On the Economic Preferences towards Household Recycling in China: The Role of Social Norm Nudges and Long-term Life Goals

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Abstract

This thesis examines the relationship between pro-environmental behaviour—specifically household waste recycling—and the impact of intervention policies and long-term personal goals. It investigates whether factors beyond the traditional neoclassical choice model, including external influences such as social norms and internal factors such as personal values, affect individuals' willingness to participate in community recycling programmes and their willingness to pay (WTP) for recycling.

Using a choice experiment (CE) approach, individual-level data was collected from residents in three Chinese cities: Zhengzhou and Shijiazhuang, which currently implement advocative policies, and Shanghai, where recycling is mandatory. The study first investigates whether differing local policy frameworks influence stated preferences (SP) for household recycling and evaluates how effective nudges are in enhancing recycling participation. Specifically, it examines the compatibility and consistency of nudges—such as descriptive social norm communication—with existing local recycling policies. A randomised experiment was designed, varying two dimensions of social norms: the proportion of residents reportedly participating in recycling and their geographical proximity. Results show that mandatory policies significantly outperform advocative approaches in promoting recycling participation. Social norms generally enhance recycling efforts; however, excessively high normative expectations can reduce motivation. Additionally, residents from cities with advocative policies demonstrated greater responsiveness to social norms than those under mandatory policies. The influence of social norms was also found to vary according to individuals' current recycling behaviours, being stronger among those who were initially less engaged.

The second aim of this thesis is to evaluate whether the integration of goal theories can enhance the Theory of Planned Behaviour (TPB) framework in the context of recycling. It examines whether life goals impact recycling preferences directly or indirectly through attitudes, perceived behavioural control, and subjective norms. Employing a Hybrid Mixed

Logit (HMXL) model, the study investigates the relationships among TPB components, life goals (categorised as hedonic, gain-oriented, and normative), demographic factors, and recycling decisions. Findings indicate a strong relationship between positive recycling preferences and the TPB latent variable, suggesting that individuals with more favourable attitudes, greater perceived control, and subjective social norm demonstrate increased engagement in recycling. Moreover, specific recycling and disposal preferences are linked to normative life goals, underscoring that individuals driven by altruistic motivations prioritise effective waste management. Structural equation modelling confirms that normative life goals indirectly influence recycling decisions by strengthening key TPB elements.

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List of Abbreviations

ABM	Agent-Based Modelling
AIC	Akaike Information Criterion
ANOVA	Analysis of Variance
ASC	Alternative-Specific Constant
BIC	Bayesian Information Criterion
CAIC	Consistent Akaike Information Criterion
CE	Choice Experiment
CL	Conditional Logit
CM	Choice Modelling
CO	Carbon Monoxide
CV	Contingent Valuation
CVM	Contingent Valuation Method
DEA	Data Envelopment Analysis
DCEs	Discrete Choice Experiments
EFA	Exploratory Factor Analysis
ERB	E-Waste Recycling Behaviours
ERIs	E-Waste Recycling Intentions
EU	European Union
HCM	Hybrid Choice Models
HMXL	Hybrid Mixed Logit Model
ICLV	Integrated Choice and Latent Variable
IID	Independent and Identically Distributed
IIA	Independence from Irrelevant Alternatives
LV	Latent Variable
MGB	Model of Goal-Directed Behaviour
MIMIC	Multiple Indicators and Multiple Causes
ML	Mixed Logit
MNL	Multinomial Logit Model
MO	Moral Obligation
MSW	Municipal Solid Waste
NOx	Nitrogen Oxides
OLS	Ordinary Least Squares
ONS	Office of National Statistics
PBE	Pro-Behavioural Experiment Program
PC	Perceived Convenience
PBC	Perceived Behavioural Control
PEBS	Pro-Environmental Behaviours
PLS-SEM	Partial Least Squares SEM
RPL	Random Parameter Logit
RP	Revealed Preference
RUM	Random Utility Maximisation
SEM	Structural Equation Modelling
SP	Stated Preferences
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
UK	United Kingdom (incl. Northern Ireland)

KMO	Kaiser-Meyer-Olkin Test	**US**	United States of America
LCA	Latent Class Analysis	**USD**	United States Dollar
LCL	Latent Class Conditional Logit	**WTP**	Willingness to Pay
LCM	Latent Class Models	**WJX**	Wenjuanxing Platform
LR	Log-Likelihood Ratio	**RUT**	Random Utility Theory

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Declaration

I certify that the thesis I have presented for examination for the PhD degree at the University of Glasgow is my own work. This thesis, and the research contained within it, was conducted by me between June 2021 and March 2025, unless stated otherwise. No part of this thesis has been submitted for the award of another degree

Signature
Jingyi Gu

Chapter 1

Introduction

1.1 Overview

Chapter 1 of my thesis serves as an introduction. Section 1.2 provides the background and motivation by briefly defining Municipal Solid Waste (MSW), discussing the associated problems, exploring the global waste crisis, examining issues specific to China, and reviewing current waste treatment methods in China. Section 1.3 outlines the research aims and objectives. Finally, Section 1.4 presents a roadmap for the remainder of the thesis.

1.2 Background and Motivation

The global challenges of overpopulation, industrial growth, and urbanisation are intensifying environmental pollution, prompting policymakers to develop sustainable solutions (Razzaq et al., 2021; Philippidis et al., 2019). These factors lead to increased consumption and waste, putting pressure on natural resources and environmental sustainability. Furthermore, waste negatively impacts ecosystems, socio-economic conditions, and climate change, obstructing mitigation efforts (Jeng et al., 2020). The mismanagement of solid waste highlights a recognised market failure, as waste represents a misallocated resource. For instance, inorganic materials such as plastic and paper could fulfil the industrial demand for recycled goods, while organic waste could enhance agriculture and reduce dependence on chemical fertilisers. Organic waste could also be utilised to generate biogas, providing renewable energy to countries facing energy shortages. However, instead of capitalising on this potential, waste continues to be a costly burden for municipal governments, which allocate substantial portions of their budgets to transport it to landfills, especially in developing nations (Matter et al., 2015).

Inadequate management of municipal solid waste (MSW) significantly harms environmental quality in urban areas (Wilson and Velis, 2014; Woretaw et al., 2017; Khattak et al., 2009).

Proper waste sorting and recycling are essential for reducing environmental pollution, preserving natural resources, and promoting sustainable development. From a policy standpoint, recycling conserves limited resources, reduces landfill waste, and diminishes the negative externalities associated with raw material extraction and production. Consequently, promoting recycling offers substantial environmental benefits and enhances sustainability. However, the success of community recycling programmes largely depends on public support and participation. Traditional economic theory suggests that individuals may not take responsibility for their environmental impact without appropriate market incentives. In a typical scenario with many participants, collective behaviour shapes the environmental outcome, while the impact of a single individual is minimal, leading to the common free-rider problem. However, in many cases, individuals choose to invest time and money into waste sorting that exceeds the measurable environmental benefits gained, despite this contradicting the standard homo economicus model (Czajkowski et al., 2014). This thesis explores the relationship between pro-environmental behaviour—specifically household waste recycling—and intervention policies and long-term personal goals. Specifically, it examines whether a range of factors beyond the standard neoclassical choice model, including external factors (such as information on social norms) and internal factors (such as personal values), influence individuals' willingness to participate in community recycling programmes and their maximum willingness to pay for recycling.

1.2.1 Municipal Solid Waste

Municipal solid waste (MSW) refers to non-air and sewage emissions managed by a municipality. It includes household rubbish, commercial waste, construction debris, dead animals, and abandoned vehicles (Cointreau, 1982). The primary components of MSW include paper, organic matter, plastics, metals, textiles, rubber, and glass (Zhou et al., 2014).

1.2.2 Types of Solid Waste Management

The four main methods of municipal solid waste management are landfilling, incineration, composting, and recycling. Although incineration, composting, and recycling all diminish waste volume, their residues still require landfilling (Seo et al., 2004; Iqbal et al., 2020).

Landfilling is the only genuine disposal method and is frequently the most cost-effective option, especially in developing countries where waste is often discarded into pits or former mining sites. (Daskalopoulos et al., 1998). However, landfills generate harmful gases, primarily methane and carbon dioxide, as well as leachate, which may contain nutrients, heavy metals, and toxins. (El-Fadel et al., 1997). Between 2003 and 2013, methane emissions from municipal solid waste (MSW) landfills in China increased from 1,141.10 Gg to 1,858.98 Gg, averaging an annual rise of 71.79 Gg. Notably, northern and western provinces experienced higher emission growth compared to southern and eastern regions (Du et al., 2017).

Incineration is the process of burning waste at high temperatures after the removal of non-combustible materials. This method reduces waste volume and generates energy. However, it emits pollutants such as dioxins, furans, and heavy metals, which pose health and environmental risks. It also produces toxic ash that necessitates careful disposal to prevent environmental contamination. Furthermore, the high costs of establishing incineration facilities render them impractical for many developing nations(Sharma et al., 2013). For instance, in Shenzhen, local residents protested against the proposed Shenzhen East Waste-to-Energy Plant due to concerns about pollution and health risks linked to incineration. This opposition underscores the difficulties policymakers encounter when attempting to implement waste management solutions that are both effective and publicly acceptable (Standaert, 2017).

Composting and anaerobic digestion utilise microbes to decompose the organic portion of waste, with the remaining material necessitating incineration or landfilling. These processes diminish landfill waste and can produce fertilisers or fuel; however, like incineration, they frequently prove too costly for poorer communities (Sonesson et al., 2000). For example, in 2019, Zhejiang Province established a composting facility to process kitchen waste and other biodegradable materials. Serving around 11,000 residents across four villages, the facility was built with a government investment of 2.7 million yuan and has a capacity of 5 tonnes per day. Operating costs are approximately 220 yuan per tonne, producing about 140 tonnes of organic fertiliser annually for local landscaping. This demonstrates that, with proper planning and investment, composting can be a viable solution even for communities with limited resources (Li et al., 2023).

