, E.B. (2012) ‘A Perfect Time for Data Use: Using Data-Driven Decision Making to Inform Practice’, *Educational Psychologist*, 47(2), pp. 71–85. Available at: https://doi.org/10.1080/00461520.2012.667064.

Mannheim, I., Varlamova, M., van Zaalen, Y. and Wouters, E.J.M. (2023) ‘The Role of Ageism in the Acceptance and Use of Digital Technology’, *https://doi.org/10.1177/07334648231163426*, 42(6), pp. 1283–1294. Available at: https://doi.org/10.1177/07334648231163426.

Mao, L., Mian Akram, A., Chovanec, D. and Underwood, M.L. (2016) ‘Embracing the Spiral’, *International Journal of Qualitative Methods*, 15(1). Available at: https://doi.org/10.1177/1609406916681005.

Maqsood, T., Finegan, A. and Walker, D. (2004) ‘Biases and Heuristics in Judgment and Decision Making: The Dark Side of Tacit Knowledge’, in. Available at: https://doi.org/10.28945/2739.

Marchington, M. and Wilkinson, A. (2005) ‘Direct participation and involvement’, *Managing human resources: Personnel management in transition*, pp. 398–423.

Marcotte, E. (2011) *Responsive web design*. Editions Eyrolles.

Marda, V. (2018) ‘Artificial intelligence policy in India: a framework for engaging the limits of data-driven decision-making’, *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2133), p. 20180087. Available at: https://doi.org/10.1098/rsta.2018.0087.

Marsh, H.W., Morin, A.J.S., Parker, P.E. and Tripathi, M. (2014) ‘Exploratory Structural Equation Modeling: An Integration of the Best Features of Exploratory and Confirmatory Factor Analysis’, *Annual Review of Clinical Psychology* [Preprint]. Available at: https://doi.org/10.1146/annurev-clinpsy-032813-153700.

Martínez-López, F.J., Anaya-Sánchez, R., Aguilar-Illescas, R. and Molinillo, S. (2016) ‘Evolution of the Web’, in, pp. 5–15. Available at: https://doi.org/10.1007/978-3-319-24826-4_2.

Martinez, R. and Masron, I.N. (2020) ‘Jakarta: A city of cities’, *Cities*, 106, p. 102868. Available at: https://doi.org/10.1016/j.cities.2020.102868.

Martins, J. and Nielsen, M.M. (2020) ‘ICT Development in the Public Sector and the Small Island States Context - Evidence from across the World’, in *2020 Seventh International Conference on eDemocracy & eGovernment (ICEDEG)*.

IEEE, pp. 67–73. Available at: https://doi.org/10.1109/ICEDEG48599.2020.9096711.

Marto, A., Gonçalves, A., Martins, J. and Bessa, M. (2019) 'Applying UTAUT Model for an Acceptance Study Alluding the Use of Augmented Reality in Archaeological Sites.', in *VISIGRAPP (2: HUCAPP)*, pp. 111–120.

Mason-Bish, H. (2019) 'The elite delusion: reflexivity, identity and positionality in qualitative research', *Qualitative Research*, 19(3), pp. 263–276. Available at: https://doi.org/10.1177/1468794118770078.

Matheus, R., Janssen, M. and Maheshwari, D. (2020) 'Data science empowering the public: Data-driven dashboards for transparent and accountable decision-making in smart cities', *Government Information Quarterly*, 37(3), p. 101284. Available at: https://doi.org/10.1016/j.giq.2018.01.006.

Mathison, S. (2005) 'Encyclopedia of Evaluation'. Thousand Oaks, California. Available at: https://doi.org/10.4135/9781412950558 NV - 0.

Matoskova, J., Rehackova, H., Sobotkova, E., Polcakova, M., Jurasek, M., Gregar, A. and Svec, V. (2013) 'Facilitating Leader Tacit Knowledge Acquisition', *Journal of Competitiveness*, 5(1), pp. 3–15. Available at: https://doi.org/10.7441/joc.2013.01.01.

Matthews, B. and Ross, L. (2010) *Research methods: a practical guide for the social sciences*, *NY Pearson Longman*. Available at: http://books.google.com/books?id=7s4ERAAACAAJ&pgis=1.

Mauthner, N.S. and Doucet, A. (2003) 'Reflexive Accounts and Accounts of Reflexivity in Qualitative Data Analysis', *Sociology*, 37(3), pp. 413–431. Available at: https://doi.org/10.1177/00380385030373002.

Mavroeidi, A.-G., Kitsiou, A. and Kalloniatis, C. (2021) 'Gamification: A Necessary Element for Designing Privacy Training Programs'. Available at: https://doi.org/10.5772/intechopen.97420.

Maxcy, S.J. (2003) ‘Pragmatic Threads In Mixed’, *Handbook of Mixed Methods in Social & Behavioral Research*, p. 51.

Maxwell, S.E., Kelley, K. and Rausch, J.R. (2008) ‘Sample size planning for statistical power and accuracy in parameter estimation’, *Annu. Rev. Psychol.*, 59, pp. 537–563.

McCambridge, J., de Bruin, M. and Witton, J. (2012) ‘The Effects of Demand Characteristics on Research Participant Behaviours in Non-Laboratory Settings: A Systematic Review’, *PLoS ONE*. Edited by H.R. Baradaran, 7(6), p. e39116. Available at: https://doi.org/10.1371/journal.pone.0039116.

McCann, E. (2017) ‘Governing urbanism: Urban governance studies 1.0, 2.0 and beyond’, *Urban Studies*, 54(2), pp. 312–326. Available at: https://doi.org/10.1177/0042098016670046.

McClure, K. and McNaughtan, J. (2021) ‘Proximity to Power: The Challenges and Strategies of Interviewing Elites in Higher Education Research’, *The Qualitative Report* [Preprint]. Available at: https://doi.org/10.46743/2160-3715/2021.4615.

McCurdie, T., Taneva, S., Casselman, M., Yeung, M., McDaniel, C., Ho, W. and Cafazzo, J. (2012) ‘mHealth Consumer Apps : The Case for User-Centered Design’, *Biomedical Instrumentation & Technology*, 46(s2), pp. 49–56. Available at: https://doi.org/10.2345/0899-8205-46.s2.49.

McLaughlin, K., Eva, K.W. and Norman, G.R. (2014) ‘Reexamining our bias against heuristics’, *Advances in Health Sciences Education*, 19(3), pp. 457–464. Available at: https://doi.org/10.1007/s10459-014-9518-4.

McNabb, D.E. (2018) ‘Introduction to Mixed-Methods Research’, *Research Methods in Public Administration and Nonprofit Management*, pp. 415–425. Available at: https://doi.org/10.4324/9781315181158-36.

McNeish, D. (2018) ‘Thanks Coefficient Alpha, We’ll Take It From Here.’, *Psychological Methods* [Preprint]. Available at: https://doi.org/10.1037/met0000144.

McTiernan, D. (2019) 'Road Safety – Is It a Local Government Priority? (What Does the Experience Suggest?)', *Journal of the Australasian College of Road Safety*, 30(1), pp. 46–53. Available at: https://doi.org/10.33492/JACRS-D-18-00285.

Mehdizadeh, A., Cai, M., Hu, Q., Yazdi, M.A.A., Mohabbati-Kalejahi, N., Vinel, A., Rigdon, S.E., Davis, K.C., Megahed, F.M., Alamdar Yazdi, M.A., Mohabbati-Kalejahi, N., Vinel, A., Rigdon, S.E., Davis, K.C. and Megahed, F.M. (2020) 'A Review of Data Analytic Applications in Road Traffic Safety. Part 1: Descriptive and Predictive Modeling', *Sensors*, 20(4), p. 1107. Available at: https://doi.org/10.3390/s20041107.

Meijer, A. and Bolívar, M.P.R. (2016) 'Governing the smart city: a review of the literature on smart urban governance', *International Review of Administrative Sciences*, 82(2), pp. 392–408. Available at: https://doi.org/10.1177/0020852314564308.

Mekonnen, A.A., Sipos, T. and Krizsik, N. (2023) 'Identifying Hazardous Crash Locations Using Empirical Bayes and Spatial Autocorrelation', *Isprs International Journal of Geo-Information* [Preprint]. Available at: https://doi.org/10.3390/ijgi12030085.

Melitski, J., Gavin, D. and Gavin, J. (2010) 'Technology adoption and organizational culture in public organizations', *International Journal of Organization Theory & Behavior*, 13(4), pp. 546–568. Available at: https://doi.org/10.1108/IJOTB-13-04-2010-B005.

Meng, S. (2017) 'Availability Heuristic Will Affect Decision-making and Result in Bias', *DEStech Transactions on Social Science, Education and Human Science* [Preprint], (msie). Available at: https://doi.org/10.12783/dtssehs/msie2017/15448.

Mensah, I.K., Adams, S., Adjei, J.K. and Mwakapesa, D.S. (2021) 'Drivers of egovernment adoption amidst COVID-19 pandemic: The Information Adoption Model (IAM) approach', *Information Development* [Preprint]. Available at: https://doi.org/10.1177/02666669211010872.

Mergel, I. (2016) ‘Big Data in Public Affairs Education’, *Journal of Public Affairs Education*, 22(2), pp. 231–248. Available at: https://doi.org/10.1080/15236803.2016.12002243.

Mergel, I., Edelmann, N. and Haug, N. (2019) ‘Defining digital transformation: Results from expert interviews’, *Government Information Quarterly*, 36(4), p. 101385. Available at: https://doi.org/10.1016/j.giq.2019.06.002.

Mesquitela, J., Elvas, L.B., Ferreira, J.C. and Nunes, L. (2022) ‘Data Analytics Process over Road Accidents Data—A Case Study of Lisbon City’, *ISPRS International Journal of Geo-Information*, 11(2), p. 143. Available at: https://doi.org/10.3390/ijgi11020143.

Meydani, E. (2017) ‘Role of Information and Communication Technologies in Government Effectiveness’, in *Proceedings of the 10th International Conference on Theory and Practice of Electronic Governance*. New York, NY, USA: ACM, pp. 494–503. Available at: https://doi.org/10.1145/3047273.3047311.

Miller, J.S. (2000) ‘Geographic Information Systems: Unique Analytic Capabilities for the Traffic Safety Community’, *Transportation Research Record: Journal of the Transportation Research Board*, 1734(1), pp. 21–28. Available at: https://doi.org/10.3141/1734-04.

Mills, D.E., Pudney, S., Pevcin, P. and Dvorak, J. (2021) ‘Evidence-Based Public Policy Decision-Making in Smart Cities: Does Extant Theory Support Achievement of City Sustainability Objectives?’, *Sustainability* [Preprint]. Available at: https://doi.org/10.3390/su14010003.

Mîndrilă, D. (2010) ‘Maximum Likelihood (ML) and Diagonally Weighted Least Squares (DWLS) Estimation Procedures: A Comparison of Estimation Bias with Ordinal and Multivariate Non-Normal Data’, *International Journal for Digital Society*, 1(1), pp. 60–66. Available at: https://doi.org/10.20533/ijds.2040.2570.2010.0010.

Mintzberg, H., Raisinghani, D. and Theoret, A. (1976) ‘The Structure of “Unstructured” Decision Processes’, *Administrative Science Quarterly*, 21(2), p.

246. Available at: https://doi.org/10.2307/2392045.

Mitchell, T.M. and Mitchell, T.M. (1997) *Machine learning*. McGraw-hill New York.

Mitieka, D., Luke, R., Twinomurinzi, H. and Mageto, J. (2023) 'Smart Mobility in Urban Areas: A Bibliometric Review and Research Agenda', *Sustainability*, 15(8), p. 6754. Available at: https://doi.org/10.3390/su15086754.

Mittal, P. (2020) 'Impact of Digital Capabilities and Technology Skills on Effectiveness of Government in Public Services', in *2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI)*. IEEE, pp. 1–5. Available at: https://doi.org/10.1109/ICDABI51230.2020.9325647.

Mlekus, L., Bentler, D., Paruzel, A., Kato-Beiderwieden, A.L. and Maier, G.W. (2020) 'How to raise technology acceptance: user experience characteristics as technology-inherent determinants', *Gruppe. Interaktion. Organisation. Zeitschrift fur Angewandte Organisationspsychologie*, 51(3), pp. 273–283. Available at: https://doi.org/10.1007/s11612-020-00529-7.

Mohammed, F., Ibrahim, O., Nilashi, M. and Alzurqa, E. (2017) 'Cloud computing adoption model for e-government implementation', *Information Development*, 33(3), pp. 303–323. Available at: https://doi.org/10.1177/0266666916656033.

Mohammed, S., Alkhereibi, A.H., Abulibdeh, A., Jawarneh, R.N. and Balakrishnan, P. (2023) 'GIS-based spatiotemporal analysis for road traffic crashes; in support of sustainable transportation Planning', *Transportation Research Interdisciplinary Perspectives*, 20, p. 100836. Available at: https://doi.org/10.1016/j.trip.2023.100836.

Mohan, D. and Bhalla, K. (2016) 'Traffic safety: Emerging concerns for low and middle income countries', *Journal of the Australasian College of Road Safety*, 27(2), pp. 9–17.

Montana, E., Nagin, D.S., Neil, R. and Sampson, R.J. (2023) 'Cohort bias in predictive risk assessments of future criminal justice system involvement', *Proceedings of the National Academy of Sciences*, 120(23). Available at: https://doi.org/10.1073/pnas.2301990120.

Monteiro, D., Ma, T., Li, Y., Pan, Z. and Liang, H.N. (2022) 'Cross-cultural factors influencing the adoption of virtual reality for practical learning', *Universal Access in the Information Society* [Preprint], (0123456789). Available at: https://doi.org/10.1007/s10209-022-00947-y.

Montella, A., Chiaradonna, S., Criscuolo, G. and De Martino, S. (2017) 'Perspectives of a web-based software to improve crash data quality and reliability in Italy', in *2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS)*. IEEE, pp. 451–456. Available at: https://doi.org/10.1109/MTITS.2017.8005714.

Moore, G.C. and Benbasat, I. (1991) 'Development of an instrument to measure the perceptions of adopting an information technology innovation', *Information Systems Research*, 2(3), pp. 192–222. Available at: https://doi.org/10.1287/ISRE.2.3.192.

Moore, J.M. and Shipman, F.M. (2000) 'A comparison of questionnaire-based and GUI-based requirements gathering', in *Proceedings ASE 2000. Fifteenth IEEE International Conference on Automated Software Engineering*. IEEE, pp. 35–43. Available at: https://doi.org/10.1109/ASE.2000.873648.

Morgan, D.L. (1997) *Focus Groups as Qualitative Research*, *Focus groups as qualitative research*. 2455 Teller Road, Thousand Oaks California 91320 United States of America: SAGE Publications, Inc. (Qualitative research methods, Vol. 16.). Available at: https://doi.org/10.4135/9781412984287.

Morita, H. and Kannari, K. (2016) 'Reliability and Validity Assessment of an Apathy Scale for Home-Care Patients With Parkinson's Disease: A Structural Equation Modeling Analysis', *Journal of Physical Therapy Science* [Preprint]. Available at: https://doi.org/10.1589/jpts.28.1724.

Morris, J. and Farrell, C. (2007) 'The "post-bureaucratic" public sector organization. New organizational forms and HRM in ten UK public sector organizations', *The International Journal of Human Resource Management*, 18(9), pp. 1575–1588. Available at: https://doi.org/10.1080/09585190701570544.

Morte-Nadal, T. and Esteban-Navarro, M.A. (2022) 'Digital Competences for Improving Digital Inclusion in E-Government Services: A Mixed-Methods Systematic Review Protocol', *International Journal of Qualitative Methods*, 21, p. 160940692110709. Available at: https://doi.org/10.1177/16094069211070935.

Mosweu, O. and Bwalya, K.J. (2018) 'A multivariate analysis of the determinants for adoption and use of the Document Workflow Management System in Botswana ' s public sector', 84(2), pp. 27–38. Available at: https://doi.org/10.7553/84-2-1767.

Mosweu, O., Bwalya, K.J. and Mutshewa, A. (2017) 'A probe into the factors for adoption and usage of electronic document and records management systems in the Botswana context', *Information Development*, 33(1), pp. 97–110. Available at: https://doi.org/10.1177/0266666916640593.

Mowatt, R. (2023) 'Fear City, Cop City and Other Tales, a Call for Police Research', *Leisure Sciences*, pp. 1–23. Available at: https://doi.org/10.1080/01490400.2023.2270981.

Mukhopadhyay, A., Zhang, C., Vorobeychik, Y., Tambe, M., Pence, K. and Speer, P. (2016) 'Optimal allocation of police patrol resources using a continuous-time crime model', in *Decision and Game Theory for Security: 7th International Conference, GameSec 2016, New York, NY, USA, November 2-4, 2016, Proceedings 7*. Springer, pp. 139–158.

Mulaik, S.A., James, L.C., Alstine, J. Van, Bennett, N.J., Lind, S.K. and Stilwell, C.D. (1989) 'Evaluation of Goodness-of-Fit Indices for Structural Equation Models.', *Psychological Bulletin* [Preprint]. Available at: https://doi.org/10.1037/0033-2909.105.3.430.

Müller, A.P.R. and Steen, T. (2019) 'Behind the Scenes of Coproduction of Smart

Mobility: Evidence From a Public Values’ Perspective’. Available at: https://doi.org/10.1007/978-3-030-27325-5_26.

Müller, A.R., Park, J. and Sonn, J.W. (2023) ‘Finding the old in the new: Smart cities in the national and local trajectories of urban development’, *International Journal of Urban Sciences*, 27(sup1), pp. 1–9. Available at: https://doi.org/10.1080/12265934.2022.2153472.

Mumford, A. (1995) ‘Learning in action’, *Industrial and Commercial Training*, 27(8), pp. 36–40. Available at: https://doi.org/10.1108/00197859510097081.

Muñoz van den Eynde, A. and Lobera, J. (2022) ‘Analysis of the tendency to select the “neither nor” option in agreement/disagreement scales on a low – salience topic: The contribution of individual differences’, *Methodological Innovations*, 15(3), pp. 289–302. Available at: https://doi.org/10.1177/20597991221127407.

Musa, A.A., Malami, S.I., Alanazi, F., Ounaies, W., Alshammari, M. and Haruna, S.I. (2023) ‘Sustainable Traffic Management for Smart Cities Using Internet-of-Things-Oriented Intelligent Transportation Systems (ITS): Challenges and Recommendations’, *Sustainability*, 15(13), p. 9859. Available at: https://doi.org/10.3390/su15139859.

Mussah, A.R. and Adu-Gyamfi, Y. (2022) ‘Machine Learning Framework for Real-Time Assessment of Traffic Safety Utilizing Connected Vehicle Data’, *Sustainability*, 14(22), p. 15348. Available at: https://doi.org/10.3390/su142215348.

Muthén, B. (1984) ‘Graduate school of education university of california los angeles, california’, *Psychometrika*, 49(1), pp. 115–132.

Muthu, P., Chelliah, P., Thurasamy, R., Alzahrani, A.I., Alfarraj, O. and Alalwan, N. (2016) ‘E-Government service delivery by a local government agency: The case of E-Licensing’, *Telematics and Informatics*, 33(4), pp. 925–935. Available at: https://doi.org/10.1016/j.tele.2016.02.003.

Myers, G. and Lampropoulou, S. (2013) ‘What place references can do in social research interviews’, *Discourse Studies*, 15(3), pp. 333–351. Available at: https://doi.org/10.1177/1461445613480589.

Nadi, P.A. and Murad, A.K. (2019) ‘Modelling Sustainable Urban Transport Performance in the Jakarta city Region: A GIS Approach’, *Sustainability*, 11(7), p. 1879. Available at: https://doi.org/10.3390/SU11071879.

Naeem, M., Ozuem, W., Howell, K. and Ranfagni, S. (2023) ‘A Step-by-Step Process of Thematic Analysis to Develop a Conceptual Model in Qualitative Research’, *International Journal of Qualitative Methods*, 22. Available at: https://doi.org/10.1177/16094069231205789.

Al Najada, H. and Mahgoub, I. (2016) ‘Big vehicular traffic Data mining: Towards accident and congestion prevention’, in *2016 International Wireless Communications and Mobile Computing Conference (IWCMC)*. IEEE, pp. 256–261. Available at: https://doi.org/10.1109/IWCMC.2016.7577067.

Nakano, Y., Okamura, K., Kosuge, R., Kihira, M. and Fujita, G. (2019) ‘Effect of visible presence of policing activities on drivers’ vigilance and intention to refrain from non-driving activities: A scenario-based survey of general Japanese drivers’, *Accident Analysis & Prevention*, 133, p. 105293. Available at: https://doi.org/10.1016/j.aap.2019.105293.

Nakash, R.A., Hutton, J.L., Jørstad-Stein, E.C., Gates, S. and Lamb, S.E. (2006) ‘Maximising Response to Postal Questionnaires – A Systematic Review of Randomised Trials in Health Research’, *BMC Medical Research Methodology* [Preprint]. Available at: https://doi.org/10.1186/1471-2288-6-5.

Nam, H., Nam, T., Oh, M. and Choi, S. (2022) ‘An Efficiency Measurement of E-Government Performance for Network Readiness: Non-Parametric Frontier Approach’, *Journal of Open Innovation: Technology, Market, and Complexity*, 8(1), p. 10. Available at: https://doi.org/10.3390/joitmc8010010.

Nam, T. and Pardo, T.A. (2011) ‘Conceptualizing smart city with dimensions of technology, people, and institutions’, *ACM International Conference Proceeding*

Series, (February 2014), pp. 282–291. Available at: https://doi.org/10.1145/2037556.2037602.

Naveed, Q.N., Alqahtani, H., Khan, R.U., Almakdi, S., Alshehri, M. and Abdul Rasheed, M.A. (2022) 'An Intelligent Traffic Surveillance System Using Integrated Wireless Sensor Network and Improved Phase Timing Optimization', *Sensors*, 22(9), p. 3333. Available at: https://doi.org/10.3390/s22093333.

Nawaratne, R., Kahawala, S., Nguyen, S. and De Silva, D. (2021) 'A Generative Latent Space Approach for Real-Time Road Surveillance in Smart Cities', *IEEE Transactions on Industrial Informatics*, 17(7), pp. 4872–4881. Available at: https://doi.org/10.1109/TII.2020.3037286.

Naziz, A. (2021) 'Sharing tacit knowledge in public sector ':, *Bangladesh Journal of Public Administration*, 29(2), pp. 87–101. Available at: https://doi.org/10.36609/bjpa.v29i2.209.

NCSA (2018) 'Overview, NHTSA's National Center for Statistics and Analysis', *Traffic Safety Facts–Research Note, DOT HS*, p. 603.

Nebeling, M. and Norrie, M.C. (2013) 'Responsive design and development: methods, technologies and current issues', in *Web Engineering: 13th International Conference, ICWE 2013, Aalborg, Denmark, July 8-12, 2013. Proceedings 13*. Springer, pp. 510–513.

Neelu, L. and Kavitha, D. (2021) 'Estimation of software quality parameters for hybrid agile process model', *SN Applied Sciences*, 3, pp. 1–11.

Neetu Kumari, S. and Pillai, A.S. (2013) 'A survey on global requirements elicitation issues and proposed research framework', in *2013 IEEE 4th International Conference on Software Engineering and Service Science*. IEEE, pp. 554–557. Available at: https://doi.org/10.1109/ICSESS.2013.6615370.

Nehls, K., Smith, B.D. and Schneider, H.A. (2014) 'Video-conferencing interviews in qualitative research', *Enhancing Qualitative and Mixed Methods Research with Technology*, (January), pp. 140–157. Available at:

https://doi.org/10.4018/978-1-4666-6493-7.ch006.

Neirotti, P., De Marco, A., Cagliano, A.C., Mangano, G. and Scorrano, F. (2014) ‘Current trends in smart city initiatives: Some stylised facts’, *Cities*, 38, pp. 25–36. Available at: https://doi.org/10.1016/j.cities.2013.12.010.

Nelson, R.R., Kattan, M.W. and Cheney, P.H. (1991) ‘An empirical re-examination of the relationship among training, ability, and the acceptance of information technology’, in *Proceedings of the 1991 conference on SIGCPR*, pp. 177–186.

Neumann, O., Guirguis, K. and Steiner, R. (2024) ‘Exploring artificial intelligence adoption in public organizations: a comparative case study’, *Public Management Review*, 26(1), pp. 114–141. Available at: https://doi.org/10.1080/14719037.2022.2048685.

Nevo, B. (1985) ‘Face validity revisited’, *Journal of educational measurement*, 22(4), pp. 287–293.

De Neys, W. (2010) ‘Heuristic Bias, Conflict, and Rationality in Decision-Making’, in, pp. 23–33. Available at: https://doi.org/10.1007/978-3-642-03129-8_2.

Nguyen-Van, P., Stenger, A. and Tiet, T. (2021) ‘Social Incentive Factors in Interventions Promoting Sustainable Behaviors: A Meta-Analysis’, *Plos One* [Preprint]. Available at: https://doi.org/10.1371/journal.pone.0260932.

NHTSA (2021) ‘NHTSA Releases 2020 Traffic Crash Fatality Data _ FARS _ NHTSA’.

Nichols, A.L. and Maner, J.K. (2008) ‘The Good-Subject Effect: Investigating Participant Demand Characteristics’, *The Journal of General Psychology*, 135(2), pp. 151–166. Available at: https://doi.org/10.3200/GENP.135.2.151-166.

Nicolaï, I. and Boennec, R. Le (2018) ‘Smart Mobility Providing Smart Cities’. Available at: https://doi.org/10.1007/978-3-319-79060-2_7.

Al Nidawy, B.Q., Sidek, S., Al-Shami, S.A. and Elzamly, A. (2020) ‘E-government trust model (egov-trust) that enhances the usage of e-government services among users in iraq', *Journal of Theoretical and Applied Information Technology*, 98(3), pp. 402–418.

Nielsen, J. (1993) *Usability Engineering*. Elsevier. Available at: https://doi.org/10.1016/C2009-0-21512-1.

Nikou, S. and Aavakare, M. (2021) 'An assessment of the interplay between literacy and digital Technology in Higher Education', *Education and Information Technologies*, 26(4), pp. 3893–3915. Available at: https://doi.org/10.1007/s10639-021-10451-0.

Norman, D.A. and Draper, S.W. (1986) 'User centered system design: New perspectives on human-computer interaction'.

Noshad, M., Choi, J., Sun, Y., Hero, A. and Dinov, I.D. (2021) 'A data value metric for quantifying information content and utility', *Journal of Big Data*, 8(1), p. 82. Available at: https://doi.org/10.1186/s40537-021-00446-6.

Nuaimi, E. Al, Neyadi, H. Al, Mohamed, N. and Al-Jaroodi, J. (2015) 'Applications of Big Data to Smart Cities', *Journal of Internet Services and Applications* [Preprint]. Available at: https://doi.org/10.1186/s13174-015-0041-5.

Nulty, D.D. (2008) 'The Adequacy of Response Rates to Online and Paper Surveys: What Can Be Done?', *Assessment & Evaluation in Higher Education* [Preprint]. Available at: https://doi.org/10.1080/02602930701293231.

Nunes, N., Adamo, G., Ribeiro, M., Gouveia, B.R., Rubio Gouveia, E., Teixeira, P. and Nisi, V. (2022) 'Modeling Adoption, Security, and Privacy of COVID-19 Apps: Findings and Recommendations From an Empirical Study Using the Unified Theory of Acceptance and Use of Technology', *JMIR Human Factors*, 9(3), pp. 1–21. Available at: https://doi.org/10.2196/35434.

Nurdin, N., Stockdale, R. and Scheepers, H. (2010) 'Examining the role of the culture of local government on adoption and use of e-government services', in *International Conference on E-Government and E-Services*. Springer, pp. 79–93.

Available at: https://doi.org/10.1007/978-3-642-15346-4_7.

Nurhumam, S.D. and Mahmudy, W.F. (2008) 'Optimasi multi travelling salesman problem (M-TSP) pada mobil patroli polisi dengan algoritma heuristic assignment Fisher-Jaikumar dan algoritma A', *Jurnal Ilmiah Kursor*, 4(1).

Obasi, J.E. (2018) 'Police officers' perceptions of body-worn camera technology', *Dissertation Abstracts International: Section B: The Sciences and Engineering*, 79(5-). Available at: http://search.ebscohost.com/login.aspx?direct=true&db=psyh&AN=2018-13260-283&site=ehost-live&scope=site.

Oberender, P., Ruckdäschel, S., Lugauer, S. and Guggenbichler, J.-P. (1999) 'Economic aspects of innovations in medical technology', *Infection*, 27(S1), pp. S78–S80. Available at: https://doi.org/10.1007/BF02561625.

Oberwittler, D. and Roché, S. (2022) 'How institutional contexts shape police-adolescent encounters. A study of France and Germany', *Policing and Society*, 32(3), pp. 378–410. Available at: https://doi.org/10.1080/10439463.2022.2037553.

Obienu, A.C. and Amadin, F.I. (2021) 'User acceptance of learning innovation: A structural equation modelling based on the GUAM framework', *Education and Information Technologies*, 26(2), pp. 2091–2123. Available at: https://doi.org/10.1007/s10639-020-10341-x.

Oeberst, A. and Imhoff, R. (2023) 'Toward Parsimony in Bias Research: A Proposed Common Framework of Belief-Consistent Information Processing for a Set of Biases', *Perspectives on Psychological Science*, 18(6), pp. 1464–1487. Available at: https://doi.org/10.1177/17456916221148147.

OECD/ITF (2016) 'Data-driven Transport Policy. International Transport Forum's Corporate Partnership Board (CPB).', pp. 1–40.

OECD (2022) 'Using Private Sector Geospatial Data to Inform Policy'. Available at: https://doi.org/https://doi.org/10.1787/242f51b8-en.

Okimoto, T.G., Hornsey, M.J. and Wenzel, M. (2019) ‘The power of grassroots expressions of remorse for promoting intergroup forgiveness’, *Journal of Experimental Social Psychology*, 80, pp. 39–51.

de Oliveira, Á., Campolargo, M. and Martins, M. (2015) ‘Constructing Human Smart Cities’, in, pp. 32–49. Available at: https://doi.org/10.1007/978-3-319-27753-0_3.

Olokun, M.S., Ipindola, O.O., Oyediji, F.T. and Falana, J.N. (2022) ‘Development of Deep Neural Network Model for the Prediction of Road Crashes in Real Time’, *Journal of Engineering Research and Reports* [Preprint]. Available at: https://doi.org/10.9734/jerr/2022/v22i1017570.

Olphert, W. and Damodaran, L. (2013) ‘Older people and digital disengagement: a fourth digital divide?’, *Gerontology*, 59(6), pp. 564–570.

Olson, D.G. and Wright, G.P. (1975) ‘Models for Allocating Police Preventive Patrol Effort’, *Journal of the Operational Research Society*, 26(4), pp. 703–715. Available at: https://doi.org/10.1057/jors.1975.150.

Olsson, U. (1979) ‘Maximum likelihood estimation of the polychoric correlation coefficient’, *Psychometrika*, 44(4), pp. 443–460. Available at: https://doi.org/10.1007/BF02296207.

Onwuegbuzie, A.J., Dickinson, W.B., Leech, N.L. and Zoran, A.G. (2009) ‘A Qualitative Framework for Collecting and Analyzing Data in Focus Group Research’, *International Journal of Qualitative Methods* [Preprint]. Available at: https://doi.org/10.1177/160940690900800301.

Onyshchuk, S., Filippova, V., Borshch, H., Vasylchyshyn, O. and Iakobchuuk, V. (2020) ‘Innovative solutions of improving efficiency in public management’, *Revista San Gregorio*, 42, pp. 215–223.

Oviedo-Trespalacios, O., Truelove, V., Watson, B. and Hinton, J.A. (2019) ‘The impact of road advertising signs on driver behaviour and implications for road safety: A critical systematic review’, *Transportation Research Part A: Policy and*

Practice, 122, pp. 85–98. Available at: https://doi.org/10.1016/j.tra.2019.01.012.