Recycling involves collecting waste materials and transforming them into new products, which benefits both the community and the environment. This approach not only helps protect the environment but also conserves natural resources. Yet such opportunities are often not taken advantage of. For instance, the recovery rate for glass packaging containers in China is notably low, with some scholars estimating that only 13% of waste glass is recycled, significantly below the global average of 50%.[1]

1.2.3 What problems can municipal solid wastes cause?

Evaluating the impacts of municipal solid waste management involves considering many factors. Health risks include exposure to toxic chemicals in air, water, and soil; infections and biological contaminants; stress from odours, noise, vermin, and unsightly waste; as well as risks of fires, explosions, subsidence, spills, accidents, and transport emissions (Rushton, 2003). Environmental impacts fall into six categories: global warming, photochemical smog, depletion of non-living resources, acidification, eutrophication, and water ecotoxicity (Seo et al., 2004).

Landfills are linked to numerous health and social issues, including unpleasant odours, ozone formation (due to reactions between NOx and organic compounds in sunlight), which can harm the lungs and central nervous system, and fire and explosion risks from methane build-up. They also attract vermin such as birds, rodents, and insects, which spread diseases, and contribute to soil and air pollution through leachate and landfill gases (Daskalopoulos et al., 1998; Schubel and Neal, 1987). Contaminated water from leachate can spread bacteria and diseases like typhoid fever, especially in developing countries where access to deep wells is limited. Therefore, landfills pose significant environmental risks, including groundwater and soil contamination.

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[1] Huajing Industrial Research Institute. (2023). Analysis of the current situation and future trends of China's waste glass recycling industry in 2023, with recycling value hitting a new record. Huajing Intelligence Network. Retrieved from https://www.huaon.com/channel/trend/877548.html (in Chinese)

Incineration affects society by producing unpleasant odours and making the facility visually unappealing (Garrod and Willis, 1998). It can also lead to surface water pollution from wastewater used to cool hot ashes. The most significant health and environmental concern comes from air emissions, which include particulates, carbon monoxide (CO), nitrogen oxides (NOx), acid gases, volatile organics, and mercury. These substances contribute to toxic bioaccumulation and acid rain (Daskalopoulos et al. 1998). Inhaling particulates is a health risk, especially smaller particles that can carry heavy metals, becoming lodged in lung tissue and entering the bloodstream (Neal and Schubel 1987). In China, incineration is a major contributor to smog and haze in northern cities like Beijing, Shijiazhuang, and Shanghai.

Therefore, recycling has long been a popular area of research for economists, particularly following the so-called landfill crisis of the 1980s, as noted by (Kinnaman and Fullerton, 2002). This is because almost all production and consumption activities generate by-products that need to be managed in some way. In recent years, attention has turned to understanding what drives people to engage in pro-environmental behaviours like recycling or volunteering for local conservation groups. In the case of recycling, a body of research highlights factors such as the cost of alternative waste disposal methods, the availability of recycling facilities, and the influence of self-image and social pressure (Iyer and Kashyap, 2007; Hanley and Czajkowski, 2019; Nixon and Saphores, 2009; Khattak et al., 2009). However, certain elements of household motivations to recycle remain unclear.

1.2.4 Global Waste Crisis

The United Nations Conference on the Human Environment, held in Stockholm in 1972, addressed the risk of 'massive and irreversible harm to the environment essential to our life and well-being'. Since then, numerous strategies, tools, and practices have been employed to address social and environmental impacts (Greyson, 2007). However, the volume and variety of waste not recycled into new resources have significantly increased, and efforts to prevent such large-scale and irreversible harm have been unsuccessful. Previous research shows that annual global waste production has reached around 17 billion tonnes, and is projected to rise to 27 billion tonnes by 2050 (Karak et al., 2012). Urban areas alone generate approximately 2 billion tonnes of waste annually, expected to reach 3.4 billion tonnes by 2050 (Kaza et al., 2018). However, only 33% of this waste is managed in an environmentally friendly manner. Currently, waste generation and poor management result in 1.6 billion tonnes of CO2 emissions, contributing to global air pollution. The cost of solid waste management is expected to rise from 205 billion USD to 376 billion USD by 2025 (Hoornweg and Bhada-Tata, 2012).

Figure 1.1 highlights the disproportionate share of global municipal solid waste (MSW) produced by developing nations, particularly among the top seven countries[2]. China (18.5%), India (18%), and Indonesia (3.7%) are the largest contributors, generating significantly more MSW compared to their population share. Brazil and Mexico also show a high percentage of waste generation, emphasising that emerging economies tend to produce more waste as urbanisation and economic growth increase, often without adequate waste management systems in place. This contrasts with developed nations like Japan, where the MSW share is more aligned with population size.

Figure 1.2 displays the waste management methods employed by G20 nations in 2019, focusing on landfilling, recycling, composting, and incineration. Figure 1.2 illustrates the different waste management methods employed by G20 countries in 2019[3], emphasising landfilling, recycling, composting, and incineration. It is clear that in developing countries such as China, Brazil, and Russia, landfilling dominates as the primary method of waste disposal. These nations demonstrate significantly lower rates of recycling, composting, and incineration compared to developed countries such as Germany and France, where these methods are more commonly used in waste management. This highlights the disparity in

[2] Circular Online (2019) 'US tops list of countries fueling "mounting waste crisis"'. Available at: https://www.circularonline.co.uk/news/us-tops-list-of-countries-fueling-mounting-waste-crisis/ (Accessed: 15 March 2025).

[3] Statista (2021) 'Waste disposal methods usage worldwide 2019, by selected country'. Available at: https://www.statista.com/statistics/1176725/methods-of-waste-disposal-by-country/ (Accessed: 15 March 2025).

infrastructure and policy between developing and developed nations regarding sustainable waste management solutions.

Figure 1. 1: Share of Global Population and MSW for G20 Countries (Source: Circular Online)

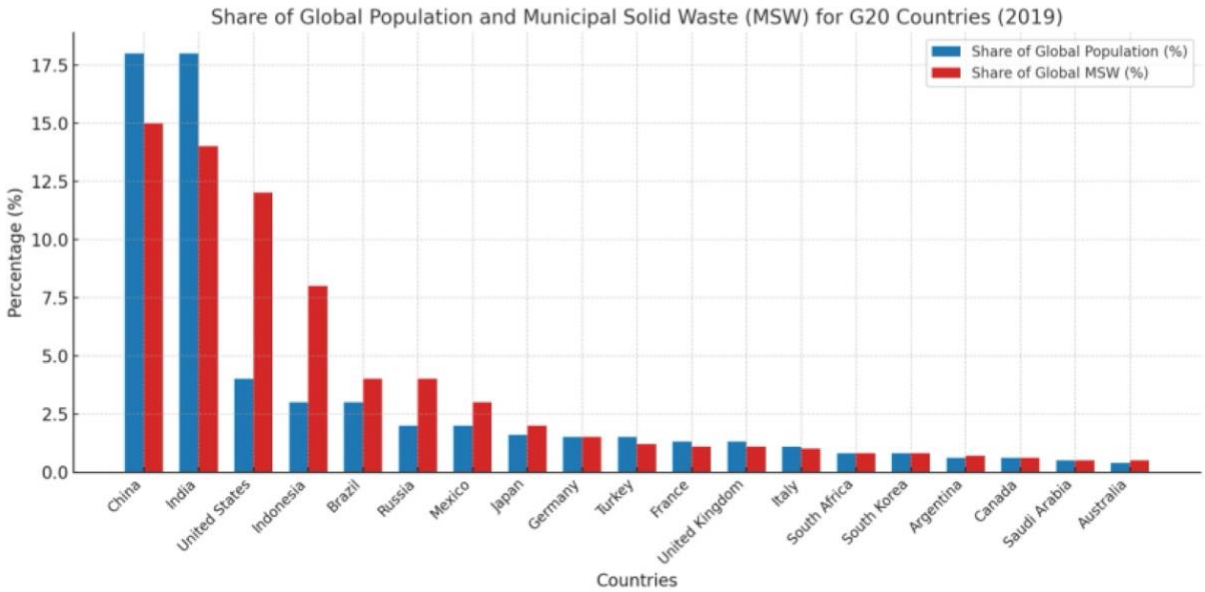
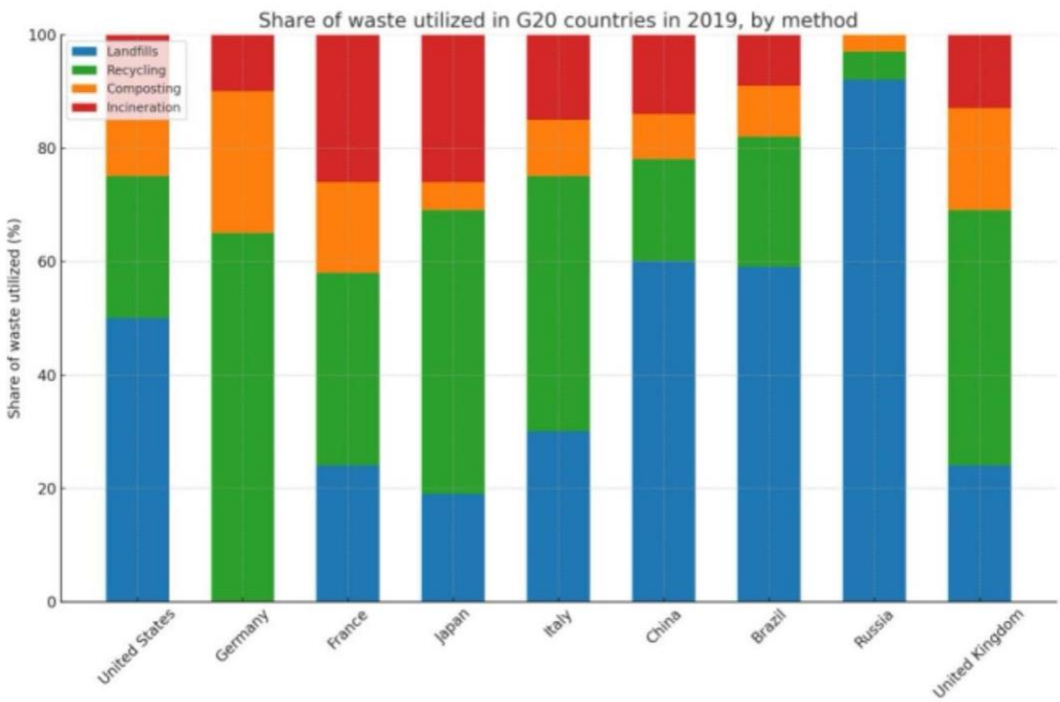


Figure 1. 2: Share of Waste utilised in G20 Countries in 2019 (Source: Statista)



1.2.5 Issues in China

Over the past three decades, China has undergone rapid urbanisation and experienced significant economic growth. According to the China Statistical Yearbook 2018[4], by 2017, 58.3% of its population lived in urban areas. However, this rapid urban expansion has put considerable pressure on sustainable development, resulting in increased environmental pollution. China's development has also led to an unprecedented rise in municipal solid waste (MSW). Data from the China Statistical Yearbook (2001-2017) shows a rapid rise in municipal solid waste (MSW) generation. Across 297 cities and 399 counties, MSW increased from 32 million tonnes in 1980 to 217 million tonnes in 2017. The per capita waste generation rate also grew from 0.50 kg/day in 1980 to 1.32 kg/day in 2018 (Zhou et al., 2017). Over the past three decades, the annual compound growth rate of MSW generation has been 5.75% (Zhang et al., 2010). No other country has faced as rapid and large an increase in solid waste as China (Lianghu et al., 2014). The significant rise in China's total MSW generation is mainly driven by population growth, urbanisation, and industrialisation (Zhang et al., 2010).