Paderno, A., Gennarini, F., Sordi, A., Montenegro, C.T., Lancini, D., Villani, F.P., Moccia, S. and Piazza, C. (2022) 'Artificial Intelligence in Clinical Endoscopy: Insights in the Field of Videomics', *Frontiers in Surgery* [Preprint]. Available at: https://doi.org/10.3389/fsurg.2022.933297.

Pallot, M., Pawar, K., Krawczyk, P., Topolewski, M., Lecossier, A. and Razek, A.R.A. (2020) 'Evaluating user experience as a means to reveal the potential adoption of innovative ideas', in *2020 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC)*. IEEE, pp. 1–11.

Pang, C., Collin Wang, Z., McGrenere, J., Leung, R., Dai, J. and Moffatt, K. (2021) 'Technology Adoption and Learning Preferences for Older Adults':, in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. New York, NY, USA: ACM, pp. 1–13. Available at: https://doi.org/10.1145/3411764.3445702.

Pang, H. (2023) 'Discussing "Tacit Knowledge" Again', *Journal of Education, Humanities and Social Sciences*, 14, pp. 65–70. Available at: https://doi.org/10.54097/ehss.v14i.8798.

Papadomichelaki, X. and Mentzas, G. (2012) 'E-GovQual: A multiple-item scale for assessing e-government service quality', *Government Information Quarterly*, 29(1), pp. 98–109. Available at: https://doi.org/10.1016/j.giq.2011.08.011.

Parappallil Mathew, B. and Bangwal, D. (2024) 'People centric governance model for smart cities development: A systematic review, thematic analysis, and findings', *Research in Globalization*, 9, p. 100237. Available at: https://doi.org/10.1016/j.resglo.2024.100237.

Pardo, T.A., Nam, T. and Burke, G.B. (2012) 'E-Government Interoperability', *Social Science Computer Review*, 30(1), pp. 7–23. Available at: https://doi.org/10.1177/0894439310392184.

Park, Y.S., Konge, L. and Artino, A.R. (2020) 'The Positivism Paradigm of Research', *Academic Medicine*, 95(5), pp. 690–694. Available at: https://doi.org/10.1097/ACM.0000000000003093.

Parmenter, K. and Wardle, J. (1999) 'Development of a General Nutrition Knowledge Questionnaire for Adults', *European Journal of Clinical Nutrition* [Preprint]. Available at: https://doi.org/10.1038/sj.ejcn.1600726.

Paskaleva, K., Evans, J., Martin, C.B., Linjordet, T., Yang, D. and Karvonen, A. (2017) 'Data Governance in the Sustainable Smart City', *Informatics* [Preprint]. Available at: https://doi.org/10.3390/informatics4040041.

Pastushenko, O., Hynek, J. and Hruška, T. (2021) 'Evaluation of user interface design metrics by generating realistic-looking dashboard samples', *Expert Systems*, 38(5). Available at: https://doi.org/10.1111/exsy.12434.

Patel, J., Gershoni, G., Krishnan, S., Nelimarkka, M., Nonnecke, B. and Goldberg, K. (2015) 'A Case Study in Mobile-Optimized vs. Responsive Web Application Design', in *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct*. New York, NY, USA: ACM, pp. 576–581. Available at: https://doi.org/10.1145/2786567.2787135.

Pathirage, C., Amaratunga, R. and Haigh, R. (2007) 'Tacit Knowledge and Organisational Performance: Construction Industry Perspective', *Journal of Knowledge Management* [Preprint]. Available at: https://doi.org/10.1108/13673270710728277.

Patriot, T. (2023) 'Effectiveness of Integrated Traffic Management of Military Police and Traffic Police in Reducing Drive Speed n Arterial Roads: An Experimental Study', *CSID Journal of Infrastructure Development*, 6(1). Available at: https://doi.org/10.7454/jid.v6.i1.1075.

Pauwels, K., Ambler, T., Clark, B.H., LaPointe, P., Reibstein, D., Skiera, B., Wierenga, B. and Wiesel, T. (2009) 'Dashboards as a Service', *Journal of Service Research*, 12(2), pp. 175–189. Available at:

https://doi.org/10.1177/1094670509344213.

Pavlov, G., Maydeu-Olivares, A. and Shi, D. (2020) ‘Using the Standardized Root Mean Squared Residual (SRMR) to Assess Exact Fit in Structural Equation Models’, *Educational and Psychological Measurement* [Preprint]. Available at: https://doi.org/10.1177/0013164420926231.

Pech, R.M. (2015) ‘Achieving the innovative edge in technology, engineering design, and entrepreneurship’, *Journal of Innovation and Entrepreneurship*, 5(1), p. 6. Available at: https://doi.org/10.1186/s13731-016-0035-y.

Peng, G.C.A., Nunes, M.B. and Zheng, L. (2017) ‘Impacts of low citizen awareness and usage in smart city services: the case of London’s smart parking system’, *Information Systems and e-Business Management*, 15(4), pp. 845–876. Available at: https://doi.org/10.1007/s10257-016-0333-8.

Pereira, G.V., Parycek, P., Falco, E. and Kleinhans, R. (2018) ‘Smart governance in the context of smart cities: A literature review’, *Information Polity*. Edited by S.A. Chun, N.R. Adam, and B. Noveck, 23(2), pp. 143–162. Available at: https://doi.org/10.3233/IP-170067.

Perera, C., Zaslavsky, A., Christen, P. and Georgakopoulos, D. (2013) ‘Sensing as a Service Model for Smart Cities Supported by Internet of Things’, *Transactions on Emerging Telecommunications Technologies* [Preprint]. Available at: https://doi.org/10.1002/ett.2704.

Pérez-Morote, R., Pontones-Rosa, C. and Núñez-Chicharro, M. (2020) ‘The effects of e-government evaluation, trust and the digital divide in the levels of e-government use in European countries’, *Technological Forecasting and Social Change*, 154(February), p. 119973. Available at: https://doi.org/10.1016/j.techfore.2020.119973.

Perrier, E. (2022) ‘The Quantum Governance Stack: Models of Governance for Quantum Information Technologies’, *Digital Society* [Preprint]. Available at: https://doi.org/10.1007/s44206-022-00019-x.

Pettersson, E. and Turkheimer, E. (2010) ‘Item selection, evaluation, and simple structure in personality data’, *Journal of Research in Personality*, 44(4), pp. 407–420. Available at: https://doi.org/10.1016/j.jrp.2010.03.002.

Pickard, A.J. (2013) *Research methods in information*. Facet publishing.

Pillow, W.S. (2003) ‘Confession, catharsis, or cure? Rethinking the uses of reflexivity as methodological power in qualitative research’, *International Journal of Qualitative Studies in Education*, 16(2), pp. 175–196. Available at: https://doi.org/10.1080/0951839032000060635.

Pliatsios, A., Kotis, K. and Goumopoulos, C. (2023) ‘A systematic review on semantic interoperability in the IoE-enabled smart cities’, *Internet of Things*, 22, p. 100754. Available at: https://doi.org/10.1016/j.iot.2023.100754.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y.Y. and Podsakoff, N.P. (2003) ‘Common method biases in behavioral research: A critical review of the literature and recommended remedies.’, *Journal of Applied Psychology*, 88(5), pp. 879–903. Available at: https://doi.org/10.1037/0021-9010.88.5.879.

Pohl, R.F., Erdfelder, E., Hilbig, B.E., Liebke, L. and Stahlberg, D. (2013) ‘Effort reduction after self-control depletion: The role of cognitive resources in use of simple heuristics’, *Journal of Cognitive Psychology*, 25(3), pp. 267–276. Available at: https://doi.org/10.1080/20445911.2012.758101.

Polanyi, M. (1962) ‘Tacit Knowing: Its Bearing on Some Problems of Philosophy’, *Reviews of Modern Physics*, 34(4), p. 601. Available at: https://doi.org/10.1103/RevModPhys.34.601.

Polit, D.F. and Beck, C.T. (2010) ‘Generalization in quantitative and qualitative research: Myths and strategies’, *International Journal of Nursing Studies*, 47(11), pp. 1451–1458. Available at: https://doi.org/10.1016/j.ijnurstu.2010.06.004.

Posit (2023) *Shiny - Hosting and deployment*, *Posit.co*. Available at: https://shiny.posit.co/r/deploy.

Pourroostaei Ardakani, S., Liang, X., Mengistu, K.T., So, R.S., Wei, X., He, B. and Cheshmehzangi, A. (2023) ‘Road Car Accident Prediction Using a Machine-Learning-Enabled Data Analysis’, *Sustainability*, 15(7), p. 5939. Available at: https://doi.org/10.3390/su15075939.

Praharaj, S., Solís, P. and Wentz, E.A. (2022) ‘Deploying Geospatial Visualization Dashboards to Combat the Socioeconomic Impacts of COVID-19’, *Environment and Planning B Urban Analytics and City Science* [Preprint]. Available at: https://doi.org/10.1177/23998083221142863.

Prakash, P., Suresh, R. and Pn, D.K. (2019) ‘Smart city video surveillance using fog computing’, *International Journal of Enterprise Network Management*, 10(3–4), pp. 389–399.

Presser, S., Couper, M.P., Lessler, J.T., Martin, E., Martin, J., Rothgeb, J.M. and Singer, E. (2004) ‘Methods for Testing and Evaluating Survey Questions’, *Public Opinion Quarterly*, 68(1), pp. 109–130. Available at: https://doi.org/10.1093/poq/nfh008.

Procaccino, J.D., Verner, J.M., Overmyer, S.P. and Darter, M.E. (2002) ‘Case study: factors for early prediction of software development success’, *Information and software technology*, 44(1), pp. 53–62.

Provost, F. and Fawcett, T. (2013) ‘Data Science and its Relationship to Big Data and Data-Driven Decision Making’, *Big Data*, 1(1), pp. 51–59. Available at: https://doi.org/10.1089/big.2013.1508.

Pu, S., Rutzinger, M., Vosselman, G. and Oude Elberink, S. (2011) ‘Recognizing basic structures from mobile laser scanning data for road inventory studies’, *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(6), pp. S28–S39. Available at: https://doi.org/10.1016/j.isprsjprs.2011.08.006.

Puron-Cid, G. and Gil-Garcia, J.R. (2022) ‘Are Smart Cities Too Expensive in the Long Term? Analyzing the Effects of ICT Infrastructure on Municipal Financial Sustainability’, *Sustainability*, 14(10), p. 6055. Available at: https://doi.org/10.3390/su14106055.

Purves, D. (2022) ‘Fairness in Algorithmic Policing’, *Journal of the American Philosophical Association*, 8(4), pp. 741–761. Available at: https://doi.org/10.1017/apa.2021.39.

Puspasari, M.A., Madani, S.T., Iqbal, B.M., Muslim, E., Sanjaya, B.P., Pribadyo, C.Y.P., Junistya, K.N., Ghanny, A., Syaifullah, D.H. and Arista, S.A. (2023) ‘Effect of Distraction and Driving Behaviour to Traffic Accidents in Jakarta Using Partial Least Squares Structural Equation Modeling (PLS-SEM)’, *International Journal of Technology*, 14(7), p. 1548. Available at: https://doi.org/10.14716/ijtech.v14i7.6676.

Qin, X., Parker, S., Liu, Y., Graettinger, A.J. and Forde, S. (2013) ‘Intelligent geocoding system to locate traffic crashes’, *Accident Analysis & Prevention*, 50, pp. 1034–1041. Available at: https://doi.org/10.1016/j.aap.2012.08.007.

Qu, L. and Weston, R. (2015) ‘Keeping up with information and communication technology’.

Qualtrics (2021) ‘Qualtrics XM // The Leading Experience Management Software’, *Qualtrics* [Preprint].

Qun, Z. and Carey, N. (2024) ‘Translating Interviews, interpreting lives: bi-lingual research analysis informing less westernised views of international student mobility’, *Qualitative Research*, 24(2), pp. 324–343. Available at: https://doi.org/10.1177/14687941221149588.

R Core Team (2021) ‘R: A language and environment for statistical computing’. Available at: https://www.r-project.org/.

Ragnoli, A., De Blasiis, M. and Di Benedetto, A. (2018) ‘Pavement Distress Detection Methods: A Review’, *Infrastructures*, 3(4), p. 58. Available at: https://doi.org/10.3390/infrastructures3040058.

Rahmadiyani, R. and Widyanti, A. (2023) ‘Prevalence of drowsy driving and modeling its intention: An Indonesian case study’, *Transportation Research Interdisciplinary Perspectives*, 19, p. 100824. Available at:

https://doi.org/10.1016/j.trip.2023.100824.

Rahman, M.S. (2020) ‘The advantages and disadvantages of using qualitative and quantitative approaches and methods in language “testing and assessment” research: A literature review’.

Raimondo, E. and Newcomer, K.E. (2017) ‘Mixed-Methods Inquiry in Public Administration: The Interaction of Theory, Methodology, and Praxis’, *Review of Public Personnel Administration*, 37(2), pp. 183–201. Available at: https://doi.org/10.1177/0734371X17697247.

Rajiv, B., Roshan, K. and Sankaradass, V. (2023) ‘Assessing The Impact of Bias in Training Data on the Fairness and Equity of Predictive Policing Models’, in *2023 International Conference on Data Science, Agents & Artificial Intelligence (ICDSAAI)*. IEEE, pp. 1–5. Available at: https://doi.org/10.1109/ICDSAAI59313.2023.10452490.

Ramya, S., Reshma, S., Manogna, V.D., Saroja, Y.S. and Gandhi, G.S. (2019) ‘Accident Severity Prediction Using Data Mining Methods’, *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, pp. 528–536. Available at: https://doi.org/10.32628/CSEIT195293.

Rana, N.P., D Williams, M. and Kumar Dwivedi, Y. (2012) ‘E-government adoption research: A meta-analysis of findings’.

Rana, N.P., Dwivedi, Y.K. and Williams, M.D. (2013) ‘E-government adoption research: an analysis of the employee’s perspective’, *International Journal of Business Information Systems*, 14(4), p. 414. Available at: https://doi.org/10.1504/IJBIS.2013.057497.

Ranchordas, S. (2020) ‘The Digitalization of Government and Digital Exclusion: Setting the Scene’, *SSRN Electronic Journal* [Preprint]. Available at: https://doi.org/10.2139/ssrn.3663051.

Rasyid, A. and Alfina, I. (2017) ‘E-Service Quality Evaluation on E-Government Website: Case Study BPJS Kesehatan Indonesia’, in *Journal of Physics:*

Conference Series. Available at: https://doi.org/10.1088/1742-6596/801/1/012036.

Rathore, M.M., Attique Shah, S., Awad, A., Shukla, D., Vimal, S. and Paul, A. (2021) 'A Cyber-Physical System and Graph-Based Approach for Transportation Management in Smart Cities', *Sustainability*, 13(14), p. 7606. Available at: https://doi.org/10.3390/su13147606.

Ravani, B. and Wang, C. (2018) 'Speeding in highway work zone: An Evaluation of methods of speed control', *Accident Analysis & Prevention*, 113, pp. 202–212. Available at: https://doi.org/10.1016/j.aap.2018.01.030.

Ravinder, E.B. and Saraswathi, A.B. (2020) 'Literature Review Of Cronbach alpha coefficient (Α) And Mcdonald's Omega Coefficient (Ω)', *European Journal of Molecular & Clinical Medicine*, 7(6), pp. 2943–2949. Available at: https://www.researchgate.net/publication/350577633.

Ravishankar, M.N. (2013) 'Public ICT Innovations: A Strategic Ambiguity Perspective', *Journal of Information Technology*, 28(4), pp. 316–332. Available at: https://doi.org/10.1057/jit.2013.18.

Razia, S. and Binti Abu Bakar Ah, S.H. (2022) 'Panoramic Mapping of Urban Social Sustainability: A 35-Year Bibliometric and Visualization Analysis', *Journal of Regional and City Planning*, 33(2), pp. 49–78. Available at: https://doi.org/10.5614/jpwk.2022.33.2.4.

Reddick, C.G., Chatfield, A.T. and Jaramillo, P.A. (2015) 'Public opinion on National Security Agency surveillance programs: A multi-method approach', *Government Information Quarterly*, 32(2), pp. 129–141. Available at: https://doi.org/10.1016/j.giq.2015.01.003.