1.2.6 Current Treatment

Managing the rising volume of solid waste is a significant challenge for the Chinese government (Suocheng et al., 2001). China is already the world's largest waste producer, with its municipal waste expected to double that of the U.S. by 2030 (Chen et al., 2010). Traditionally, waste has been dealt with through incineration or landfilling, which causes environmental damage and energy loss. Despite a growing focus on waste-to-energy conversion since 2003 (Cheng et al., 2007), much of China's waste still ends up in landfills, even though more incinerators were planned (Li et al., 2016).

Between 2003 and 2017, incineration of waste in China increased by 33%, while landfilling decreased by 34% (Xin-Gang et al., 2016; Zhou et al., 2017). By 2017, around 57% of municipal solid waste (MSW) in cities was landfilled, 40% incinerated, and 1.6% composted.

[4] National Bureau of Statistics of China (2018) *China Statistical Yearbook 2018*. Available at: https://www.stats.gov.cn/tjsj/ndsj/2018/indexeh.htm (Accessed: 15 March 2025).

Notably, over 40% of these landfills do not meet U.S. sanitary landfill standards, and nearly 30% are open dumps, which harm the environment and create odour issues (Wen et al., 2014). Although China has made progress in developing sanitary landfills, significant challenges remain (Robinson et al., 2004). Of the 696 cities above town level, nearly two-thirds face a "waste siege," with landfills surrounding suburban areas, leading to an increasing reliance on incinerators for power generation (Zheng et al., 2014; Zhen-Shan et al., 2009). The large volumes of MSW pose both environmental and health hazards (Xue et al., 2011; Zhao et al., 2011). Therefore, to promote sustainable development, A shift towards mandatory classification emerged in 2017, which is China's MSW classification policy, leading to a 2017 initiative launching 46 cities for enforced sorting, with a goal set to reach a 30% recycling rate for household MSW by 2021 (General Office of the CPC Central Committee, 2017)[5]. However, despite 17 years of effort, China's MSW policies, being primarily advocatory, have not achieved significant progress in practical sorting outcomes. (Chu et al., 2023a).

Until July 2019, following the publication of the Shanghai MSW management regulation, Shanghai was selected as one of the first pilot cities for China's MSW classification policy (Zhou et al., 2019; Xiao et al., 2020)[6]. According to the Official Website of the Shanghai Municipal People's Government[7], Shanghai leads China in waste sorting, with over 95% of

[5] General Office of the State Council (2017) 'Notice of the General Office of the State Council on Issuance of Reform Plan for Solid Waste Import Management', *International Journal of Environmental Research and Public Health*, 16(17), p. 3099. Available at: https://www.mdpi.com/1660-4601/16/17/3099 (Accessed: 6 March 2025).

[6] The MSW sorting program aligns with the Regulation on Shanghai MSW Management, which was enacted on July 1, 2019, by the Shanghai Municipal People's Congress (2019a; 2019b). This policy mandates a four-category classification system for MSW sorting in Shanghai. The specific categories in this system include hazardous waste, recyclable waste, household food waste, and residual waste (Xiao et al., 2020). This policy mandates strict adherence to waste separation standards across Shanghai's waste management process, from initial sorting to transportation and final treatment. Consequently, the Shanghai Municipal Government has implemented a bidirectional monitoring system covering the entire cycle, including classified collection, transportation, transit, and disposal.

[7] Shanghai Municipal People's Government (2024) 'Implementation of waste sorting sees 97% citizen compliance after five years, achieving significant "three increases and one decrease" results', *Shanghai Municipal People's Government Official Website*, 1 July. Available

residents participating in 2021, making it the only pilot case to achieve significant success. However, implementing a mandatory waste sorting policy demands extensive regulatory resources and administrative efforts, increasing the burden on the government. Moreover, the emergence of negative sentiments can diminish the public's willingness for policy implementation (Min et al., 2020; Chen et al., 2022). Until now, China's MSW classification policy, except for Shanghai , has not been fully enforced in 46 cities such as Zhengzhou and Shijiazhuang (Han and Zhang, 2017; Chu et al., 2023a). These cities remain in the advocacy phase, lacking effective supervision and enforcement mechanisms.

Figure 1. 3: Classification of Municipal Solid Waste in Shanghai

In this context, China's waste-sorting policies are broadly divided into two types: advocative policies, under which local governments issue directives to residents on the correct categorisation of waste. Under these policies, non-compliance may lead to social disapproval but not economic penalties, as observed in Zhengzhou and Shijiazhuang. In contrast, mandatory policies, as implemented in Shanghai, go beyond merely informing households of their responsibilities. A stringent crackdown has been implemented and is scheduled to continue until 2025. During this period, waste-sorting activities will be actively monitored and subject to economic penalties. The principal difference between the advocative policies

at: https://www.shanghai.gov.cn/nw4411/20240701/535c23075d574b29bd4290eba9e4d586.html (Accessed: 6 March 2025).

and the mandatory policy lies in the level of supervision and the enforcement of economic penalties.

Therefore, the question arises: when comparing the impact of mandatory and advocative policies on the effectiveness of MSW classification, which policy better enhances local residents' recycling intentions? Furthermore, recent studies on environmental policies indicate that the introduction of one policy can influence public support for additional measures. Since waste management encompasses a coordinated approach involving waste sorting, collection, and disposal (Pires and Martinho, 2019), it's essential to consider whether China's MSW classification policy lead to positive or negative spillover effect on people's intentions towards the early (waste collection) and later (waste disposal) of waste recycling.

1.3 Research aims

The literature on recycling spans from economics to sociology journals, covering studies on pro-environmental behaviour and preferences. It highlights factors such as the cost of alternative waste disposal methods, the availability of recycling facilities, and the role of self-image, social pressures, and social norms (Czajkowski et al., 2017). However, some aspects of what motivates households to recycle remain unclear. Furthermore, the use of nudges in managing municipal solid waste (MSW) has been relatively rare (Carlsson et al., 2021), with most research on causal relationships focusing on Western countries. Notably, no study has yet compared the effects of social norm nudges in voluntary versus mandatory waste management systems. Additionally, recent literature has extensively investigated the direct and indirect effects of internal factors—such as self-image, environmental attitudes, moral obligations, and perceived behavioural control—on pro-environmental behaviour. However, there remains a notable lack of empirical research addressing how higher-level personal goals, such as broader life aspirations or identities, influence specific pro-environmental actions in practice. Understanding these relationships could provide valuable insights into the mechanisms underlying sustained behavioural change.

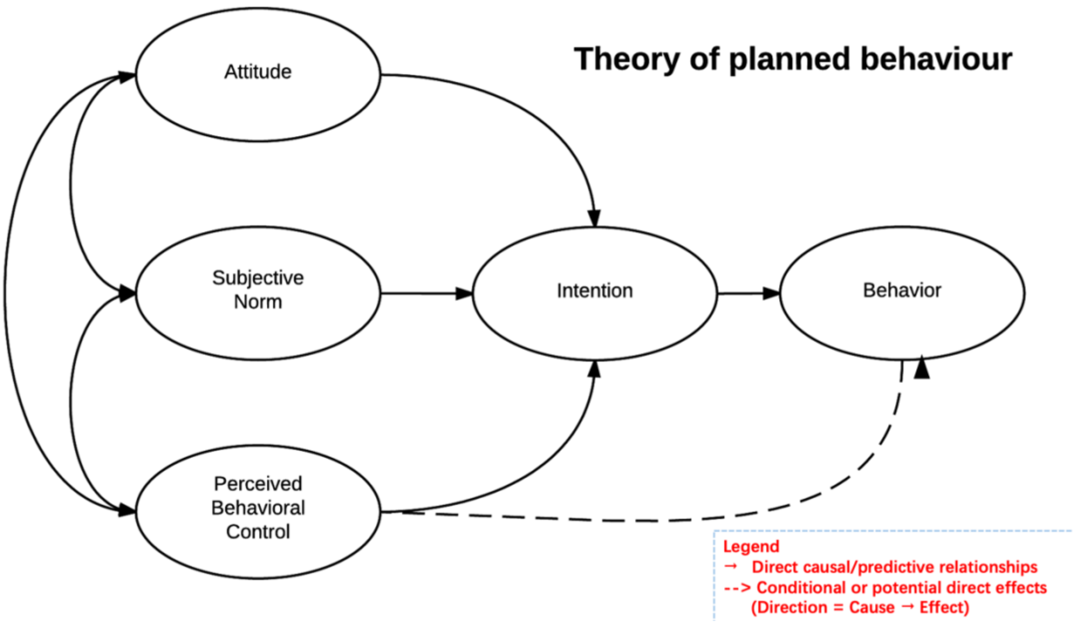
This thesis covers two main topics. Chapter 4 looks at how different policies influence pro-environmental behaviour, especially household recycling. It focuses on whether external factors, such as different current MSW managements, nudges based on social norms, can encourage more people to participate in recycling schemes. Chapter 5 explores how individuals' long-term personal goals relate to their recycling behaviour. It investigates whether internal factors—like personal values, attitudes towards the environment, and life goals—affect people's willingness to join local recycling programmes and how much they are willing to pay for them. Together, these chapters aim to show how external policies and internal motivations shape recycling behaviours beyond traditional economic models.

Therefore, Chapter 4 focuses specifically on China as a suitable context for our first topic. We conducted a stated preference (SP) study comparing Zhengzhou and Shijiazhuang, which are currently under advocative policies, with Shanghai, where mandatory waste sorting is enforced. We aim to explore the relationships between past recycling behaviours, social norm nudges, local mandatory or advocative waste sorting policies, and the willingness to financially support recycling initiatives in China. We employed a randomised experimental design to alter the magnitude of the social norm presented to each participant by varying information about others' recycling efforts. Subsequently, we utilised respondents' stated WTP for enhanced recycling standards required by a waste collection agreement as an indicator of households' intentions to recycle. For the econometric analysis, we applied a mixed logit (ML) model (McFadden and Train, 2000), incorporating interaction terms between varying levels of waste sorting policies and social norm nudges. Additionally, respondents' self-reported past recycling behaviours were analysed to determine whether prior recycling habits influence the effectiveness of social norm nudges.

In addition, to better explore and understand why people choose to engage in recycling, we included questions related to participants' long-term life goals and cognitive behavioural theories in our survey. In this thesis, long-term life goals are defined as personal strivings, characterised by ongoing and long-term goal-pursuing behaviours (Emmons, 1986). We argue that Allport's views on the connection between long-term goals and the intent to execute current actions have not been sufficiently acknowledged in existing cognitive behavioural theories, particularly the Theory of Reasoned Action (TRA) (Fishbein, 1979; Ajzen, 2011; Ajzen and Driver, 1992; Ajzen and Driver, 1991; Fishbein, 1975) and the Theory of Planned Behaviour (Ajzen, 1985; Ajzen, 1991; Ajzen and Driver, 1992). According to Figure 1.4, The TPB suggests that behaviour is influenced by an individual's attitude (whether the behaviour is viewed positively or negatively), subjective norms (perceived social pressure to engage in a behaviour), perceived behavioural control (the perceived ease or difficulty of performing the behaviour), and behavioural intention. However, according to (Carver and Scheier, 2001) Control Theory, self-related or life goals (e.g., "become a responsible citizen") are at the top of the hierarchy, abstract action goals (e.g., "actively participate in waste sorting") sit in the middle, and specific action plans (e.g., "separate recyclable items and organic waste into different bins") are at the bottom. This raises the question: if recycling is viewed as altruistic, but someone's life goal is to become wealthy, would their long-term goal affect the effort they put into recycling?

Therefore, the second aim of this thesis, addressed in Chapter 5, is to investigate whether TPB theories should be augmented with insights from goal theories by considering pro-environmental behaviour. Specifically, it examines whether different life goals directly influence stated preferences for recycling or indirectly influence them through current attitude, perceived behavioural control, and subjective norms. The empirical context involves choices regarding household waste contracts and recycling actions in China. To investigate the relationships among individuals' theories of planned behaviour variables, life goals (including various types of long-term intentions such as happiness, success, and altruism for the benefit of the next generation), demographic factors, and decision-making preferences for recycling, we employ the Hybrid Mixed Logit (HMXL) model. This approach enables us to integrate both measurable characteristics of the decision-maker and other elements that cannot be directly measured, like attitudes towards recycling and different tendencies in life goals. In this chapter, I address two primary research questions. Firstly, I investigate whether the three components of the Theory of Planned Behaviour—attitudes, perceived behavioural control, and subjective norms—individually or collectively have positive relationships with recycling preferences. Secondly, recognising that goals are structured hierarchically, with broad, long-term objectives guiding more specific short-term actions, I explore whether different types of self-reported life goals (such as aspirations to benefit future generations) influence recycling preferences directly or indirectly via attitudes, perceived behavioural control, and subjective norms.

Figure 1. 4: The Theory of Planned Behaviour (Ajzen, 1991),
Intention is shaped by attitude, social norms, and perceived control, which predict behaviour.



This thesis aims to model residents' preferences towards recycling in three Chinese cities—Shanghai (with mandatory waste management), Zhengzhou, and Shijiazhuang (with advocated waste management)—using economic theories and methods. The focus is on examining the economic preferences for household recycling in China, particularly the role of social norm nudges and long-term life goals. Based on the two main research topics outlined above, I have established four specific research objectives (ROs):

RO1: Using the stated preference method and WTP (willingness to pay) as indicators of individual intentions, I aim to compare the impact of mandatory waste sorting policies with that of advocated policies on recycling preference.

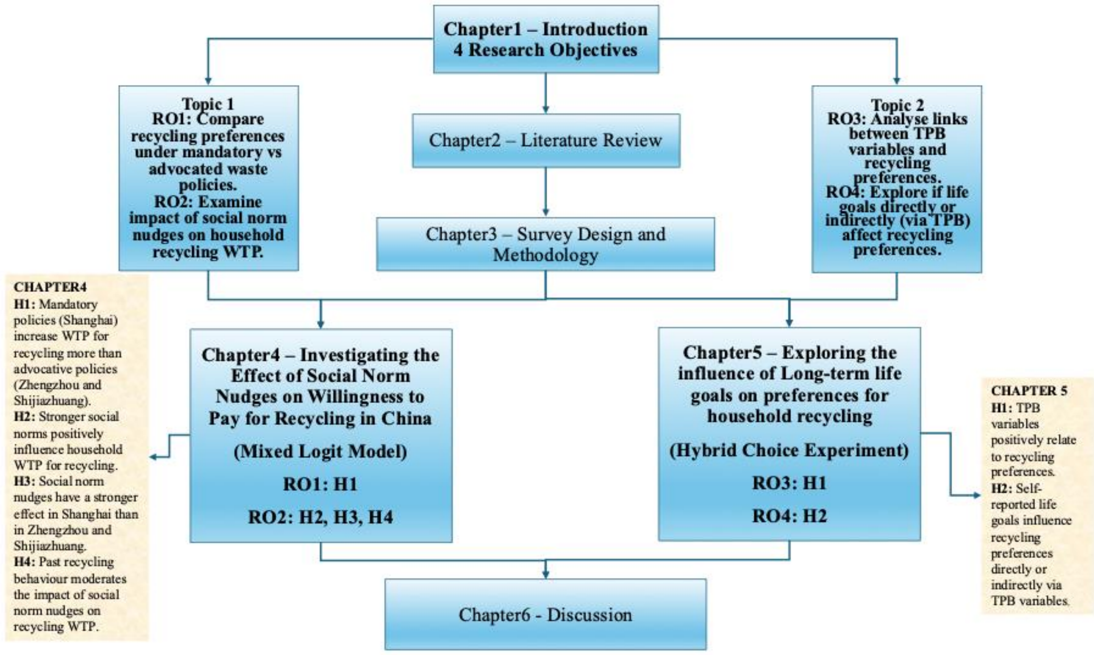
RO2: Exploring how different types of social norm nudges influence household WTP for increased recycling in Chinese cities and assessing the compatibility of these nudges with local waste sorting policies.

RO3: Analysing whether the variables from the Theory of Planned Behaviour (TPB) are related to preference parameters for recycling.

RO4: Investigating whether variables representing different self-reported well-being goals (e.g., benefiting future generations) are directly related to recycling preferences, or indirectly through TPB variables.

As illustrated in Figure 1.5, Chapter 4 investigates household recycling preferences and the effects of social norm nudges. Specifically, it addresses two main research objectives. RO1 tests whether households under mandatory recycling policies (Shanghai) have a higher willingness-to-pay (WTP) for recycling compared to those under advocative policies (Zhengzhou and Shijiazhuang), as stated in Hypothesis 1 (H1). RO2 explores how social norm nudges influence households' WTP: whether stronger social norms enhance recycling WTP (H2), whether this effect is greater under Shanghai's mandatory policy than in cities with voluntary policies (H3), and whether past recycling experience moderates responses to these nudges (H4). Chapter 5 analyses the relationship between recycling preferences, the Theory of Planned Behaviour (TPB), and personal goal theories. It covers two main objectives: RO3 assesses if TPB variables—attitudes, subjective norms, and perceived behavioural control—positively affect recycling preferences (H1). RO4 examines if personal life goals (e.g., benefiting future generations) directly or indirectly influence recycling preferences via TPB variables (H2). For further details, refer to Sections 4.2 and 5.2.

Figure 1. 5: Hierarchical Structure of Thesis Research Objectives and Hypotheses



1.4 Road map

As illustrated in Figure 1.5, this thesis is organised into six chapters, contributing to the literature on discrete choice experiments in environmental economics, particularly concerning citizens' preferences for recycling in China. Each chapter highlights the study's key contributions.

Chapter 1 introduces the thesis, outlining the background and aims of the research.

Chapter 2 reviews existing literature on social norms, social norm nudges, pro-environmental behaviours, the Theory of Planned Behaviour (TPB), and life goal theory.

Chapter 3 explains the main methodology used in the economic analysis, discrete choice experiments (DCEs). It discusses the concept, models employed, and key stages in conducting a DCE.

Chapter 4 uses the DCE method to estimate citizens' preferences for recycling in China, comparing the effects of mandatory and advocated waste sorting policies. It also explores the influence of different social norm nudges on household WTP for increased recycling and their compatibility with local waste management policies.

Chapter 5 analyses whether TPB variables are related to recycling preference parameters and investigates whether self-reported well-being goals (e.g., benefiting future generations) are directly or indirectly related to these preferences through TPB variables.

Chapter 6 summarises the thesis's overall findings and discusses potential avenues for future research.

Chapter 2

Literature review

2.1 Overview

Chapter 2 reviews the relevant literature on social norms, social norm nudges, the Theory of Planned Behaviour (TPB), goal theories, and pro-environmental behaviour. The chapter is structured as follows: Section 2.2 examines previous research on social norms, norm nudges, economic penalties, mandatory policies, and pro-environmental behaviours. Section 2.3 focuses on studies related to social norm nudges, mandatory policies, and environmental behaviours in China. Section 2.4 reviews the Theory of Planned Behaviour and its associated literature, while Section 2.5 explores goal theories. Finally, Section 2.6 provides a summary and conclusion.