Reeves, T.D. and Li, Z. (2012) 'Teachers' technological readiness for online professional development: evidence from the US e-Learning for Educators initiative', *Journal of Education for Teaching*, 38(4), pp. 389–406. Available at: https://doi.org/10.1080/02607476.2012.707921.

Rehan Anwar, M., Hardini, M. and Anggraeni, M. (2021) ‘Review of Responsive Design Concept Based On Framework Materialize On The Website’, *ADI Journal on Recent Innovation (AJRI)*, 3(1), pp. 59–66. Available at: https://doi.org/10.34306/ajri.v3i1.290.

Rehouma, M. Ben (2017) ‘The impact of participation on Goverment employees’ adoption of IT-Empirical research focusing on e-file’, *INFORMATIK 2017* [Preprint].

Rehouma, M. Ben (2019) ‘Employees’ Participation in IT-Projects in the Public Sector’, *International Journal of Public Administration in the Digital Age*, 6(2), pp. 20–34. Available at: https://doi.org/10.4018/IJPADA.2019040102.

Rehouma, M. Ben (2020) ‘Exploring the Role of Participation in Government Employees’ Adoption of IT’, *International Journal of Public Administration in the Digital Age*, 7(1), pp. 33–46. Available at: https://doi.org/10.4018/IJPADA.2020010103.

Rehouma, M. Ben and Hofmann, S. (2018) ‘Government employees’ adoption of information technology’, in *Proceedings of the 19th Annual International Conference on Digital Government Research: Governance in the Data Age*. New York, NY, USA: ACM, pp. 1–10. Available at: https://doi.org/10.1145/3209281.3209311.

Reinartz, W., Haenlein, M. and Henseler, J. (2009) ‘An empirical comparison of the efficacy of covariance-based and variance-based SEM’, *International Journal of Research in Marketing*, 26(4), pp. 332–344. Available at: https://doi.org/10.1016/j.ijresmar.2009.08.001.

Rennie, K.M. (1997) ‘Exploratory and confirmatory rotation strategies in exploratory factor analysis.’

Rettig, M. (1994) ‘Prototyping for tiny fingers’, *Communications of the ACM*, 37(4), pp. 21–27.

Revelle, W. and Zinbarg, R.E. (2008) ‘Coefficients Alpha, Beta, Omega, and the

Glb: Comments on Sijtsma', *Psychometrika* [Preprint]. Available at: https://doi.org/10.1007/s11336-008-9102-z.

Reza, S., Oliveira, H.S., Machado, J.J.M. and Tavares, J.M.R.S. (2021) 'Urban Safety: An Image-Processing and Deep-Learning-Based Intelligent Traffic Management and Control System', *Sensors*, 21(22), p. 7705. Available at: https://doi.org/10.3390/s21227705.

Rezapour, M., Wulff, S.S. and Ksaibati, K. (2018) 'Effectiveness of enforcement resources in the highway patrol in reducing fatality rates', *IATSS Research*, 42(4), pp. 259–264. Available at: https://doi.org/10.1016/j.iatssr.2018.04.001.

Riaz, Z., Dürr, F. and Rothermel, K. (2015) 'Optimized Location Update Protocols for Secure and Efficient Position Sharing'. Available at: https://doi.org/10.1109/netsys.2015.7089083.

Ribeiro, C., Farinha, C., Pereira, J. and Mira da Silva, M. (2014) 'Gamifying requirement elicitation: Practical implications and outcomes in improving stakeholders collaboration', *Entertainment Computing*, 5(4), pp. 335–345. Available at: https://doi.org/10.1016/j.entcom.2014.04.002.

Richards, D.D.D. (2002) 'Blurring the Distinction between Tacit and Explicit Knowledge', *Journal of Decision Systems*, 11(2), pp. 149–164. Available at: https://doi.org/10.3166/jds.11.149-164.

Richardson, S.M., Courtney, J.F. and Haynes, J.D. (2006) 'Theoretical principles for knowledge management system design: Application to pediatric bipolar disorder', *Decision support systems*, 42(3), pp. 1321–1337.

Richman, M.B. (1986) 'Rotation of Principal Components', *Journal of Climatology* [Preprint]. Available at: https://doi.org/10.1002/joc.3370060305.

Richter Lagha, R., Burningham, Z., Sauer, B.C., Leng, J., Peters, C., Huynh, T., Patel, S., Halwani, A.S. and Kramer, B.J. (2020) 'Usability Testing a Potentially Inappropriate Medication Dashboard: A Core Component of the Dashboard Development Process', *Applied Clinical Informatics*, 11(04), pp. 528–534.

Available at: https://doi.org/10.1055/s-0040-1714693.

Riddell, W.C. and Song, X. (2017) 'The Role of Education in Technology Use and Adoption: Evidence from the Canadian Workplace and Employee Survey', *ILR Review*, 70(5), pp. 1219–1253. Available at: https://doi.org/10.1177/0019793916687719.

Rob, U. and Talukder, N. (2013) 'Urbanization Prospects in Asia: A Six-Country Comparison', *International Quarterly of Community Health Education* [Preprint]. Available at: https://doi.org/10.2190/iq.33.1.c.

Robertson, S.P., Buie, E.A. and Murray, D. (2011) 'Interaction design for citizen engagement and digital government', in *Proceedings of the 12th Annual International Digital Government Research Conference: Digital Government Innovation in Challenging Times*. New York, NY, USA: ACM, pp. 376–377. Available at: https://doi.org/10.1145/2037556.2037634.

Robson, C. (2002) 'Real world research: A resource for social scientists and practitioner-researchers', *(No Title)* [Preprint].

Rocha, N.P., Dias, A., Santinha, G., Rodrigues, M., Queirós, A. and Rodrigues, C. (2019) 'Smart Cities and Public Health: A Systematic Review', *Procedia Computer Science*, 164, pp. 516–523. Available at: https://doi.org/10.1016/j.procs.2019.12.214.

Rodríguez Bolívar, M.P. (2016) 'Characterizing the Role of Governments in Smart Cities: A Literature Review', in, pp. 49–71. Available at: https://doi.org/10.1007/978-3-319-17620-8_3.

Rogers, E.M. (1962) *Diffusion of innovations*, *An Integrated Approach to Communication Theory and Research, Third Edition*. Available at: https://doi.org/10.4324/9780203710753-35.

Roopa, S. and Rani, M.S. (2012) 'Questionnaire designing for a survey', *Journal of Indian Orthodontic Society*, 46(4_suppl1), pp. 273–277.

Rosenfeld, A., Maksimov, O. and Kraus, S. (2017) 'Optimizing Traffic Enforcement: From the Lab to the Roads', *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 10575 LNCS, pp. 3–20. Available at: https://doi.org/10.1007/978-3-319-68711-7_1.

Rosseel, Y. (2012) 'lavaan : An R Package for Structural Equation Modeling', *Journal of Statistical Software*, 48(2). Available at: https://doi.org/10.18637/jss.v048.i02.

Rothengatter, T. (1982) 'The effects of police surveillance and law enforcement on driver behaviour', *Current Psychological Research*, 2(3), pp. 349–358. Available at: https://doi.org/10.1007/BF02684467.

Ruffini, M., Pillay, K., Xie, C., Shi, L., Smith, D., Monga, I., Wang, X. and Wey, J.S. (2019) 'Connected OFCity Challenge: Addressing the Digital Divide in the Developing World', *IEEE\/OSA Journal of Optical Communications and Networking*, 11(7), pp. 354–361. Available at: https://doi.org/10.1364/JOCN.11.000354.

Ruijten, P.A.M., Kruyt-Beursken, E. and IJsselsteijn, W.A. (2018) 'Towards the Simplicity of Complex Interfaces: Applying Ephemeral Adaptation to Enhance User Performance and Satisfaction', in, pp. 86–97. Available at: https://doi.org/10.1007/978-3-319-91593-7_10.

Rukmana, D. (2018) 'Rapid urbanization and the need for sustainable transportation policies in Jakarta', *IOP Conference Series: Earth and Environmental Science*, 124, p. 012017. Available at: https://doi.org/10.1088/1755-1315/124/1/012017.

Russell, C. and Meehan, J. (2014) 'Exploring legitimacy in major public procurement projects', *Journal of Public Procurement*, 14(4), pp. 495–537. Available at: https://doi.org/10.1108/JOPP-14-04-2014-B003.

Ryu, E. (2014) 'Model Fit Evaluation in Multilevel Structural Equation Models', *Frontiers in Psychology* [Preprint]. Available at:

https://doi.org/10.3389/fpsyg.2014.00081.

Sabani, A., Thai, V. and Hossain, M.A. (2023) ‘Factors Affecting Citizen Adoption of E-Government in Developing Countries’, *Journal of Global Information Management*, 31(1), pp. 1–23. Available at: https://doi.org/10.4018/JGIM.318131.

Sachan, A., Kumar, Rajiv and Kumar, Ritu (2018) ‘Examining the impact of e-government service process on user satisfaction’, *Journal of Global Operations and Strategic Sourcing*, 11(3), pp. 321–336. Available at: https://doi.org/10.1108/JGOSS-11-2017-0048.

Sahin, M.D., Öztürk, G., Şahin, M.D. and OZTURK, G. (2019) ‘Mixed Method Research: Theoretical Foundations, Designs and Its Use in Educational Research.’, *International Journal of Contemporary Educational Research*, 6(2), pp. 301–310. Available at: https://doi.org/10.33200/ijcer.574002.

Sam, E.F. (2022) ‘How Effective Are Police Road Presence and Enforcement in a Developing Country Context?’, *Humanities and Social Sciences Communications*, 9(1), pp. 1–11. Available at: https://doi.org/10.1057/s41599-022-01071-1.

Sambasivan, M., Wemyss, G.P. and Rose, R.C. (2010) ‘User Acceptance of a G2B System: A Case of Electronic Procurement System in Malaysia’, *Internet Research* [Preprint]. Available at: https://doi.org/10.1108/10662241011032236.

Samek, W., Wiegand, T. and Müller, K.-R. (2017) ‘Explainable artificial intelligence: Understanding, visualizing and interpreting deep learning models’, *arXiv preprint arXiv:1708.08296* [Preprint].

Sánchez González, S., Bedoya-Maya, F. and Calatayud, A. (2021) ‘Understanding the Effect of Traffic Congestion on Accidents Using Big Data’, *Sustainability*, 13(13), p. 7500. Available at: https://doi.org/10.3390/su13137500.

Sanctis, M. De, Iovino, L., Rossi, M.T. and Wimmer, M. (2021) ‘MIKADO: A Smart City KPIs Assessment Modeling Framework’, *Software & Systems Modeling* [Preprint]. Available at: https://doi.org/10.1007/s10270-021-00907-9.

Sanford, S., Schwartz, B. and Khan, Y. (2020) 'The role of tacit knowledge in communication and decision-making during emerging public health incidents', *International Journal of Disaster Risk Reduction*, 50, p. 101681. Available at: https://doi.org/10.1016/j.ijdrr.2020.101681.

Sansom, R.S., Choate, P.G., Keating, J.N. and Randle, E. (2018) 'Parsimony, not Bayesian analysis, recovers more stratigraphically congruent phylogenetic trees', *Biology Letters*, 14(6), p. 20180263. Available at: https://doi.org/10.1098/rsbl.2018.0263.

Santos, D., Saias, J., Quaresma, P. and Nogueira, V.B. (2021) 'Machine Learning Approaches to Traffic Accident Analysis and Hotspot Prediction', *Computers*, 10(12), p. 157. Available at: https://doi.org/10.3390/computers10120157.

Santos, E.M. dos and Reinhard, N. (2012) 'Electronic Government Interoperability', *Social Science Computer Review*, 30(1), pp. 71–82. Available at: https://doi.org/10.1177/0894439310392196.

Santoso, H.B., Hadi Putra, P.O. and Farras Hendra S, F.F. (2021) 'Development ; Evaluation of E-Learning Module Based on Visual and Global Preferences Using a User-Centered Design Approach', *International Journal of Emerging Technologies in Learning (iJET)*, 16(15), p. 139. Available at: https://doi.org/10.3991/ijet.v16i15.24163.

Sarasati, R. and Madyatmadja, E.D. (2020) 'Evaluation of e-government LAKSA services to improve the interest of use of applications using Technology Acceptance Model (TAM)', in *IOP Conference Series: Earth and Environmental Science*. Available at: https://doi.org/10.1088/1755-1315/426/1/012165.

Sarasua, W.A., Ogle, J.H. and Geoghegan, K. (2008) 'Use of Global Positioning System to Identify Crash Locations in South Carolina', *Transportation Research Record: Journal of the Transportation Research Board*, 2064(1), pp. 43–50. Available at: https://doi.org/10.3141/2064-07.

Sarikaya, A., Correll, M., Bartram, L., Tory, M. and Fisher, D. (2019) 'What Do We Talk About When We Talk About Dashboards?', *IEEE Transactions on*

Visualization and Computer Graphics, 25(1), pp. 682–692. Available at: https://doi.org/10.1109/TVCG.2018.2864903.

Sarker, I.H. (2022) ‘Smart City Data Science: Towards data-driven smart cities with open research issues’, *Internet of Things (Netherlands)*, 19(December 2020). Available at: https://doi.org/10.1016/j.iot.2022.100528.

Sass, D.A., Schmitt, T.A. and Marsh, H.W. (2014) ‘Evaluating Model Fit With Ordered Categorical Data Within a Measurement Invariance Framework: A Comparison of Estimators’, *Structural Equation Modeling*, 21(2), pp. 167–180. Available at: https://doi.org/10.1080/10705511.2014.882658.

Satria, R., Tsoi, K.H., Castro, M. and Loo, B.P.Y. (2020) ‘A Combined Approach to Address Road Traffic Crashes beyond Cities: Hot Zone Identification and Countermeasures in Indonesia’, *Sustainability 2020, Vol. 12, Page 1801*, 12(5), p. 1801. Available at: https://doi.org/10.3390/SU12051801.

Saunders, M., Lewis, P. and Thornhill, A. (2009) *Research methods for business students*. Pearson education.

Saunders, M.N.K. and Townsend, K. (2016) ‘Reporting and Justifying the Number of Interview Participants in Organization and Workplace Research’, *British Journal of Management*, 27(4), pp. 836–852. Available at: https://doi.org/10.1111/1467-8551.12182.

Sauro, J. and Lewis, J.D. (2011) ‘When Designing Usability Questionnaires, Does It Hurt to Be Positive?’ Available at: https://doi.org/10.1145/1978942.1979266.

Savolainen, P.T., Mannering, F.L., Lord, D. and Quddus, M.A. (2011) ‘The statistical analysis of highway crash-injury severities: A review and assessment of methodological alternatives’, *Accident Analysis & Prevention*, 43(5), pp. 1666–1676. Available at: https://doi.org/10.1016/j.aap.2011.03.025.

Schall, M.C., Cullen, L., Pennathur, P., Chen, H., Burrell, K. and Matthews, G. (2017) ‘Usability Evaluation and Implementation of a Health Information Technology Dashboard of Evidence-Based Quality Indicators’, *CIN: Computers,* *Informatics, Nursing*, 35(6), pp. 281–288. Available at: https://doi.org/10.1097/CIN.0000000000000325.

Scherer, R., Tondeur, J., Siddiq, F. and Baran, E. (2018) 'The Importance of Attitudes Toward Technology for Pre-Service Teachers' Technological, Pedagogical, and Content Knowledge: Comparing Structural Equation Modeling Approaches', *Computers in Human Behavior* [Preprint]. Available at: https://doi.org/10.1016/j.chb.2017.11.003.

Scholl, H.J. and Alawadhi, S. (2016) 'Smart governance as key to multi-jurisdictional smart city initiatives: The case of the eCityGov Alliance', *Social Science Information*, 55(2), pp. 255–277. Available at: https://doi.org/10.1177/0539018416629230.

Scholl, H.J. and Scholl, M.C. (2014) 'Smart Governance: A Roadmap for Research and Practice', (1). Available at: https://doi.org/10.9776/14060.

Schomakers, E.-M., Lidynia, C. and Ziefle, M. (2022) 'The Role of Privacy in the Acceptance of Smart Technologies: Applying the Privacy Calculus to Technology Acceptance', *International Journal of Human–Computer Interaction*, 38(13), pp. 1276–1289. Available at: https://doi.org/10.1080/10447318.2021.1994211.