2.2. Previous work on social norms, social norm nudges, economic penalties, mandatory policy, and pro-environmental behaviours

The impact of social norms on individual behaviour is a classic topic in social psychology. Social norms indicate typical or standard behaviours and inspire actions by highlighting what is considered effective, adaptive, and fitting within a social context (Göckeritz et al., 2010). Some economists have used insights based on moral and social norms to explain the occurrence of voluntary contributions (Rabin, 1998; Festinger, 1957; Deci and Ryan, 2013; Frey, 1994). Social norms, seen as shared ideals of behaviour, play a crucial role in shaping individual actions, as noted by Ostrom (2000), Burke and Young (2011), and Fishbein (1975), who assert that awareness and adherence to these norms can lead to behaviour change. As outlined by Fehr and Fischbacher (2004) and Thøgersen (2006), these social expectations influence behaviour in two ways: through the fear of sanctions in case of non-conformity (consequentialism) and through a sense of moral duty to do what is considered "right" (logic of appropriateness). In addition, according to Nyborg and Rege (2003), it is important to note that the disapproval expressed by environmental contributors towards non-environmental contributors might not always stem from a conscious or deliberate choice. Such sanctions can occur spontaneously and sometimes even unconsciously. Additionally, sanctioning behaviours do not always have to be costly or substantial for the one imposing the sanction. Even minor gestures, like a frown or simply the notion that someone may disapprove of one's behaviour, can be enough to convey social disapproval towards non-environmental contributors. Cialdini and Kallgren distinguish between injunctive norms and descriptive norms, injunctive norms, the norms of "ought" can be expressed in terms of what is commonly approved or disapproved, and descriptive norms, the norm of "is" can be expressed in terms of what commonly done by some relevant reference group (Cialdini et al., 1990; Kallgren et al., 2000).[8] In our research, we present social norms as the commonness of recycling actions across various groups, identifying these as descriptive norms (further elaborated in Chapter 4.3).

Recent studies highlight that the effect of social norms on behaviour can vary based on factors like personal identification with one's social group, the specific norms invoked, and the context (Farrow et al., 2017). Identity diversity within groups may foster a resistance to conformity (Smith and Silva, 2011). For example, Nolan et al. (2008) found that norms applied at a local level, such as those for hotel room guests, have a greater impact than broader norms. Thus, individuals are more influenced by those in close proximity or emotional connection, leveraging social networks for both contextual influence and guidance in interpreting information (Lu and Wang, 2022).

In the economics of recycling literature, there's a trend to associate social norms with the concept of 'warm-glow'. Research discussed hypotheses for seemingly unselfish behaviour is Andreoni (1990) concept of the 'warm glow of giving,' a private benefit for contributing

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[8] Previous research has demonstrated distinct impacts of descriptive and injunctive social norms. According to normative conduct theory, their effectiveness hinges on saliency (Cialdini et al., 1991). Descriptive norms have shown significant influence in altering behaviors (Lewis and Neighbors, 2006), whereas injunctive norms are notably more effective in contexts where undesirable behaviors are prevalent (Cialdini et al., 2006; Cialdini, 2009). A few scholars have found no significant difference in the effects of injunctive and descriptive norms on prosocial behavior (Jacobson et al., 2011). According to Kallgren et al., (2000), the influence of social norms is shaped by how prominently a norm is emphasized and the consistency of norms.

to a collective good. This idea clarified the previous paradox by integrating personal satisfaction into the impure altruism model. Clark et al. (2003) describe 'warm-glow' as deriving personal satisfaction from an activity, regardless of its outcome. Similarly, De Young (1996) and Young (2000) highlight intrinsic satisfaction as a key motivator for involvement in activities, suggesting that self-interest is the underlying driver. He emphasises that intrinsic motivations, rather than external incentives, are the main influencers of behaviour and have a more lasting impact. The fact that households continue to recycle despite lacking financial incentives indicates alternative motivations. Kinnaman (2006) proposes that this motivation is linked to the 'warm-glow' effect. He observes that households don't just recycle, but they are also prepared to incur costs for the chance to do so, underscoring a deeper, non-monetary motivation behind their recycling efforts. According to Halvorsen (2008), this warm-glow feeling comes from adhering to social and moral norms, making the two concepts inseparable. Brekke et al. (2003) link warm-glow to a positive self-image, which is influenced by how socially responsible individuals consider their behaviour. They view socially responsible behaviour as a moral ideal, internally set by and varying across individuals. Brekke et al. (2007); Brekke et al. (2010) and Bruvoll and Nyborg (2004) shift this benchmark from a moral to a social norm, externally defined, where a positive self-image depends on how an individual’s recycling efforts compare with their perception of a social norm. In addition, according to Brekke et al. (2003), if household recycling is primarily driven by social norms, implementing economic (monetary) rewards could potentially crowd out intrinsic motivations. This is because such incentives might diminish one's self-perception, and bring up concerns regarding income distribution and fairness, as highlighted by Frey (1997).

A significant body of research demonstrates the impact of social norm nudges on various environmentally-focused decisions and actions (Farrow et al., 2017), with most studies indicating a strong influence of social norms on personal choices (Ben-Nun Bloom and Levitan, 2011). These studies predominantly reveal that descriptive social norms, when communicated through written messages rather than direct observation, effectively drive behavioural change (Zeng et al., 2020).[9] A notable example in the environmental domain by Allcott (2011) showed that information allowing individuals to compare their electricity usage to the neighbourhood average reduced consumption by 2% compared to a control group, with high consumers significantly cutting back and low consumers not increasing their use, thus avoiding boomerang effects. Bergquist et al. (2019), in their meta-analysis of field experiments utilising social norms to encourage pro-environmental behaviours (PEBs), found a consistently positive effect on the targeted behaviours.

The most relevant paper for my research, Czajkowski et al. (2019), shows the impact of conveying descriptive social norms on household recycling behaviour and WTP for waste collection contracts. They discover a non-linear response to social norm information, where high levels of norms do not always enhance but can sometimes deter recycling efforts, particularly among highly engaged households. However, social norm based nudge is not always effective for changing Pro-Environmental Behaviours (PEBs). Richter et al. (2018) found insignificant relationships between sustainable seafood consumption and a social norm. Schultz (2014) found that the relationship between PEB and social norms was significantly positive, but only for some respondents. Therefore, Brandon et al. (2017) suggest that nudges have unstable/unpredictable impacts on PEBs. One possible reason is inter-personal heterogeneity.

Pro-environmental behaviours are traditionally encouraged via behavioural interventions or modest incentives such as social norm nudges above. Nevertheless, nudges have not proven universally effective as tools for environmental policy (Andor et al., 2020), and the outcomes of financial rewards strategies are ambiguous, as discussed in the introduction (Deci et al., 1999; Kinnaman, 2006; Varotto and Spagnolli, 2017). Rewards that are less noticeable are particularly ineffectual (John et al., 2022). Therefore, the potential efficacy of introducing threats of sanctions merits further inquiry and scholarly attention. The true effectiveness of punishment policies remains elusive due to the lack of widespread studies on the subject

[9] Zeng et al. (2019) found that exposure to descriptive norms increased Chinese farmers' participation in environmentally-friendly agricultural practices.

(exceptions include Vollaard and van Soest (2024); additional studies will be examined in the later stages of the literature review). According to Browne et al. (2023), smart meters were used to enforce water conservation in Fresno, CA. Automated enforcement of water conservation reduced use by 3% and violations by 17%, but a 1,102% surge in complaints led to its cancellation, underscoring the political limits on technological enforcement. The punishment policy elevates the costs of non-compliant behaviour, thereby encouraging adherence to regulations, similar to how fines and points deductions for running red lights reduce such infractions. Due to the extensive regulatory resources and administrative efforts required, policymakers often implement short-term crackdowns to achieve long-lasting deterrent effects. This is similar to the situation in Shanghai, where the supervision and enforcement of mandatory residential waste sorting are prohibitively costly. Consequently, this crackdown in Shanghai is scheduled to end in 2025.

Based on studies by Banerjee et al. (2019), Elliott and Broughton (2005), and Sherman (1990), police crackdowns show immediate deterrent effects. Sherman (1990) highlighted that among eighteen crackdown case studies, fifteen showed initial deterrence. But sustained effects post-crackdown was minimal. Despite continued or intensified enforcement, the deterrent impact typically diminished quickly. According to Banerjee et al. (2019), the deterrent effect diminishes over time as individuals learn they can evade prohibited behaviour consequences, leading to a reduced expectation of penalties. Dur and Vollaard (2019) note that this deterrent impact further declines as the recency of penalties fades. However, the negative aspects of behavioural responses are notable, contrasting with previous research showing that crackdown effects are typically effective (Fehr and Gächter, 2002; Fehr et al., 2007; Gneezy and Rustichini, 2000). Holmås et al. (2010) found fines for extended hospital stays in Norway reduced intrinsic motivation, lengthening stays compared to hospitals without fines. Fehr et al. (2007) observed similar results regarding punishment in labour contracts. As highlighted in the introduction, external incentives can potentially reduce intrinsic motivations. The extent to which this reduction in intrinsic drive adversely affects people's behaviour hinges on the potency of the external incentives (Gneezy and Rustichini, 2000).

It is surprising that the papers we can find on punishment policies for waste sorting report positive effects. Vollaard and van Soest (2024) carried out a natural field experiment in Tilburg, targeting 70,000 households with potential fines for failing to separate waste. They observed a significant immediate increase in waste separation rates, which, unlike typical short-lived enforcement impacts seen in areas like traffic regulation, also remained stable over many months. They suggest this sustained change indicates a shift in habits. Habits reduce the perceived cost of effort, as in their case, where the effort towards more extensive waste sorting effectively dropped to nearly zero.[10] Consequently, the cognitive effort required for increased waste separation likely diminished over time.

2.3. Previous work on social norm nudges, mandatory policies and pro-environmental behaviours in China

Based on the review of studies examining the effects of social norm nudges on waste sorting in China, Zhang and Wang (2020) analysed selective waste collection schemes since 2000 across eight pilot cities. They utilised data from the Chinese General Social Survey to discover that the pilot program notably increased household waste sorting frequency, not only within the pilot cities but also in adjacent areas, thereby also boosting waste prevention and reduction efforts among the population. Ceschi et al. (2021) conducted a simulation based on real data from a community district in Taiwan, demonstrating the effectiveness and reliability of Agent-Based Modelling (ABM) as a method for assessing waste management policies. Their findings showed an uptick in recycling activities, especially in scenarios characterised by lower waste levels. Furthermore, Lu and Wang (2022) in their online survey spanning 46 cities in China, found that social norms significantly mediate the link between incentives and recycling behaviours, with descriptive norms exerting a stronger influence

[10] Gardner (2015) delves into psychological studies on habit development, highlighting how habit formation leads to the reduction of conscious thought and the automatic activation of behaviors upon encountering familiar situations. Simon (1976) describes this as the procedural rationality of habits, noting their role in conserving mental effort and aiding in the efficient distribution of limited cognitive resources. Waste separation being a habit is supported by evidence that past behavior strongly predicts current actions (Carrus et al., 2008; Hanley et al., 2019). Prugsamatz et al. (2010) demonstrate the automatic nature of waste sorting, evidencing the existence of habits as outlined in psychological studies.

than injunctive norms. To date, no literature has employed stated preference methods to investigate whether the different absolute levels of descriptive social norm influence residents' waste sorting behaviour intentions, using willingness to pay as an indicator in Chinese cities.

Based on a review of all studies we found on the impact of mandatory waste sorting policy in China, such as those by Zhao et al. (2022); Liu et al. (2022); Chu et al. (2023b); (Chu et al., 2023a),[11] reveal that mandatory policies positively influence waste sorting behaviours among both urban and rural residents. Liu et al. (2022) conducted a field survey among 1,293 residents in Jinan, inquiring about their willingness to sort domestic waste. They discovered that perceived penalty effectiveness directly enhances recycling intentions and behaviours, with perceived penalty effectiveness having the most significant impact on recycling behaviour (23.6%). In addition, Applying the Polynomial Distributed Lag model to compare and forecast the overall implementation effects of compulsory and advocative policies on MSW classification, with Shanghai (compulsory policy) and Tianjin (advocative policy) as case studies for 2021-2025, Chu and Wang (2023b) found that compulsory MSW classification policy generally outperformed advocative policy. Shanghai's overall MSW classification compliance rate improved from 28% to 77%, while Tianjin's increased from 9% to 15%. To date, no literature has employed stated preference methods to investigate whether the current mandatory waste sorting policy in Shanghai more positively influences residents' waste sorting behaviour intentions, using WTP as an indicator, compared to advocative policies in other Chinese cities.

Finally, increasing attention is being paid to nudges as a supplement to financial incentives, yet evidence on their interplay is limited and mixed. Some studies suggest positive synergies (Chen et al., 2021; List et al., 2017; Hilton et al., 2014), others indicate negative effects

[11] According to (Chu et al., 2023a), a three-stage DEA model was established to evaluate the effectiveness of Shanghai's compulsory MSW classification policy from February 2019 to July 2020, using the total amount of MSW classified as the output variable. They found that the average efficiency of the policy during the period was 0.906, indicating a fairly good implementation effect of Shanghai's compulsory MSW classification policy.

(Sudarshan, 2017; Chapman et al., 2010; Dolan and Metcalfe, 2013; Fanghella et al., 2021), and still others find no synergy at all (Bettinger et al., 2012; Mizobuchi and Takeuchi, 2013; Pellerano et al., 2017; Panzone et al., 2021). Drews et al. (2020), highlight the scarcity and uncertainty of available evidence from behavioural sciences regarding the synergy between these two tools, partly due to methodological limitations. Therefore, we conducted a stated preference (SP) study comparing Zhengzhou and Shijiazhuang, which are currently subject to advocative policies, with Shanghai, where mandatory waste sorting is enforced. The aim of this paper is to explore whether the current mandatory waste sorting policy in Shanghai exerts a more positive influence on WTP for household recycling compared to the other two cities under advocative policies. Additionally, we examine the stability and predictability of the effects of nudges on households' stated preferences for recycling and the compatibility of these nudges with existing local waste sorting policies.

2.4 The Theory of Planned Behaviour

The Theory of Planned Behaviour (Ajzen, 1985), building on the earlier Theory of Reasoned Action (Ajzen, 2011), serves as a well-known socio-psychological model for understanding social behaviour (Ajzen, 1991). Over the past three decades, it has been a key framework for investigating pro-environmental behaviours. Widely recognised by scholars, practitioners, and policymakers, the Theory of Planned Behaviour has been consistently validated in prior research as a highly effective model for predicting the factors influencing specific intentions and behaviours (Ramayah et al., 2012; Wan et al., 2012; Ayob et al., 2017). The Theory of Planned Behaviour integrates social influences and rational decision-making processes to predict intentions and behaviours (Ajzen and Fishbein, 1980). It is specifically aimed at forecasting the execution of behaviours, such as recycling, which may not be fully within an individual's voluntary control (Keong and Hirst, 2010).

The standard Theory of Planned Behaviour (TPB) comprises five key components: behaviour, behavioural intention, attitude, subjective norm and perceived behavioural control (PBC), as shown in Figure 1.3. Similar to the Theory of Reasoned Action (TRA), the TPB suggests that behaviour is primarily determined by an individual's intention to perform or avoid performing a specific behaviour. Intentions are, in turn, shaped by two key factors: attitude, which reflects an individual's beliefs and evaluations about the potential outcomes of the behaviour, and subjective norm, which captures the perceived social pressure to engage in the behaviour. The TPB extends the TRA by incorporating perceived behavioural control (PBC), drawing on Bandura's theory of self-efficacy (Bandura and Wessels, 1997; Locke, 1997). PBC reflects an individual's perceived ability to carry out the behaviour and influences both intention—since actions perceived as impossible are less likely to be intended—and actual behaviour, especially when perceived control corresponds with actual control (Abraham and Sheeran, 2003). This indicates that PBC can indirectly influence behaviour through intention while also having a direct effect on behaviour. In addition, as summarised by Zhang et al. (2020), individual factors such as personality, age, occupation, and gender can only indirectly influence behavioural intention through their effects on attitude, subjective norm, and perceived behavioural control. In general, individuals are more likely to engage in a behaviour when they hold a positive attitude towards it, perceive stronger social pressure, and feel a greater sense of control. However, the influence of each factor can vary depending on the specific context (Rhodes et al., 2015; Liu et al., 2021). According to Ajzen (1991), the impact of attitude, subjective norm, and perceived behavioural control (PBC) on intentions and behaviour can differ depending on the type of behaviour, and not all factors will strongly influence or directly predict the behaviour.

2.4.1 The Theory of Planned Behaviour and Pro-environmental behaviours

The Theory of Planned Behaviour (TPB) has been extensively applied across various fields to examine the relationship between key determinants and behaviours, ranging from early studies on investment decisions (East, 1993; Akhtar and Das, 2019), leisure choices (Ajzen and Driver, 1991; Ulker-Demirel and Ciftci, 2020), human health behaviours (Godin and Kok, 1996), dishonest actions (Harding et al., 2007) and driving violations (Elliott et al., 2003), to more recent and validated applications in pro-environmental behaviours, such as low-carbon consumption (Tan et al., 2023; Kaffashi and Shamsudin, 2019), public transportation use (Heath and Gifford, 2002), electricity consumption (Tan et al., 2017; Liobikienė et al., 2021), organic food purchasing(Al-Swidi et al., 2014), and recycling behaviours (Cheung et al., 1999; Liu et al., 2021; Tonglet et al., 2004; Ma et al., 2023). Recycling requires significant effort from individuals, as it involves sorting, preparing, and storing household waste. As a result, the decision to recycle is often complex and influenced by various factors (Boldero, 1995). The TPB offers a systematic framework for identifying these factors, and numerous studies have validated its effectiveness in examining the determinants of recycling behaviour (Davies et al., 2002; Cheung et al., 1999). Empirical evidence for the Theory of Planned Behaviour demonstrates that attitudes, subjective norms, and perceived behavioural control are reliable and positive predictors of recycling behaviours across different contexts. For example, according to Strydom (2018a), Structural Equation Modelling (SEM) was applied to data from a representative urban sample (n = 2004) in Africa, showing a strong fit with the Theory of Planned Behaviour. The model explained 26.4% of the variance in recycling behaviour and 46.4% in recycling intention.

Not surprisingly, research on recycling consistently identifies attitude as the strongest predictor of behavioural intention (Tonglet et al., 2004; Tang et al., 2011), with individuals holding positive attitudes towards recycling more likely to continue the behaviour and become more effective recyclers over time (Ayob et al., 2017; Greaves et al., 2013). Wang (2021) analysed waste separation behaviour in Shanghai using the Theory of Planned Behaviour. The study found that attitude was the strongest predictor, directly influencing intention and indirectly affecting waste separation behaviour, while subjective norms and perceived behavioural control had little effect.

In addition, research on recycling consistently highlights subjective norm as a key predictor of behavioural intention. Given that recycling often involves moral and social responsibility, subjective norm has been identified as a significant predictor of recycling behaviour(Gonul Kochan et al., 2016; Cheng, 2020; Juliana et al., 2022; Jia et al., 2023). According to the TPB, it is assumed that individuals are more likely to engage in behaviours such as recycling if their peer groups view it as the right thing to do. For instance, someone might think, "My family members expect me to take part in waste separation," or "My neighbours would appreciate knowing I practise waste separation." Such perceptions of approval from important referents can significantly enhance both waste separation intentions and behaviours (Ayob et al., 2017). Numerous previous studies have shown that subjective norm positively influences recycling behaviour(Chan, 1998). Jia et al. (2023) analysed plastic waste recycling behaviour and found that subjective norms significantly influenced recycling intention ($\beta = 0.12$, $p < 0.05$), based on Partial Least Squares Structural Equation Modelling PLS-SEM analysis of 577 survey responses.