Schrepp, M. (2019) 'User Experience Questionnaire Handbook Version 8', *URL: https://www. researchgate. net/publication/303880829_User_Experience_Questionnaire_Handbook_Version_2.(Accessed: 02.02. 2017)*, (September 2015), pp. 1–15. Available at: https://www.ueq-online.org/Material/Handbook.pdf.

Schrom-Feiertag, H., Lorenz, F., Regal, G. and Settgast, V. (2018) 'Augmented and Virtual Reality Applied for Innovative, Inclusive and Efficient Participatory Planning', in *Proceedings of 7th Transport Research Arena TRA 2018*.

Schuler, S.R., Lenzi, R. and Yount, K.M. (2011) 'Justification of Intimate Partner Violence in Rural Bangladesh: What Survey Questions Fail to Capture', *Studies in Family Planning* [Preprint]. Available at: https://doi.org/10.1111/j.1728-4465.2011.00261.x.

Scott, K., Gharai, D., Sharma, M., Choudhury, N., Mishra, B., Chamberlain, S. and LeFevre, A. (2019) ‘Yes, no, maybe so: the importance of cognitive interviewing to enhance structured surveys on respectful maternity care in northern India’, *Health Policy and Planning* [Preprint]. Available at: https://doi.org/10.1093/heapol/czz141.

Seger, E. (2022) ‘In Defence of Principlism in AI Ethics and Governance’, *Philosophy & Technology*, 35(2), p. 45. Available at: https://doi.org/10.1007/s13347-022-00538-y.

Sengupta, Ushnish and Sengupta, Ulysses (2022) ‘SDG-11 and Smart Cities: Contradictions and Overlaps Between Social and Environmental Justice Research Agendas’, *Frontiers in Sociology* [Preprint]. Available at: https://doi.org/10.3389/fsoc.2022.995603.

Seo, H. and Myeong, S. (2021) ‘Determinant Factors for Adoption of Government as a Platform in South Korea: Mediating Effects on the Perception of Intelligent Information Technology’, *Sustainability*, 13(18), p. 10464. Available at: https://doi.org/10.3390/su131810464.

Sepasgozar, S.M.E., Hawken, S., Sargolzaei, S. and Foroozanfa, M. (2019) ‘Implementing citizen centric technology in developing smart cities: A model for predicting the acceptance of urban technologies’, *Technological Forecasting and Social Change*, 142(September 2018), pp. 105–116. Available at: https://doi.org/10.1016/j.techfore.2018.09.012.

Sexton, A., Shepherd, E., Duke-Williams, O. and Eveleigh, A. (2017) ‘A balance of trust in the use of government administrative data’, *Archival Science*, 17(4), pp. 305–330. Available at: https://doi.org/10.1007/s10502-017-9281-4.

Shachak, A., Kuziemsky, C. and Petersen, C. (2019) ‘Beyond TAM and UTAUT: Future directions for HIT implementation research’, *Journal of Biomedical Informatics*, 100(October), p. 103315. Available at: https://doi.org/10.1016/j.jbi.2019.103315.

Shah, H. (2023) ‘Beyond Smart: How ICT Is Enabling Sustainable Cities of the

Future', *Sustainability*, 15(16), p. 12381. Available at: https://doi.org/10.3390/su151612381.

Shahzad, F., Xiu, G., Khan, I. and Wang, J. (2019) 'm-Government Security Response System: Predicting Citizens' Adoption Behavior', *International Journal of Human–Computer Interaction*, 35(10), pp. 899–915. Available at: https://doi.org/10.1080/10447318.2018.1516844.

Shamkuwar, M., More, R. and Patil, P. (2023) 'Smart city - An assessment of information technology dimensions', *Prayukti – Journal of Management Applications*, 03(01), pp. 01–11. Available at: https://doi.org/10.52814/PJMA.2023.3101.

Shapiro, J.M. (2006) 'Growth Effects of Human Capital', *The Review of Economics and Statistics*, 88(May), pp. 324–335.

Sharifi, A., Allam, Z., Feizizadeh, B. and Ghamari, H. (2021) 'Three decades of research on smart cities: Mapping knowledge structure and trends', *Sustainability (Switzerland)*, 13(13), pp. 1–23. Available at: https://doi.org/10.3390/su13137140.

Sharma, R. and Panigrahi, P.K. (2015) 'Developing a Roadmap for Planning and Implementation of Interoperability Capability in E-Government', *Transforming Government People Process and Policy* [Preprint]. Available at: https://doi.org/10.1108/tg-06-2014-0023.

Sharma, S.K. (2015) 'Adoption of E-Government Services', *Transforming Government People Process and Policy* [Preprint]. Available at: https://doi.org/10.1108/tg-10-2014-0046.

Sharmin, S., Ivan, J.N., Zhao, S., Wang, K., Hossain, J., Равишанкер, H. and Jackson, E. (2020) 'Incorporating Demographic Proportions Into Crash Count Models by Quasi-Induced Exposure Method', *Transportation Research Record Journal of the Transportation Research Board* [Preprint]. Available at: https://doi.org/10.1177/0361198120930230.

Shaw, N.C., DeLone, W.H. and Niederman, F. (2002) 'Sources of dissatisfaction in end-user support', *ACM SIGMIS Database: the DATABASE for Advances in Information Systems*, 33(2), pp. 41–56. Available at: https://doi.org/10.1145/513264.513272.

Shayan, S., Kim, K.P., Ma, T. and Nguyen, T.H.D. (2020) 'The First Two Decades of Smart City Research From a Risk Perspective', *Sustainability* [Preprint]. Available at: https://doi.org/10.3390/su12219280.

Shevlin, M. and Miles, J.N. V (1998) 'Effects of sample size, model specification and factor loadings on the GFI in confirmatory factor analysis', *Personality and Individual Differences*, 25(1), pp. 85–90. Available at: https://doi.org/https://doi.org/10.1016/S0191-8869(98)00055-5.

Shi, D., Lee, T. and Maydeu-Olivares, A. (2018) 'Understanding the Model Size Effect on SEM Fit Indices', *Educational and Psychological Measurement* [Preprint]. Available at: https://doi.org/10.1177/0013164418783530.

Shikhar, A., J.S., N., B.J., S. and Srinivas, K.G. (2016) 'Data analytics on accident data for smarter cities and safer lives', in *2016 International Conference on Computation System and Information Technology for Sustainable Solutions (CSITSS)*. IEEE, pp. 243–248. Available at: https://doi.org/10.1109/CSITSS.2016.7779365.

Shimray, S.R. and Ramaiah, C.K. (2019) 'Use of Internet through Mobile Devices: A Survey', *SRELS Journal of Information Management*, pp. 100–105. Available at: https://doi.org/10.17821/srels/2019/v56i2/141631.

Shin, E. (2012) 'Attitudinal determinants of e-government technology use among US local public managers', in *2012 45th Hawaii International Conference on System Sciences*. IEEE, pp. 2613–2622.

Shinar, D. and Stiebel, J. (1986) 'The Effectiveness of Stationary versus Moving Police Vehicles on Compliance with Speed Limit', *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 28(3), pp. 365–371. Available at: https://doi.org/10.1177/001872088602800313.

Shoara Akter, Milon Molla and S. M. Robiul Islam (2019) ‘Unequivocal ICT in Enhancing the Essence of Democracy and Good Governance’, *Journal of Modern Accounting and Auditing*, 15(1). Available at: https://doi.org/10.17265/1548-6583/2019.01.003.

Shrivastava, S.R. and Shrivastava, P.S. (2019) ‘Role of leadership in ensuring road safety in low- and middle-income nations: World Health Organization’, *Medical Journal of Babylon*, 16(4), p. 362. Available at: https://doi.org/10.4103/MJBL.MJBL_30_19.

Shrivastava, S.R., Shrivastava, P.S. and Ramasamy, J. (2014) ‘Scope of public health measures in ensuring road safety’, *Journal of Injury and Violence Research*, 6(2). Available at: https://doi.org/10.5249/jivr.v6i2.542.

Shuey, R. (2019) ‘Sharing road safety education and enforcement knowledge and practice throughout developing nations - challenges create opportunities!’, *Journal of the Australasian College of Road Safety*, 30(1), pp. 58–65. Available at: https://doi.org/10.33492/jacrs-d-18-00259.

Shuey, R., Mooren, L. and King, M. (2020) ‘Road safety lessons to learn from Low and Middle-Income Countries’, *Journal of road safety*, 31(3), pp. 69–78.

Shyr, J. and Spisic, D. (2014) ‘Automated Data Analysis’, *Wiley Interdisciplinary Reviews Computational Statistics* [Preprint]. Available at: https://doi.org/10.1002/wics.1318.

Sial, M.A., Paul, Z.I., Rafiq, Z. and Abid, G. (2023) ‘Does mobile technology shape employee socialization and enable tacit knowledge sharing in public sector organizations’, *Journal of Open Innovation: Technology, Market, and Complexity*, 9(3), p. 100089. Available at: https://doi.org/10.1016/j.joitmc.2023.100089.

Siddiquee, N.A. and Mohamed, M.Z. (2015) ‘E-Government and Transformation of Service Delivery in Malaysia’, *International Journal of Public Administration in the Digital Age*, 2(3), pp. 45–60. Available at: https://doi.org/10.4018/ijpada.2015070103.

Sieveneck, S. and Sutter, C. (2021) ‘Predictive policing in the context of road traffic safety: A systematic review and theoretical considerations’, *Transportation Research Interdisciplinary Perspectives*, 11, p. 100429. Available at: https://doi.org/10.1016/j.trip.2021.100429.

Sihotang, D.M., Hidayanto, A.N., Purwandari, B., Wijoyono, E., Diana, E. and Putra, R.R. (2023) ‘Factors Affecting E-government Adoption at the Micro Level of Government in Developing Countries: A Systematic Literature Review’, *7th International Conference on Business and Information Management, ICBIM 2023*, pp. 26–30. Available at: https://doi.org/10.1109/ICBIM59872.2023.10303127.

Silaban, P.H., Chen, W.K., Sormin, S., Yehezkiel, Y.N. and Silalahi, A.D.K. (2023) ‘How does electronic word of mouth on Instagram affect travel behaviour in Indonesia: A perspective of the information adoption model’, *Cogent Social Sciences*, 9(1). Available at: https://doi.org/10.1080/23311886.2022.2163525.

Silva, R.S.S. da, Junior, C.M.D. and Lacerda, R.T. de O. (2022) ‘Data-Driven Decision Making in the Public Sector: A Systematic Review’, *International Journal of Advanced Engineering Research and Science*, 9(9), pp. 217–229. Available at: https://doi.org/10.22161/ijaers.99.21.

Simonofski, A., Chantillon, M., Crompvoets, J., Vanderose, B. and Snoeck, M. (2020) ‘The influence of public values on user participation in e-government: An exploratory study’.

Singh, A.S., Vik, F.N., Chinapaw, M.J.M., Uijtdewilligen, L., Verloigne, M., Fernández-Alvira, J.M., Stomfai, S., Manios, Y., Martens, M. and Brug, J. (2011) ‘Test-Retest Reliability and Construct Validity of the ENERGY-child Questionnaire on Energy Balance-Related Behaviours and Their Potential Determinants: The ENERGY-project’, *International Journal of Behavioral Nutrition and Physical Activity* [Preprint]. Available at: https://doi.org/10.1186/1479-5868-8-136.

Singh, D. and Mohan, C.K. (2019) ‘Deep Spatio-Temporal Representation for Detection of Road Accidents Using Stacked Autoencoder’, *IEEE Transactions on Intelligent Transportation Systems*, 20(3), pp. 879–887. Available at: https://doi.org/10.1109/TITS.2018.2835308.

Singh, I. and Punia, D.K. (2011) ‘Employees adoption of e-procurement system: an empirical study’, *arXiv preprint arXiv:1112.2699* [Preprint].

Singh, V. and Chobotaru, J. (2022) ‘Digital Divide: Barriers to Accessing Online Government Services in Canada’, *Administrative Sciences*, 12(3), p. 112. Available at: https://doi.org/10.3390/admsci12030112.

Sipos, T., Afework Mekonnen, A. and Szabó, Z. (2021) ‘Spatial Econometric Analysis of Road Traffic Crashes’, *Sustainability*, 13(5), p. 2492. Available at: https://doi.org/10.3390/su13052492.

Sitorus, M., Melisa, M. and Herninda, D. (2023) ‘Driver Predicting Behavior Based on Accelerometer and Gyroscope Sensors with K-Means Algorithm Method’, *RIGGS: Journal of Artificial Intelligence and Digital Business*, 2(1), pp. 12–17. Available at: https://doi.org/10.31004/riggs.v2i1.29.

Sjøberg, D.I.K. and Bergersen, G.R. (2023) ‘Improving the Reporting of Threats to Construct Validity’. Available at: https://doi.org/10.1145/3593434.3593449.

Smith, E.A. (2001) ‘The Role of Tacit and Explicit Knowledge in the Workplace’, *Journal of Knowledge Management* [Preprint]. Available at: https://doi.org/10.1108/13673270110411733.

Smith, K.G., Collins, C.J. and Clark, K.D. (2005) ‘Existing Knowledge, Knowledge Creation Capability, and the Rate of New Product Introduction in High-Technology Firms’, *Academy of Management Journal*, 48(2), pp. 346–357. Available at: https://doi.org/10.5465/amj.2005.16928421.

Smith, M.D. (1996) ‘Structural Equation Modeling: Concepts, Issues, and Applications.’, *Journal of the Royal Statistical Society Series D (The Statistician)* [Preprint]. Available at: https://doi.org/10.2307/2988418.

Smith, R.B. (1988) ‘Linking quality & quantity’, *Quality & Quantity*, 22(1), pp. 3–30. Available at: https://doi.org/10.1007/BF00430635.

Smith, R.L., Avrunin, G.S., Clarke, L.A. and Osterweil, L.J. (2002) ‘PROPEL’, in

Proceedings of the 24th international conference on Software engineering - ICSE ’02. New York, New York, USA: ACM Press, p. 11. Available at: https://doi.org/10.1145/581339.581345.

Smith, V.S. (2013) ‘Data Dashboard as Evaluation and Research Communication Tool’, *New Directions for Evaluation*, 2013(140), pp. 21–45. Available at: https://doi.org/10.1002/ev.20072.

Snow, C.C., Håkonsson, D.D. and Obel, B. (2016) ‘A Smart City Is a Collaborative Community’, *California Management Review*, 59(1), pp. 92–108. Available at: https://doi.org/10.1177/0008125616683954.

Snyder, C. (2003) *Paper prototyping: The fast and easy way to design and refine user interfaces*. Morgan Kaufmann.

Soehodho, S. (2017) ‘Public transportation development and traffic accident prevention in Indonesia’, *IATSS Research*, 40(2), pp. 76–80. Available at: https://doi.org/10.1016/j.iatssr.2016.05.001.

Von Soest, C. (2022) ‘Why Do We Speak to Experts? Reviving the Strength of the Expert Interview Method’, *Perspectives on Politics*, 21(1), pp. 277–287. Available at: https://doi.org/10.1017/S1537592722001116.

Sofyan, M., Rahman, A., Bima, M.J. and Nujum, S. (2016) ‘The effect of career development and working discipline towards working satisfaction and employee performance in the Regional Office of Ministry of Religious Affairs in South Sulawesi’, *International Journal Of Scientific & Technology Research*, 5(03), pp. 51–57.

Sohail, A., Cheema, M.A., Ali, M.E., Toosi, A.N. and Rakha, H.A. (2023) ‘Data-driven approaches for road safety: A comprehensive systematic literature review’, *Safety Science*, 158, p. 105949. Available at: https://doi.org/10.1016/j.ssci.2022.105949.

van Sonderen, E., Sanderman, R. and Coyne, J.C. (2013) ‘Ineffectiveness of Reverse Wording of Questionnaire Items: Let’s Learn from Cows in the Rain’, *PLoS ONE*, 8(7), pp. 1–7. Available at: https://doi.org/10.1371/journal.pone.0068967.

Song, H. and Szafir, D.A. (2019) 'Where's my data? Evaluating visualizations with missing data', *IEEE Transactions on Visualization and Computer Graphics*, 25(1), pp. 914–924. Available at: https://doi.org/10.1109/TVCG.2018.2864914.

Soomro, K., Bhutta, M.N.M., Khan, Z. and Tahir, M.A. (2019) 'Smart city big data analytics: An advanced review', *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 9(5), pp. 1–25. Available at: https://doi.org/10.1002/widm.1319.

Sousa, V.E.C. de, Matson, J.T. and Lopez, K.D. (2016) 'Questionnaire Adapting: Little Changes Mean a Lot', *Western Journal of Nursing Research* [Preprint]. Available at: https://doi.org/10.1177/0193945916678212.

Sovacool, B.K., Kim, J. and Yang, M. (2021) 'The hidden costs of energy and mobility: A global meta-analysis and research synthesis of electricity and transport externalities', *Energy Research and Social Science*, 72, p. 101885. Available at: https://doi.org/10.1016/j.erss.2020.101885.

Spoletini, P., Brock, C., Shahwar, R. and Ferrari, A. (2016) 'Empowering Requirements Elicitation Interviews with Vocal and Biofeedback Analysis', *Proceedings - 2016 IEEE 24th International Requirements Engineering Conference, RE 2016*, pp. 371–376. Available at: https://doi.org/10.1109/RE.2016.56.

Srivastava, S.C. (2011) 'Is e-government providing the promised returns?: A value framework for assessing e-government impact', *Transforming Government: People, Process and Policy*, 5(2), pp. 107–113. Available at: https://doi.org/10.1108/17506161111131159.

St.Germain, L. and Quinn, D.M. (2006) 'Investigation of Tacit Knowledge in Principal Leadership', *The Educational Forum*, 70(1), pp. 75–90. Available at: https://doi.org/10.1080/00131720508984873.

Stahl, B.C. and Jirotka, M. (2017) ‘The ORBIT Journal- An Online Journal for Responsible Research and Innovation in ICT’, *Orbit Journal* [Preprint]. Available at: https://doi.org/10.29297/orbit.v1i1.29.

Stahlknecht, P. and Hasenkamp, U. (2002) ‘Istanalyse’, *Stahlknecht, P., Hasenkamp, U.(2002). Einführung in die Wirtschaftsinformatik*, 10, pp. 230–235.

Stainson, T. (2018) ‘Assessing Midwestern Police Leaders ’ Perceptions And Adoption Intent Of Body-Worn Cameras’, (June).

Statnickė, G., Savanevičienė, A. and Šakys, I. (2019) ‘The Relationship Between Work Engagement of Different Generations and Mobile Learning’, *Acta Universitatis Agriculturae Et Silviculturae Mendelianae Brunensis* [Preprint]. Available at: https://doi.org/10.11118/actaun201967061627.

Staton, C.A., De Silva, V., Krebs, E., Andrade, L., Rulisa, S., Mallawaarachchi, B.C., Jin, K., RicardoVissoci, J. and Østbye, T. (2015) ‘High road utilizers surveys compared to police data for road traffic crash hotspot localization in Rwanda and Sri Lanka’, *BMC Public Health*, 16(1), p. 53. Available at: https://doi.org/10.1186/s12889-015-2609-1.

Stefanovic, D., Marjanovic, U., Delić, M., Culibrk, D. and Lalic, B. (2016) ‘Assessing the success of e-government systems: An employee perspective’, *Information & Management*, 53(6), pp. 717–726. Available at: https://doi.org/10.1016/j.im.2016.02.007.

Stehle, S. and Kitchin, R. (2019) ‘Real-Time and Archival Data Visualisation Techniques in City Dashboards’, *International Journal of Geographical Information Science* [Preprint]. Available at: https://doi.org/10.1080/13658816.2019.1594823.

Steinhardt, J. (2020) ‘The role of numeric and statistical content on risk perception in infographics about road safety’, *Journal of Risk Research*, 23(5), pp. 613–625. Available at: https://doi.org/10.1080/13669877.2019.1596147.

Stevens, M., Glendinning, C., Jacobs, S., Moran, N., Challis, D., Manthorpe, J., Fernandez, J.-L., Jones, K., Knapp, M., Netten, A. and Wilberforce, M. (2011) ‘Assessing the Role of Increasing Choice in English Social Care Services’, *Journal of Social Policy*, 40(2), pp. 257–274. Available at: https://doi.org/10.1017/S004727941000111X.

Stiles, J., Li, Y. and Miller, H.J. (2022) ‘How does street space influence crash frequency? An analysis using segmented street view imagery’, *Environment and Planning B: Urban Analytics and City Science*, 49(9), pp. 2467–2483. Available at: https://doi.org/10.1177/23998083221090962.

Stone, B.M. (2021) ‘The Ethical Use of Fit Indices in Structural Equation Modeling: Recommendations for Psychologists’, *Frontiers in Psychology* [Preprint]. Available at: https://doi.org/10.3389/fpsyg.2021.783226.

Stronach, I., Garratt, D., Pearce, C. and Piper, H. (2007) ‘Reflexivity, the picturing of selves, the forging of method’, *Qualitative Inquiry*, 13(2), pp. 179–203. Available at: https://doi.org/10.1177/1077800406295476.

Sugandha, Freestone, R. and Favaro, P. (2022) ‘The social sustainability of smart cities: A conceptual framework’, *City, Culture and Society*, 29, p. 100460. Available at: https://doi.org/10.1016/j.ccs.2022.100460.

Sukackė, V. (2019) ‘Towards Extending The Original Technology Acceptance Model (Tam) For A Better Understanding Of Educational Technology Adoption’, *SOCIETY. INTEGRATION. EDUCATION. Proceedings of the International Scientific Conference*, 5, p. 525. Available at: https://doi.org/10.17770/sie2019vol5.3798.

Sun, D., Liu, X., Ni, A. and Peng, C. (2014) ‘Traffic Congestion Evaluation Method for Urban Arterials’, *Transportation Research Record Journal of the Transportation Research Board* [Preprint]. Available at: https://doi.org/10.3141/2461-02.

Surbakti, F.P.S., Wang, W., Indulska, M. and Sadiq, S. (2020) ‘Factors influencing effective use of big data: A research framework’, *Information & Management*, 57(1), p. 103146. Available at: https://doi.org/10.1016/j.im.2019.02.001.

Sürücü, L. and Maslakci, A. (2020) 'Validity and Reliability in Quantitative Research', *Business and Management Studies an International Journal* [Preprint]. Available at: https://doi.org/10.15295/bmij.v8i3.1540.

Syed, R., Bandara, W. and Eden, R. (2023) 'Public sector digital transformation barriers: A developing country experience', *Information Polity*, 28(1), pp. 5–27. Available at: https://doi.org/10.3233/IP-220017.

Syed, R., Bandara, W., French, E. and Stewart, G. (2018) 'Getting it right! Critical Success Factors of BPM in the Public Sector: A Systematic Literature Review', *Australasian Journal of Information Systems*, 22. Available at: https://doi.org/10.3127/ajis.v22i0.1265.

Symon, G. and Clegg, C. (2005) 'Constructing identity and participation during technological change', *Human Relations*, 58(9), pp. 1141–1166. Available at: https://doi.org/10.1177/0018726705058941.

Syväjärvi, A., Kivivirta, V., Stenvall, J. and Laitinen, I. (2019) 'Digitalization and Information Management in Smart City Government', in *Smart Cities and Smart Spaces*. IGI Global, pp. 1428–1444. Available at: https://doi.org/10.4018/978-1-5225-7030-1.ch064.

Tabachnick, B.G. and Fidell, L.S. (2007) 'Using multivariate statistics, 5th ed.', *Using multivariate statistics, 5th ed.* Boston, MA: Allyn & Bacon/Pearson Education, pp. xxvii, 980–xxvii, 980.

Tabachnick, B.G., Fidell, L.S. and Ullman, J.B. (2013) *Using multivariate statistics*. pearson Boston, MA.

Taeihagh, A. and Lim, H.S.M. (2019) 'Governing autonomous vehicles: emerging responses for safety, liability, privacy, cybersecurity, and industry risks', *Transport Reviews*, 39(1), pp. 103–128. Available at: https://doi.org/10.1080/01441647.2018.1494640.

Taherdoost, H. (2018) 'A review of technology acceptance and adoption models and theories', *Procedia Manufacturing*, pp. 960–967. Available at:

https://doi.org/10.1016/j.promfg.2018.03.137.

Taherdoost, H., Business, H., Sdn, S., Group, C. and Lumpur, K. (2018) ‘Validity and Reliability of the Research Instrument; How to Test the Validation of a Questionnaire/Survey in a Research’, *SSRN Electronic Journal*, 5(3), pp. 28–36. Available at: https://doi.org/10.2139/ssrn.3205040.

Talukder, M. (2012) ‘Factors affecting the adoption of technological innovation by individual employees: An Australian study’, *Procedia - Social and Behavioral Sciences*, 40, pp. 52–57. Available at: https://doi.org/10.1016/j.sbspro.2012.03.160.

Tamilarasi, R., Kumar, P.N.S., Ghantasala, G.S.P., Rao, D.N., Bathla, P., Gupta, G. and Sonia (2024) ‘Machine Learning Challenges of E-government Models of Cloud Computing in Developing Countries’, *Proceedings of the 18th INDIAcom; 2024 11th International Conference on Computing for Sustainable Global Development, INDIACom 2024*, pp. 1804–1809. Available at: https://doi.org/10.23919/INDIACOM61295.2024.10498915.

Tanahashi, Y., Chen, C.-K., Marchesin, S. and Ma, K.-L. (2010) ‘An Interface Design for Future Cloud-Based Visualization Services’, in *2010 IEEE Second International Conference on Cloud Computing Technology and Science*. IEEE, pp. 609–613. Available at: https://doi.org/10.1109/CloudCom.2010.46.

Tarka, P. (2017) ‘The comparison of estimation methods on the parameter estimates and fit indices in SEM model under 7-point Likert scale’, *Archives of Data Science*, 2(1), pp. 1–16. Available at: https://doi.org/10.5445/KSP/1000058749/10.

Tarnowski, A., Olejniczak-Serowiec, A. and Marszalec, A. (2017) ‘Roadside advertising and the distraction of driver’s attention’, *MATEC Web of Conferences*. Edited by K. Jamroz and J. Żukowska, 122, p. 03010. Available at: https://doi.org/10.1051/matecconf/201712203010.

Tarus, J.K., Gichoya, D. and Muumbo, A. (2015) ‘Challenges of implementing e-learning in Kenya: A case of Kenyan public universities’, *The International*

Review of Research in Open and Distributed Learning, 16(1). Available at: https://doi.org/10.19173/irrodl.v16i1.1816.

Tashakkori, A. and Teddlie, C. (1998) *Mixed Methodology: Combining Qualitative and Quantitative Approaches*, *Relations Industrielles-industrial Relations*. sage.

Telep, C.W. and Gross Shader, C. (2019) ‘Creating a “what works” translational tool for police: a researcher-city government partnership’, *Police Practice and Research*, 20(6), pp. 603–616. Available at: https://doi.org/10.1080/15614263.2019.1657630.

Teo, T.S.H., Srivastava, S.C. and Jiang, L. (2008) ‘Trust and electronic government success: An empirical study’, *Journal of Management Information Systems*, 25(3), pp. 99–132. Available at: https://doi.org/10.2753/MIS0742-1222250303.

The Jakarta Post (2021) *Govt to impose curbs on year-end holidays*. Available at: https://www.thejakartapost.com/paper/2021/11/18/govt-to-impose-curbs-on-year-end-holidays.html (Accessed: 19 November 2021).

Thompson, B. (2004) *Exploratory and confirmatory factor analysis: Understanding concepts and applications*. Washington: American Psychological Association. Available at: https://doi.org/10.1037/10694-000.

Thompson, J.R. and Siciliano, M.D. (2021) ‘The “Levels” Problem in Assessing Organizational Climate: Evidence From the Federal Employee Viewpoint Survey’, *Public Personnel Management*, 50(1), pp. 133–156. Available at: https://doi.org/10.1177/0091026020917710.

Tocci, G. (2020) ‘La governance delle città intelligenti. Tecnologia, innovazione e smartness’, *SOCIOLOGIA URBANA E RURALE*, (122), pp. 44–61. Available at: https://doi.org/10.3280/SUR2020-122004.

Todisco, L., Tomo, A., Canonico, P., Mangia, G. and Sarnacchiaro, P. (2021) ‘Exploring social media usage in the public sector: Public employees’ perceptions of ICT’s usefulness in delivering value added’, *Socio-Economic*

Planning Sciences, 73, p. 100858. Available at: https://doi.org/10.1016/j.seps.2020.100858.

TomTom (2023) ‘Jakarta traffic report | TomTom Traffic Index’. Available at: https://www.tomtom.com/traffic-index/jakarta-traffic/.

Townsend, A. (2013) *smart cities*.

Tripathi, R., Gupta, M.P. and Bhattacharya, J. (2012) ‘Interoperability adoption among government and corporate portals in India: a study’, *Journal of Enterprise Information Management*, 25(2), pp. 98–122. Available at: https://doi.org/10.1108/17410391211204374.

Trkman, M., Popovič, A. and Trkman, P. (2021) ‘The impact of perceived crisis severity on intention to use voluntary proximity tracing applications.’, *International journal of information management*, 61, p. 102395. Available at: https://doi.org/10.1016/j.ijinfomgt.2021.102395.

Trkman, M., Popovič, A. and Trkman, P. (2023) ‘The roles of privacy concerns and trust in voluntary use of governmental proximity tracing applications’, *Government Information Quarterly*, 40(1). Available at: https://doi.org/10.1016/j.giq.2022.101787.

Trochim, W.M.K. and Donnelly, J.P. (2001) *Research methods knowledge base*. Atomic Dog Pub. Macmillan Publishing Company, New York.

Tsai, T.-I., Luck, L., Jefferies, D. and Wilkes, L. (2023) ‘Challenges in adapting a survey: ensuring cross-cultural equivalence’, *Nurse Researcher*, 31(2).

Turhan, Z. and Bernard, C. (2022) ‘Challenges and strategies of translation in a qualitative and sensitive research’, *Qualitative Research*, 22(3), pp. 487–495. Available at: https://doi.org/10.1177/1468794121999003.

Twinn, S. (1997) ‘An exploratory study examining the influence of translation on the validity and reliability of qualitative data in nursing research’, *Journal of Advanced Nursing*, 26(2), pp. 418–423. Available at:

https://doi.org/10.1046/j.1365-2648.1997.1997026418.x.

Twizeyimana, J.D. (2017) ‘User-centeredness and usability in e-government’, in *Proceedings of the Internationsl Conference on Electronic Governance and Open Society: Challenges in Eurasia*. New York, NY, USA: ACM, pp. 172–178. Available at: https://doi.org/10.1145/3129757.3129786.

Tzermias, Z., Prevelakis, V. and Ioannidis, S. (2014) ‘Privacy Risks from Public Data Sources’, in, pp. 156–168. Available at: https://doi.org/10.1007/978-3-642-55415-5_13.

Ubaldi, B. (2013) ‘Open Government Data: Towards Empirical Analysis of Open Government Data Initiatives’, *OECD Working Papers on Public Governance*, NO.22(22), p. 61. Available at: http://www.oecd-ilibrary.org/docserver/download/5k46bj4f03s7.pdf?expires=1400038714&id=id&accname=guest&checksum=0A581F24362C40FF67A6EF59C2B31BBB.

Uematsu, H. and Mishra, A.K. (2010) *Can education be a barrier to technology adoption?*

Ulak, M.B. and Ozguven, E.E. (2024) ‘Identifying the latent relationships between factors associated with traffic crashes through graphical models’, *Accident Analysis & Prevention*, 197, p. 107470. Available at: https://doi.org/10.1016/j.aap.2024.107470.

Ullman, J.B. (2006) ‘Structural Equation Modeling: Reviewing the Basics and Moving Forward’, *Journal of Personality Assessment* [Preprint]. Available at: https://doi.org/10.1207/s15327752jpa8701_03.

UN-Habitat (2004) *Global campaign on urban governance: Principles*. Available at: https://mirror.unhabitat.org/content.asp?typeid=19&catid=25&cid=2097.

UN Habitat (2002) *The global campaign on urban governance : an inventory*.