The third key factor influencing waste separation intention is perceived behavioural control (PBC), which relates to an individual's confidence in their ability to carry out the behaviour. Higher self-confidence in waste separation enhances the intention to engage in the activity (Greaves et al., 2013; Wang et al., 2021; Lou et al., 2022). For example, citizens confident in their ability to separate waste before disposal are more likely to intend to engage in waste separation than those who lack such confidence. Higher confidence levels are strongly associated with a greater intention to perform waste separation. Sudin et al. (2023) conducted a study involving 400 Malaysian public university students, utilising Partial Least Squares Structural Equation Modelling. The findings revealed that perceived behavioural control was the most significant predictor of recycling behaviour, with a path coefficient of 0.45 ($p < 0.01$). This indicates that students who feel a higher sense of control over recycling are more likely to engage in such activities. Here, for the theory of planned behavioural model, we will focus solely on the direct relationships between the variables, specifically the direct associations of attitude, subjective norms, and perceived behavioural control with recycling intention.

While numerous studies have identified a significant positive impact of attitude, subjective norms, and perceived behavioural control on behavioural intention, some research has found that certain elements or all of these factors are not statistically significant in explaining recycling behaviour (Islam, 2021; Mohamad et al., 2022; Khan et al., 2019; White and Hyde, 2012; Davis et al., 2006). For example, Mohamad's study investigated e-waste recycling intentions (ERIs) and behaviours (ERB) in Malaysia using an extended Theory of Planned Behaviour (TPB) model. The findings revealed that moral obligation (MO) and perceived convenience (PC) were the most significant predictors of ERIs, while attitude showed no notable impact on recycling intentions in this context. Wang and Wang (2015) investigated physical activity among children aged 9 to 13 and found that intention significantly influenced their activity levels. Additionally, both attitude and perceived behavioural control had significant effects on the intention to engage in physical activity, whereas subjective norm did not. Liu et al. (2021) investigated the impact of a public service announcement (PSA) video on recycling intentions among New York State residents (N = 707). The study found that the PSA increased recycling intention through attitude, but this effect was significant only among individuals with low perceived behavioural control, suggesting that perceived behavioural control moderated the relationship between attitude and recycling intention. Šorytė and Pakalniškienė (2021) investigated recycling intentions and behaviours among children aged 8 to 11. Initially, their findings indicated that affective attitude and perceived behavioural control significantly influenced the intention to recycle, and both perceived behavioural control and intention significantly affected actual recycling behaviour. However, upon incorporating variables such as parental behaviour, gender, and social desirability into their model, intention no longer served as a significant predictor of recycling behaviour, nor did perceived behavioural control significantly predict the intention to recycle. Therefore, despite widespread support for the TPB, some researchers have criticised its limited ability to fully explain recycling behaviour, suggesting the inclusion of additional variables in the model (Islam, 2021). Ajzen (1991) suggested that adding new predictors to the Theory of Planned Behaviour is acceptable if they significantly increase the model's explanatory power. Researchers have expanded the Theory of Planned Behaviour by adding factors like knowledge, social norms, descriptive norms, moral norms, awareness of consequences, and goal orientation to improve its predictive power (Keong and Hirst, 2010; Czajkowski et al., 2017; Czajkowski et al., 2019; Liao and Li, 2019; Xie and Lu, 2022; Qalati et al., 2022; Wan et al., 2017). For instance, integrating goal orientation has been shown to improve the model's ability to predict innovation adoption behaviour (Keong and Hirst, 2010). Therefore, this study aims to extend the Theory of Planned Behaviour by incorporating goal theories as an additional individual construct.

2.5 Goal Theories

This section aims to clarify goals and explore key ideas commonly accepted by researchers of goal theory. As noted by Austin and Vancouver (1996), goals are defined as desired internal states that encompass outcomes, events, or processes. People generally strive for multiple interconnected goals, making it challenging to understand a single goal in isolation without acknowledging its connection to other goals and the cognitive, behavioural, and emotional responses that accompany goal achievement. In simpler terms, a goal represents something that an individual wishes to attain or experience, closely intertwined with other goals and the ways individuals think, act, and feel during their pursuit. In 1968, Locke examined the relationship between goals and work performance, establishing the foundation for Goal-Setting Theory (Locke, 1968). Researchers typically apply Goal-Setting Theory by asking participants to set clear and measurable targets, such as reducing electricity use by 10% or recycling a specific amount each week. These approaches, often combined with regular feedback on progress, have successfully changed behaviour, showing the theory's effectiveness beyond workplaces. Additionally, goal-setting has been successfully used at larger community and policy levels in waste management. For example, Ishimura et al. (2024) found that when Japanese municipalities set clear goals for reducing household waste (e.g., cutting food waste by a certain percentage each year), household waste decreased significantly. This shows that community-level goals effectively encourage individual behaviours like recycling and composting, supporting the broader application of Goal-Setting Theory in sustainability efforts.

Later, in 1973, Powers introduced Perceptual Control Theory, conceptualising goal pursuit as a continuous feedback system that compares the current state to the desired state (Powers and Powers, 1973). According to this theory, living beings act to keep their perceptions of the environment in line with internal goals or reference points. Instead of merely reacting to external events, individuals actively adjust their actions to control what they perceive. I have not found any mature, empirical studies in recent years that apply Perceptual Control Theory specifically as the core framework for researching environmental behaviour.

This perspective was further advanced by Carver and Scheier in 1981, who emphasised self-regulation and feedback loops. They highlighted the importance of monitoring discrepancies between current and desired states, thereby deepening the understanding of self-regulation within social-cognitive frameworks (Carver and Scheier, 2012). Carver and Scheier's self-regulation theory is useful for understanding and promoting pro-environmental behaviour. It suggests that encouraging sustainability involves setting clear goals and providing feedback to help people align their actions with environmental targets. Nielsen (2017) highlights the value of using self-regulation—especially goal setting and goal striving—in environmental research. Unlike traditional models like the Theory of Planned Behaviour, self-regulation explains why people often fail to reach their environmental goals and gives practical advice on bridging this gap.

The late 1970s and 1980s witnessed the rise of research on social cognition and achievement motivation. Among the most influential theories was Achievement Goal Theory, developed by scholars such as Dweck, Nicholls, and Ames. This theory distinguished between mastery goals (focused on learning and competence development) and performance goals (concerned with demonstrating ability and outperforming others), emphasising their effects on achievement behaviour (Nicholls, 1984; Dweck, 1986). This line of research belongs to educational psychology, specifically within the domain of achievement motivation. In education and social settings, mastery goals encourage people to persist and feel internally motivated, whereas performance goals often lead to shallow involvement or avoiding challenging tasks. Recently, researchers have applied this idea to environmental behaviour. For instance, Wang et al. (2025) studied recycling in Chinese communities and found that communities with an approach-oriented goal climate—focusing on improvement and achievement—effectively increased residents' recycling behaviour. Here, climate means the shared attitudes, values, and ways of motivating people in a community. A goal climate isn't about the weather—it's the general feeling or culture around how people aim to achieve things together.

From 1985 to 1992, there was a growing emphasis on action control and self-regulation theories. A significant contribution was Action Control Theory (Kuhl, 1985), which distinguished state orientation (difficulty in starting or maintaining goal-directed action) from action orientation (effective regulation of intentions to achieve goals). This framework offered insights into how intention execution and self-regulation function in goal pursuit (Kuhl, 1985). According to this theory, action-oriented people quickly start goal-focused tasks and concentrate on finding solutions, even when facing stress or negative emotions. They handle problems easily without being distracted by setbacks. In contrast, state-oriented people find it difficult to turn intentions into actions because they get stuck thinking repeatedly about their feelings or failures. This constant thinking makes it harder for them to act decisively and move ahead. Simply put, action-oriented people manage their goals well by controlling distracting thoughts, while state-oriented people often become stuck, making it harder to achieve their goals. Koole and Van den Berg (2005) examined how action versus state orientation influences responses to wilderness. They found that action-oriented individuals saw wilderness as more beautiful and effectively managed fear-related thoughts triggered by nature. In contrast, state-oriented people struggled to control anxious thoughts, resulting in more negative views. However, direct reminders of death reduced wilderness appreciation for everyone, showing limits to emotional self-control. In 1992, Bagozzi's Model of Goal-Directed Behaviour (MGB) became a key framework in social psychology and consumer research. It proposed that desires, emotions, and instrumental behaviours influence intentions and actions (Bagozzi, 1992). A milestone in goal research was the 1996 review by Austin and Vancouver titled Goal Constructs in Psychology: Structure, Process, and Content. This work integrated existing goal theories, arguing that goals are multifaceted constructs involving cognitive, behavioural, and emotional components, interacting with various competing or complementary goals. Their contribution consolidated diverse perspectives on goal-setting and motivation.

In the 2000s, theoretical advancements emerged, notably Goal Systems Theory and Goal Framing Theory. Kruglanski et al. (2018) introduced Goal Systems Theory, which explored the cognitive representation and organisation of goals. This approach highlighted how goal-directed behaviours are influenced by a network of interrelated goals and pathways to achieve them. In an environmental context, consumers often pursue multiple goals simultaneously. For example, when buying food, an individual may primarily aim for a tasty meal but also hold secondary goals such as saving money or protecting the environment. Whether these goals complement or conflict with each other can strongly affect their pro-environmental choices. Wong et al. (2021) applied Goal Systems Theory to investigate how attending green events influences people's environmental behaviours. They found that participation strengthened attendees' environmental goals and motivated sustainable actions afterward, especially if participants valued event sustainability or attended frequently. However, the effect weakened over time as other daily goals (e.g., convenience) became more prominent again, highlighting the need for continuous reinforcement to maintain long-term eco-friendly habits. Meanwhile, Lindenberg and Steg (2007) proposed Goal Framing Theory, identifying three primary goal orientations—hedonic (pleasure-seeking), gain (utility-driven), and normative (moral standards-driven)—that shape individuals' information processing and behaviour. This theory has been widely applied in environmental psychology, particularly in studies on pro-environmental behaviour.