United Nations (2018a) ‘Indicators for Voluntary Global Performance Targets’, pp. 1–20.

United Nations (2018b) ‘TRANSPORT AND Series No 10 Road Safety - Considerations in Support of the 2030 Agenda for Sustainable Development Considerations in Support of the 2030 Agenda for Sustainable Development’, (10).

Urie, Y., Velaga, N.R. and Maji, A. (2016) ‘Cross-sectional study of road accidents and related law enforcement efficiency for 10 countries: A gap coherence analysis’, *Traffic Injury Prevention*, 17(7), pp. 686–691. Available at: https://doi.org/10.1080/15389588.2016.1146823.

User Interface Design GmbH (2022) *AttrakDiff Work Model*. Available at: http://www.attrakdiff.de/sience-en.html.

Vaismoradi, M. and Snelgrove, S. (2019) ‘Theme in qualitative content analysis and thematic analysis’, *Forum Qualitative Sozialforschung*, 20(3). Available at: https://doi.org/10.17169/fqs-20.3.3376.

Vallerand, R.J. (2000) ‘Deci and Ryan’s self-determination theory: A view from the hierarchical model of intrinsic and extrinsic motivation’, *Psychological inquiry*, 11(4), pp. 312–318.

Vanderburgh, W.L. (2014) ‘Quantitative Parsimony, Explanatory Power and Dark Matter’, *Journal for General Philosophy of Science*, 45(2), pp. 317–327. Available at: https://doi.org/10.1007/s10838-014-9261-9.

Vartak, M., Huang, S., Siddiqui, T., Madden, S. and Parameswaran, A. (2017) ‘Towards Visualization Recommendation Systems’, *Acm Sigmod Record* [Preprint]. Available at: https://doi.org/10.1145/3092931.3092937.

Vazquez-Ingelmo, A., Garcia-Penalvo, F.J. and Theron, R. (2019) ‘Information Dashboards and Tailoring Capabilities-A Systematic Literature Review’, *IEEE Access*, 7, pp. 109673–109688. Available at: https://doi.org/10.1109/ACCESS.2019.2933472.

Vázquez-Ingelmo, A., García-Peñalvo, F.J., Therón, R. and Conde-González, M.Á. (2020) ‘Representing Data Visualization Goals and Tasks Through Meta-

Modeling to Tailor Information Dashboards', *Applied Sciences* [Preprint]. Available at: https://doi.org/10.3390/app10072306.

van Veenstra, A.F. and Kotterink, B. (2017) 'Data-Driven Policy Making: The Policy Lab Approach', in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, pp. 100–111. Available at: https://doi.org/10.1007/978-3-319-64322-9_9.

Veit, D.J., Parasie, N.P. and Huntgeburth, J.C. (2011) 'E-Procurement Adoption at the Municipal Level: Influence of Organizational, Technological and Environmental Factors', in *2011 44th Hawaii International Conference on System Sciences*. IEEE, pp. 1–10. Available at: https://doi.org/10.1109/HICSS.2011.177.

Velez, B.L., Breslow, A.S., Brewster, M.E., Cox, R.A. and Foster, A.B. (2016) 'Building a Pantheoretical Model of Dehumanization With Transgender Men: Integrating Objectification and Minority Stress Theories.', *Journal of Counseling Psychology* [Preprint]. Available at: https://doi.org/10.1037/cou0000136.

Velsberg, O., Westergren, U.H. and Jonsson, K. (2020) 'Exploring Smartness in Public Sector Innovation - Creating Smart Public Services With the Internet of Things', *European Journal of Information Systems* [Preprint]. Available at: https://doi.org/10.1080/0960085x.2020.1761272.

Venkatesh, V. and Bala, H. (2008) 'Technology Acceptance Model 3 and a Research Agenda on Interventions', *Decision Sciences*, 39(2), pp. 273–315. Available at: https://doi.org/10.1111/j.1540-5915.2008.00192.x.

Venkatesh, V., Bala, H. and Sykes, T.A. (2010) 'Impacts of Information and Communication Technology Implementations on Employees' Jobs in Service Organizations in India: A Multi-Method Longitudinal Field Study', *Production and Operations Management*, 19(5), pp. 591–613. Available at: https://doi.org/10.1111/j.1937-5956.2010.01148.x.

Venkatesh, V., Brown, S.A. and Bala, H. (2013) 'Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems', *MIS quarterly*, pp. 21–54.

Venkatesh, V., Chan, F.K.Y. and Thong, J.Y.L. (2011) ‘Designing E-government Services: Key Service Attributes and Citizens’ Preference Structures’, *Journal of Operations Management* [Preprint]. Available at: https://doi.org/10.1016/j.jom.2011.10.001.

Venkatesh, V. and Davis, F.D. (2000) ‘Theoretical extension of the Technology Acceptance Model: Four longitudinal field studies’, *Management Science*, 46(2), pp. 186–204. Available at: https://doi.org/10.1287/mnsc.46.2.186.11926.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003) ‘User acceptance of information technology: Toward a unified view’, *MIS Quarterly: Management Information Systems*, 27(3), pp. 425–478. Available at: https://doi.org/10.2307/30036540.

Venkatesh, V., Thong, J.Y.L., Chan, F.K.Y. and Hu, P.J.H. (2016) ‘Managing Citizens’ Uncertainty in E-Government Services: The Mediating and Moderating Roles of Transparency and Trust’, *Information Systems Research*, 27(1), pp. 87–111. Available at: https://doi.org/10.1287/isre.2015.0612.

Venkatesh, V., Thong, J.Y.L. and Xu, X. (2012) ‘Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology’, *MIS Quarterly: Management Information Systems*, 36(1), pp. 157–178. Available at: https://doi.org/10.2307/41410412.

Verhulst, M. and Rutkowski, A.-F. (2017) ‘Catch Me If You Can: Technological Constraints/Affordances and Mindfulness during Collaborative Police Emergency Response’, in. Available at: https://doi.org/10.24251/HICSS.2017.093.

Verkijika, S.F. (2018) ‘Quality assessment of e - government websites in Sub - Saharan Africa : A public values perspective’, pp. 1–17. Available at: https://doi.org/10.1002/isd2.12015.

Verschuren, P. (2003) ‘Case study as a research strategy: Some ambiguities and opportunities’, *International Journal of Social Research Methodology*, 6(2), pp. 121–139. Available at: https://doi.org/10.1080/13645570110106154.

Verstraete, J., Acar, F., Concilio, G. and Pucci, P. (2021) ‘Turning Data into Actionable Policy Insights’, in, pp. 73–89. Available at: https://doi.org/10.1007/978-3-030-63693-7_6.

Vila, R.A., Estevez, E. and Fillottrani, P.R. (2018) ‘The design and use of dashboards for driving decision-making in the public sector’, in *Proceedings of the 11th International Conference on Theory and Practice of Electronic Governance*. New York, NY, USA: ACM, pp. 382–388. Available at: https://doi.org/10.1145/3209415.3209467.

Vinet, L. and Zhedanov, A. (2011) ‘A “missing” family of classical orthogonal polynomials’, *Journal of Physics A: Mathematical and Theoretical*, 44(8), p. 223. Available at: https://doi.org/10.1088/1751-8113/44/8/085201.

van der Voet, J., Groeneveld, S. and Kuipers, B.S. (2014) ‘Talking the Talk or Walking the Walk? The Leadership of Planned and Emergent Change in a Public Organization’, *Journal of Change Management*, 14(2), pp. 171–191. Available at: https://doi.org/10.1080/14697017.2013.805160.

Vrabie, C.I. and Tirziu, A.-M. (2017) ‘E-participation – a Key Factor in Developing Smart Cities’, (77707).

Wacker, J.G. (1998) ‘A definition of theory: research guidelines for different theory-building research methods in operations management’, *Journal of Operations Management*, 16(4), pp. 361–385. Available at: https://doi.org/10.1016/S0272-6963(98)00019-9.

Walker, M., Takayama, L. and Landay, J.A. (2002) ‘High-fidelity or low-fidelity, paper or computer? Choosing attributes when testing web prototypes’, in *Proceedings of the human factors and ergonomics society annual meeting*. Sage Publications Sage CA: Los Angeles, CA, pp. 661–665.

Walker, S., Read, S. and Priest, H. (2013) ‘Use of reflexivity in a mixed-methods study’, *Nurse Researcher*, 20(3), pp. 38–43. Available at: https://doi.org/10.7748/nr2013.01.20.3.38.c9496.

Walker, W. (2005) 'The strengths and weaknesses of research designs involving quantitative measures', *Journal of Research in Nursing*, 10(5), pp. 571–582. Available at: https://doi.org/10.1177/136140960501000505.

Wan, Y., He, W. and Zhou, J. (2021) 'Urban road accident black spot identification and classification approach: A novel grey Verhuls-empirical Bayesian combination method', *Sustainability (Switzerland)*, 13(20). Available at: https://doi.org/10.3390/su132011198.

Wang, C., Quddus, M.A. and Ison, S.G. (2013) 'The effect of traffic and road characteristics on road safety: A review and future research direction', *Safety Science*, 57, pp. 264–275. Available at: https://doi.org/10.1016/j.ssci.2013.02.012.

Wang, Q., Leng, S., Fu, H. and Zhang, Y. (2012) 'An IEEE 802.11p-Based Multichannel MAC Scheme With Channel Coordination for Vehicular Ad Hoc Networks', *IEEE Transactions on Intelligent Transportation Systems*, 13(2), pp. 449–458. Available at: https://doi.org/10.1109/TITS.2011.2171951.

Wang, S. and Feeney, M.K. (2016) 'Determinants of Information and Communication Technology Adoption in Municipalities', *The American Review of Public Administration*, 46(3), pp. 292–313. Available at: https://doi.org/10.1177/0275074014553462.

Wang, Y. (2016) 'Information Adoption Model, a Review of the Literature', *Journal of Economics, Business and Management*, 4(11), pp. 618–622. Available at: https://doi.org/10.18178/joebm.2016.4.11.462.

Wang, Y.A. and Rhemtulla, M. (2021) 'Power Analysis for Parameter Estimation in Structural Equation Modeling: A Discussion and Tutorial', *Advances in Methods and Practices in Psychological Science*, 4(1), p. 251524592091825. Available at: https://doi.org/10.1177/2515245920918253.

Warner, K. and Wäger, M. (2019) 'Building Dynamic Capabilities for Digital Transformation: An Ongoing Process of Strategic Renewal', *Long Range Planning* [Preprint]. Available at: https://doi.org/10.1016/j.lrp.2018.12.001.

Watson, J., Burtch, G. and Greenwood, B.N. (2024) ‘Do digital technologies reduce racially biased reporting? Evidence from NYPD administrative data’, *Proceedings of the National Academy of Sciences of the United States of America*, 121(24). Available at: https://doi.org/10.1073/PNAS.2402375121.

Watson, J.C. (2017) ‘Establishing Evidence for Internal Structure Using Exploratory Factor Analysis’, *Measurement and Evaluation in Counseling and Development*, 50(4), pp. 232–238. Available at: https://doi.org/10.1080/07481756.2017.1336931.

Weber, M. and Žarko, I.P. (2019) ‘A Regulatory View on Smart City Services’, *Sensors* [Preprint]. Available at: https://doi.org/10.3390/s19020415.

Weerakkody, V., Irani, Z., Lee, H., Osman, I. and Hindi, N. (2015) ‘E-government implementation: A bird’s eye view of issues relating to costs, opportunities, benefits and risks’, *Information Systems Frontiers*, 17(4), pp. 889–915. Available at: https://doi.org/10.1007/s10796-013-9472-3.

Weger, U. (2019) ‘Avoiding “False Alarms” and “Misses” in Psychological Theory Building: Complementing the Principle of Parsimony With the Principle of Tentative Affirmation’, *Psychological Reports* [Preprint]. Available at: https://doi.org/10.1177/0033294119835760.

Wegman, F., Berg, H.-Y., Cameron, I., Thompson, C., Siegrist, S. and Weijermars, W. (2015) ‘Evidence-based and data-driven road safety management’, *IATSS Research*, 39(1), pp. 19–25. Available at: https://doi.org/10.1016/j.iatssr.2015.04.001.

Wehner, C., Roemer, L. and Ziegler, M. (2020) ‘Construct Validity’, *Definitions* [Preprint]. Available at: https://api.semanticscholar.org/CorpusID:20559426.

Weinberg, B.A. (2004) ‘Experience and Technology Adoption’, *SSRN Electronic Journal* [Preprint]. Available at: https://doi.org/10.2139/ssrn.522302.

Wells, J.D., Campbell, D.E., Valacich, J.S. and Featherman, M. (2010) ‘The Effect of Perceived Novelty on the Adoption of Information Technology

Innovations: A Risk/Reward Perspective', *Decision Sciences*, 41(4), pp. 813–843. Available at: https://doi.org/10.1111/j.1540-5915.2010.00292.x.

Wen, X., Xie, Y., Jiang, L., Pu, Z. and Ge, T. (2021) 'Applications of machine learning methods in traffic crash severity modelling: current status and future directions', *Transport Reviews*, 41(6), pp. 855–879. Available at: https://doi.org/10.1080/01441647.2021.1954108.

Wenhua, X. and Jian, Y. (2010) 'E-government and the Change of Government Management Mode', in *2010 International Conference on E-Business and E-Government*. IEEE, pp. 675–678. Available at: https://doi.org/10.1109/ICEE.2010.176.

Westland, J.C. (2010) 'Lower bounds on sample size in structural equation modeling', *Electronic Commerce Research and Applications*, 9(6), pp. 476–487. Available at: https://doi.org/10.1016/j.elerap.2010.07.003.

WhatsApp LLC (2024) *WhatsApp*. Available at: https://www.whatsapp.com/.

Whelehan, O. (1983) 'Applied Multivariate Statistical Analysis.', *Journal of the Royal Statistical Society Series C (Applied Statistics)* [Preprint]. Available at: https://doi.org/10.2307/2347962.

Whetten, D.A. (1989) 'What Constitutes a Theoretical Contribution? The Academy of Management Review What Constitutes a Theoretical Contribution?', *Source: The Academy of Management ReviewAcaderyof Management Review*, 14(4), pp. 490–495. Available at: http://www.jstor.org/stable/258554%5Cnhttp://www.jstor.org/stable/258554?seq=1&cid=pdf-reference#references_tab_contents%5Cnhttp://about.jstor.org/terms.

Whitman, L.E., Santanu, D. and Panetto, H. (2006) 'An Enterprise Model of Interoperability', *Ifac Proceedings Volumes* [Preprint]. Available at: https://doi.org/10.3182/20060517-3-fr-2903.00311.

WHO (2018) 'WHO | Road traffic injuries', *WHO* [Preprint]. WHO. Available at:

http://www.who.int/mediacentre/factsheets/fs358/en/.

Wickramasinghe, V. and Wickramasekara, J. (2022) ‘Putting Public Services into Enterprise System- Predicting Employees’ Acceptance of Transformational Government Technology in an Expanded Technology Acceptance Model’, *Public Organization Review*, 22(2), pp. 345–365. Available at: https://doi.org/10.1007/s11115-021-00528-2.

Wilbanks, B.A. and Langford, P.A. (2014) ‘A Review of Dashboards for Data Analytics in Nursing’, *CIN: Computers, Informatics, Nursing*, 32(11), pp. 545–549. Available at: https://doi.org/10.1097/CIN.0000000000000106.

Wildman, R.C. (1977) ‘Effects of Anonymity and Social Setting on Survey Responses’, *Public Opinion Quarterly*, 41(1), p. 74. Available at: https://doi.org/10.1086/268354.

Wilkinson, A. (2010) *The Oxford handbook of participation in organizations*. Oxford University Press, USA.

Willis, G. and Artino, A.R. (2013) ‘What Do Our Respondents Think We’re Asking? Using Cognitive Interviewing to Improve Medical Education Surveys’, *Journal of Graduate Medical Education* [Preprint]. Available at: https://doi.org/10.4300/jgme-d-13-00154.1.

Willis, G.B. (1999) ‘Cognitive Interviewing. A “how to” guide’, *Evaluation* [Preprint].

Wimmer, M.A., Boneva, R. and di Giacomo, D. (2018) ‘Interoperability governance’, in *Proceedings of the 19th Annual International Conference on Digital Government Research: Governance in the Data Age*. New York, NY, USA: ACM, pp. 1–11. Available at: https://doi.org/10.1145/3209281.3209306.

Wirtz, B., Lütje, S. and Schierz, P.G. (2009) ‘An Empirical Analysis of the Acceptance of E-Procurement in the German Public Sector’, *International Journal of Public Administration*, 33(1), pp. 26–42. Available at: https://doi.org/10.1080/01900690903188768.

Wirtz, B.W., Piehler, R., Thomas, M.-J. and Daiser, P. (2016) ‘Resistance of Public Personnel to Open Government: A cognitive theory view of implementation barriers towards open government data’, *Public Management Review*, 18(9), pp. 1335–1364. Available at: https://doi.org/10.1080/14719037.2015.1103889.

Wolf, E.J., Harrington, K.M., Clark, S.L. and Miller, M.W. (2013) ‘Sample size requirements for structural equation models: An evaluation of power, bias, and solution propriety’, *Educational and psychological measurement*, 73(6), pp. 913–934. Available at: https://doi.org/10.1177/0013164413495237.

Wood, P. (2008) ‘Confirmatory Factor Analysis for Applied Research’, *The American Statistician* [Preprint]. Available at: https://doi.org/10.1198/tas.2008.s98.

World Bank (2024) *Indonesia Overview: Development news, research, data | World Bank*. Available at: https://www.worldbank.org/en/country/indonesia/overview (Accessed: 20 April 2024).

Worthington, R.L. and Whittaker, T.A. (2006) ‘Scale development research: A content analysis and recommendations for best practices’, *The counseling psychologist*, 34(6), pp. 806–838.

Wright, K.B. (2006) ‘Researching Internet-Based Populations: Advantages and Disadvantages of Online Survey Research, Online Questionnaire Authoring Software Packages, and Web Survey Services’, *Journal of Computer-Mediated Communication* [Preprint]. Available at: https://doi.org/10.1111/j.1083-6101.2005.tb00259.x.

Wu, M.-J., Zhao, K. and Fils-Aime, F. (2022) ‘Response rates of online surveys in published research: A meta-analysis’, *Computers in Human Behavior Reports*, 7, p. 100206. Available at: https://doi.org/10.1016/j.chbr.2022.100206.

Wu, P.F., Vitak, J. and Zimmer, M. (2019) ‘A Contextual Approach to Information Privacy Research’, *Journal of the Association for Information*

Science and Technology [Preprint]. Available at: https://doi.org/10.1002/asi.24232.

Wu, X. and Lum, C. (2019) ‘The Practice of Proactive Traffic Stops’, *Policing an International Journal* [Preprint]. Available at: https://doi.org/10.1108/pijpsm-06-2019-0089.

Xia, Y. and Yang, Y. (2018) ‘RMSEA, CFI, and TLI in Structural Equation Modeling With Ordered Categorical Data: The Story They Tell Depends on the Estimation Methods’, *Behavior Research Methods* [Preprint]. Available at: https://doi.org/10.3758/s13428-018-1055-2.

Xu, B., Li, Q., Guo, T. and Du, D. (2019) ‘A Scenario-Based Approach for Formal Modelling and Verification of Safety Properties in Automated Driving’, *IEEE Access*, 7, pp. 140566–140587. Available at: https://doi.org/10.1109/ACCESS.2019.2943184.

Xu, Q., Wang, Wei, Wang, Wenfu and Liu, P. (2013) ‘Real-time Freeway Sideswipe Crash Prediction by Support Vector Machine’, *Iet Intelligent Transport Systems* [Preprint]. Available at: https://doi.org/10.1049/iet-its.2011.0230.

Yaduvanshi, R., None, N., Bansal, P. (Dr) S., Kumar, D.A., None, N. and None, N. (2019) ‘Factors Affecting Traffic Management Using Two Step Cluster’, *International Journal of Engineering and Advanced Technology* [Preprint]. Available at: https://doi.org/10.35940/ijeat.a9516.109119.

Yaghmaie, F. (2003) ‘Content validity and its estimation’, *Journal of medical education*, 3(1).

Yahya, M.N., Faulks, I.J., Hambleton, P. and Wass, C. (2013) ‘Development of an integrated road safety management system in Indonesia: Traffic police as lead agents in a Safe System approach’, *Journal of the Australasian College of Road Safety*, 24(2), pp. 28–38. Available at: http://acrs.org.au/wp-content/uploads/ACRSjournalinsideVol24No2may13WEB.pdf.

Yang, D., Li, D., Chen, Y., Siano, P., Lim, S.B. and Yigitcanlar, T. (2022)

‘Participatory Governance of Smart Cities: Insights from e-Participation of Putrajaya and Petaling Jaya, Malaysia’, *Smart cities*, 5(1), pp. 71–89. Available at: https://doi.org/10.3390/SMARTCITIES5010005.

Yang, D., Tong, L., Ye, Y. and Wu, H. (2006) ‘Supporting Effective Operation of E-Governmental Services Through Workflow and Knowledge Management’, in, pp. 102–113. Available at: https://doi.org/10.1007/11912873_13.

Yang, H., Wang, Z., Xie, K. and Dai, D. (2017) ‘Use of ubiquitous probe vehicle data for identifying secondary crashes’, *Transportation Research Part C: Emerging Technologies*, 82, pp. 138–160. Available at: https://doi.org/10.1016/j.trc.2017.06.016.

Yap, C.S., Thong, J.Y.L. and Raman, K.S. (1994) ‘Effect of government incentives on computerisation in small business’, *European Journal of Information Systems*, 3(3), pp. 191–206. Available at: https://doi.org/10.1057/ejis.1994.20.

Ye, J., Zhou, Y., Li, M. and Wang, C. (2010) ‘Research and implement of traffic accident analysis system based on accident black spot’, in *2010 5th International Conference on Computer Science & Education*. IEEE, pp. 1805–1809. Available at: https://doi.org/10.1109/ICCSE.2010.5593800.

Yigitbasioglu, O.M. and Velcu, O. (2012) ‘A review of dashboards in performance management: Implications for design and research’, *International Journal of Accounting Information Systems*, 13(1), pp. 41–59. Available at: https://doi.org/10.1016/j.accinf.2011.08.002.

Yin, C., Zhang, X., Chen, H., Wang, J., Cooper, D. and David, B. (2015) ‘A Literature Survey on Smart Cities’, *Science China Information Sciences* [Preprint]. Available at: https://doi.org/10.1007/s11432-015-5397-4.

Young, G.W. and Kitchin, R. (2020) ‘Creating design guidelines for building city dashboards from a user’s perspectives’, *International Journal of Human Computer Studies*, 140(November 2019), p. 102429. Available at: https://doi.org/10.1016/j.ijhcs.2020.102429.

Young, G.W., Kitchin, R. and Naji, J. (2021) ‘Building City Dashboards for Different Types of Users’, *Journal of Urban Technology*, 28(1–2), pp. 289–309. Available at: https://doi.org/10.1080/10630732.2020.1759994.

Young, M.S., Mahfoud, J.M., Stanton, N.A., Salmon, P.M., Jenkins, D.P. and Walker, G.H. (2009) ‘Conflicts of interest: The implications of roadside advertising for driver attention’, *Transportation Research Part F: Traffic Psychology and Behaviour*, 12(5), pp. 381–388. Available at: https://doi.org/10.1016/j.trf.2009.05.004.

Yousef, D.A. (2017) ‘Organizational Commitment, Job Satisfaction and Attitudes toward Organizational Change: A Study in the Local Government’, *International Journal of Public Administration*, 40(1), pp. 77–88. Available at: https://doi.org/10.1080/01900692.2015.1072217.

Yu, R., Wang, X., Yang, K. and Abdel-Aty, M. (2016) ‘Crash Risk Analysis for Shanghai Urban Expressways: A Bayesian Semi-Parametric Modeling Approach’, *Accident Analysis & Prevention* [Preprint]. Available at: https://doi.org/10.1016/j.aap.2015.11.029.

Yu, Y., Xu, M. and Gu, J. (2019) ‘Vision-based traffic accident detection using sparse spatio-temporal features and weighted extreme learning machine’, *IET Intelligent Transport Systems*, 13(9), pp. 1417–1428. Available at: https://doi.org/10.1049/iet-its.2018.5409.

Yumami, E., Budiyanto, S. and Suyoto, S. (2018) ‘Factors influencing the adoption of e-tilang: Empirical evidence from the UTAUT model’, *Journal of Process Management. New Technologies*, 6(2), pp. 52–64. Available at: https://doi.org/10.5937/jouproman6-16650.

Yunus, S. and Abdulkarim, I.A. (2022) ‘Road traffic crashes and emergency response optimization: a geo-spatial analysis using closest facility and location-allocation methods’, *Geomatics, Natural Hazards and Risk*, 13(1), pp. 1535–1555. Available at: https://doi.org/10.1080/19475705.2022.2086829.

Zanella, A., Bui, N., Castellani, A., Vangelista, L. and Zorzi, M. (2014) ‘Internet of Things for Smart Cities', *Ieee Internet of Things Journal* [Preprint]. Available at: https://doi.org/10.1109/jiot.2014.2306328.

Zeadally, S., Hunt, R., Chen, Y.-S., Irwin, A. and Hassan, A. (2012) 'Vehicular ad hoc networks (VANETS): status, results, and challenges', *Telecommunication Systems*, 50(4), pp. 217–241. Available at: https://doi.org/10.1007/s11235-010-9400-5.

Zhan, Y., Wang, P. and Xia, S. (2011) 'Exploring the Drivers for ICT Adoption in Government Organization in China', in *2011 Fourth International Conference on Business Intelligence and Financial Engineering*. IEEE, pp. 220–223. Available at: https://doi.org/10.1109/BIFE.2011.63.

Zhang, G., Hattori, M., Trichtinger, L.A. and Wang, X. (2019) 'Target Rotation With Both Factor Loadings and Factor Correlations.', *Psychological Methods* [Preprint]. Available at: https://doi.org/10.1037/met0000198.

Zhang, H., Bi, Y., Kang, F. and Wang, Z. (2022) 'Incentive mechanisms for government officials' implementing open government data in China', *Online Information Review*, 46(2), pp. 224–243. Available at: https://doi.org/10.1108/OIR-05-2020-0154.

Zhang, P., Wang, C., Chen, F., Cui, S., Cheng, J. and Bo, W. (2022) 'A Random-Parameter Negative Binomial Model for Assessing Freeway Crash Frequency by Injury Severity: Daytime versus Nighttime', *Sustainability*, 14(15), p. 9061. Available at: https://doi.org/10.3390/su14159061.

Zhang, X., Qi, S., Zheng, A., Luo, Y. and Hao, S. (2023) 'Data-Driven Analysis of Fatal Urban Traffic Accident Characteristics and Safety Enhancement Research', *Sustainability*, 15(4), p. 3259. Available at: https://doi.org/10.3390/su15043259.

Zhang, Y., Ye, N., Wang, R. and Malekian, R. (2016) 'A Method for Traffic Congestion Clustering Judgment Based on Grey Relational Analysis', *Isprs International Journal of Geo-Information* [Preprint]. Available at: https://doi.org/10.3390/ijgi5050071.

Zhang, Z., Xu, N., Liu, J. and Jones, S. (2024) ‘Exploring spatial heterogeneity in factors associated with injury severity in speeding-related crashes: An integrated machine learning and spatial modeling approach’, *Accident Analysis & Prevention*, 206, p. 107697. Available at: https://doi.org/10.1016/j.aap.2024.107697.

Zhou, S., Loiacono, E.T. and Kordzadeh, N. (2023) ‘Smart cities for people with disabilities: a systematic literature review and future research directions’, *European Journal of Information Systems*, pp. 1–18. Available at: https://doi.org/10.1080/0960085X.2023.2297974.

Zhou, T. (2011) ‘The impact of privacy concern on user adoption of location-based services’, *Industrial Management and Data Systems*, 111(2), pp. 212–226. Available at: https://doi.org/10.1108/02635571111115146.

Zhou, Z., Luo, B.N. and Tang, T.L. (2017) ‘Corporate Social Responsibility Excites “Exponential” Positive Employee Engagement: The Matthew Effect in CSR and Sustainable Policy’, *Corporate Social Responsibility and Environmental Management* [Preprint]. Available at: https://doi.org/10.1002/csr.1464.

Zhu, H., Zhou, Y. and Chen, Y. (2020) ‘Identification of potential traffic accident hot spots based on accident data and GIS’, *MATEC Web of Conferences*. Edited by S. Moridpour, 325, p. 01005. Available at: https://doi.org/10.1051/matecconf/202032501005.

Zhu, J. and Hou, H. (2021) ‘Research on User Experience Evaluation of Mobile Applications in Government Services’, *Ieee Access* [Preprint]. Available at: https://doi.org/10.1109/access.2021.3070365.

Zhu, M., Zhang, W. and Xu, C. (2024) ‘Ethical governance and implementation paths for global marine science data sharing’, *Frontiers in Marine Science*, 11. Available at: https://doi.org/10.3389/fmars.2024.1421252.

Zhu, W., Yang, H., Yang, B. and Sosik, J.J. (2024) ‘Innovative leadership in organizations: Dimensions, measurement, and validation’, *Journal of Business Research*, 172, p. 114445. Available at:

https://doi.org/10.1016/j.jbusres.2023.114445.

Ziemba, E., Papaj, T. and Descours, D. (2014) ‘Assessing the quality of e-government portals – the Polish experience’, 2, pp. 1259–1267. Available at: https://doi.org/10.15439/2014F121.

Zimmermann, G., Strobbe, C. and Ziegler, D. (2019) ‘Inclusive Responsiveness – Why Responsive Web Design Is Not Enough and What We Can Do About This’, in, pp. 203–215. Available at: https://doi.org/10.1007/978-3-319-94622-1_20.

Zinko, R., Ferris, G.R., Humphrey, S.E., Meyer, C.J. and Aime, F. (2011) ‘Personal Reputation in Organizations: Two-study Constructive Replication and Extension of Antecedents and Consequences’, *Journal of Occupational and Organizational Psychology* [Preprint]. Available at: https://doi.org/10.1111/j.2044-8325.2010.02017.x.

Zinko, R. and Rubin, M. (2015) ‘Personal reputation and the organization’, *Journal of Management & Organization*, 21(2), pp. 217–236. Available at: https://doi.org/10.1017/jmo.2014.76.

Zioło, M., Niedzielski, P., Kuzionko-Ochrymiuk, E., Marcinkiewicz, J., Łobacz, K., Dyl, K. and Szanter, R. (2022) ‘E-Government Development in European Countries: Socio-Economic and Environmental Aspects’, *Energies*, 15(23), p. 8870. Available at: https://doi.org/10.3390/en15238870.

Ziosi, M. and Pruss, D. (2024) ‘Evidence of What, for Whom? The Socially Contested Role of Algorithmic Bias in a Predictive Policing Tool’. Available at: http://arxiv.org/abs/2405.07715.

Zowghi, D. (2018) ‘“Affects” of User Involvement in Software Development’, in *2018 1st International Workshop on Affective Computing for Requirements Engineering (AffectRE)*. IEEE, pp. 13–13. Available at: https://doi.org/10.1109/AffectRE.2018.00008.

Zowghi, D. and Coulin, C. (2005) ‘Requirements elicitation: A survey of techniques, approaches, and tools’, *Engineering and managing software* *requirements*, pp. 19–46.

Zumbo, B.D. (2005) 'Structural Equation Modeling and Test Validation', *Encyclopedia of Statistics in Behavioral Science* [Preprint], (June). Available at: https://doi.org/10.1002/0470013192.bsa654.

Zumbo, B.D. and Chan, E.C.Y. (2014) *Validity and Validation in Social, Behavioral, and Health Sciences*. Available at: https://doi.org/10.1007/978-3-319-07794-9.

Zvolensky, M.J., Vujanovic, A.A., Bernstein, A., Bonn-Miller, M.O., Marshall, E.A. and Leyro, T.M. (2007) 'Marijuana Use Motives: A Confirmatory Test and Evaluation Among Young Adult Marijuana Users', *Addictive Behaviors* [Preprint]. Available at: https://doi.org/10.1016/j.addbeh.2007.06.010.