Not all goals hold equal significance (Ryan et al., 1996). Most theorists concur that goals are organised hierarchically, with higher-level abstract goals decomposed into lower-level goals that ultimately direct physical actions (Pribram et al., 1960; Carver and Scheier, 1990; Carver and Scheier, 2001; Carver and Scheier, 2012; Karoly, 1992; Karoly, 1993; Powers and Powers, 1973; Powers, 1978; Baumeister and Heatherton, 1996). Several theories provide frameworks for understanding goal-directed behaviour, including Perceptual Control Theory (Carver & Scheier, 1981), Action Control Theory (Kuhl, 1985), Goal Systems Theory (Kruglanski et al., 2002), and Goal-Framing Theory (Steg & Lindenberg, 2007).

Control Theory suggests that people aim to reduce gaps between their current state and their desired goals. It highlights a goal hierarchy: broad, abstract ideals and intentions are progressively broken down into intermediate steps, leading to tangible actions like muscle movements. Individuals constantly track and modify their behaviour via negative feedback loops to stay aligned with their goals. Carver and Scheier expanded on this foundation by introducing the control-process model in self-regulation psychology. This model indicates that overarching goals, which encompass self-concept and values, are gradually refined into precise lower-level objectives or behavioural directives, ultimately resulting in actions such as muscle movements.

The hierarchical nature of goals carries significant implications. Firstly, achieving broader objectives often necessitates the completion of subordinate goals. Bagozzi (1992) introduced a theoretical framework on self-regulation and goal-directed behaviour, known as the Model of Goal-Directed Behaviour (MGB), which incorporates the concept of hierarchical goals and instrumental actions. He posited that attaining higher-order, abstract goals typically requires the accomplishment of specific, actionable steps, aligning with the notion of "goal hierarchies" or the progression "from abstract to concrete." In essence, Bagozzi supports the hierarchical nature of goals, centring his research on the relationships among goals, emotions, self-regulation, and desires/intentions. For instance, sorting waste may be a crucial step towards engaging in more environmentally beneficial activities, which, in turn, contributes to the overarching aim of becoming an environmentally conscious individual. Furthermore, sub-goals like waste sorting can involve additional subordinate tasks, such as correctly placing sorted materials into appropriate bins. Consequently, effective goal attainment often requires meticulous planning. Secondly, the hierarchical structure of goals introduces the potential for goal conflict, which occurs when two or more goals cannot be pursued simultaneously (Carver and Scheier, 2001). For instance, an individual aspiring to achieve professional success may find that this ambition conflicts with the commitment to engage in proper waste sorting—an environmentally responsible behaviour. In such situations, the individual is compelled to prioritise or rearrange these competing objectives (Dodge et al., 1989). Karoly (1998) emphasised the significance of planning action sequences and resolving goal conflicts, referring to “unclear goals” and “goal conflict” as the “dual devils” of action regulation. Practically, when faced with conflicting objectives, such as advancing one’s career versus adhering to rigorous recycling practices, individuals must make difficult decisions regarding which goal to prioritise. Research in environmental psychology indicates that although many individuals value sustainable practices, the immediacy and convenience of career-related activities can often overshadow pro-environmental actions (Lindenberg & Steg, 2007).

Furthermore, Klinger (1975) suggests that goals function as cognitive-motivational constructs. He proposed the idea of “current concerns” to illustrate the goals that people are dedicated to and mentally focused on. These concerns signify "unfinished business"—meaningful goals that linger in one's mind until they are either accomplished or let go. For example, someone recently concerned about climate change frequently reminds themselves to reduce plastic waste and avoid single-use products. Little (1983) expanded goal research by introducing the concept of personal projects, which he defined as "goal-directed action units." According to Little, personal projects encompass extended real-life pursuits that structure daily behaviour, ranging from short-term tasks to lifelong ambitions. He also developed an open-ended approach to identifying and evaluating these projects. To illustrate, a person might create a six-month plan to gradually replace household items with sustainable or recyclable alternatives, thus reducing their environmental impact. Emmons (1986) proposed the concept of personal strivings as part of an idiographic approach to personality and motivation. He characterised personal strivings as recurring goals that individuals generally seek to achieve in their daily lives, reflecting what they “typically intend to do” across various situations. For instance, A person consistently seeks to live sustainably, regularly choosing local organic food and making eco-friendly choices in daily life. Emmons further contended that these idiographic goal patterns offer insight into consistent motivational tendencies and their connection with well-being. Cantor et al. (1987) and Zirkel and Cantor (1990) introduced the concept of life tasks, which denote significant challenges or responsibilities that individuals confront during distinct life stages. According to Cantor, life tasks frequently reflect normative developmental or situational demands and provide a means for individuals to ascribe personal meaning to their experiences while organising their efforts towards important goals. In practice, a community volunteer takes responsibility for promoting waste recycling and environmental education, aiming to improve community awareness and sustainability.

Therefore, individual goals have been more specifically categorised into four types: 1) Current Concerns, 2) Personal Projects, 3) Life Tasks, and 4) Personal Strivings. In our study, life goals are defined as Personal Strivings, characterised by recurring, long-term goal-pursuing behaviours (Emmons, 1986). For instance, Carver and Scheier’s (1998) control theory positions self-related goals or systems (e.g., "become an environmentally conscious person") at the top of the hierarchy, more abstract action goals (e.g., "do more things that benefit the environment") in the middle, and specific actions (e.g., "sort household waste carefully") at the bottom.

Goal-Framing Theory

Lindenberg and Steg (2013) assert that Goal-Framing Theory emphasises the hierarchical structure of goals while incorporating modularity in human perception, cognition, and decision-making. They propose that cognitive modules are not wholly independent but exhibit semi-modularity, allowing for interaction between processes. This structure enhances adaptability by enabling selective attention and efficient responses to sensory inputs.

While some cognitive modules, such as facial recognition, are hardwired, others—like reading and habitual behaviours—develop through learning (Barrett and Kurzban, 2006). Given the complexities of social life, humans require flexible modularity, likely shaped by evolutionary pressures, to support adaptive cognition. This adaptability is primarily enabled by goals, which serve as dynamic cognitive control mechanisms. Goals adjust to situational cues, directing selective attention and optimising cognitive and emotional processes to enhance decision-making.

Three Higher-Order Goals

Heath and Gifford (2002) assert that human decision-making is influenced by various factors. While individuals naturally strive to improve their circumstances, cognitive modularity restricts their ability to enhance all aspects of life simultaneously. Consequently, behaviour is often unidimensional, with individuals prioritising specific areas of improvement based on the most prominent higher-order goal at any given moment. From an evolutionary perspective, three primary higher-order goals have emerged: hedonic, normative, and gain-oriented goals. Hedonic goals focus on enhancing immediate well-being, such as minimising effort or pursuing instant gratification. Gain-oriented goals involve acquiring and safeguarding resources or advantages, such as wealth and social status. Normative goals motivate individuals to behave in ways that align with societal expectations, such as demonstrating kindness or supporting environmental initiatives (Lindenberg, 2001; Lindenberg, 2006). These overarching goals shape decision-making by directing attention and influencing adaptive responses to environmental challenges.

2.5.1 Goal Theory and Pro-environmental behaviours

An increasing number of studies are now examining the role of goal theories in shaping pro-environmental behaviour (Lindenberg and Steg, 2013; Reyes and Mendiola, 2021; Yin et al., 2024; Wong et al., 2022; do Canto et al., 2023; Unanue et al., 2016; Lindenberg and Steg, 2007; Staples et al., 2020; Donmez-Turan and Kiliclar, 2021; Abraham and Sheeran, 2003; Chakraborty et al., 2017). According to Do Canto and Grunert (2023), this study examines goal-framing theory as a way to understand pro-environmental behaviour, focusing on the conflict between differing goals. Unlike other approaches, it considers the interaction of normative, gain, and hedonic goals, thereby providing a broader explanation of why individuals adopt or avoid sustainable actions. By reviewing 25 empirical studies, the research evaluates the theory's effectiveness in comparison to other behavioural models. Another example examines the relationship between life goals and environmentally responsible behaviour, arguing that prioritising intrinsic goals (self-development, community involvement, relationships) over extrinsic ones (wealth, fame, status) fosters both personal well-being and pro-social behaviour, including environmental protection. Using correlational and longitudinal data from the UK and Chile, it explores how intrinsic goals influence sustainable actions beyond environmental attitudes and identity. This suggests that nurturing intrinsic life goals may not only enhance individual well-being but also contribute to sustainability, reinforcing their significance for future generations(Unanue et al., 2016). According to (Hurst et al., 2013), most research on the relationship between life goals and environmental behaviour has been conducted in developed Western nations, which constitute only a small fraction of the global population. Individuals in these affluent societies may differ considerably from those in developing countries regarding environmental attitudes and behaviours. While some studies have identified a link between life goals and environmentally responsible behaviour, the evidence remains limited, with significant research gaps. To address these limitations, this study focuses on urban areas in China.

Goal Theories, TPB and Pro-environmental behaviours

Moreover, an increasing body of research examines how goal theories and the Theory of Planned Behaviour (TPB) influence pro-environmental behaviours (Perugini and Bagozzi, 2001; Sideridis and Kaissidis-Rodafinos, 2001; Keong and Hirst, 2010; Reyes and Mendiola, 2021; Abraham and Sheeran, 2003).

The Theory of Planned Behaviour (TPB) suggests that behavioural intention is the primary determinant of behaviour, influenced by attitudes, social norms, and perceived control. Goal theories expand on this by integrating motivation-related factors, such as goals, desires, and goal-setting, to clarify how intentions develop. The inclusion of these goal constructs into TPB enhances the understanding of environmental behaviour, as demonstrated by various studies.

In addition, Perugini and Bagozzi (2001) expanded the Theory of Planned Behaviour (TPB) through their Model of Goal-Directed Behaviour, incorporating desires—a motivational state of wanting—as a mediator between TPB's standard predictors and behavioural intention. They asserted that while attitudes, norms, and control beliefs provide justifications for action, explicit desires or goals offer the essential motivation to convert these justifications into actual intention. For example, an individual may hold positive attitudes towards recycling and perceive themselves as capable of doing so; however, only a strong desire to be environmentally responsible transforms these cognitions into a firm behavioural intention. Furthermore, this extended model introduced anticipated emotions related to goal attainment, thereby enhancing predictive validity compared to the traditional TPB framework.

Furthermore, Sideridis and Kaissidis-Rodafinos (2001) highlighted that the importance of a goal can directly impact behavioural intention. They suggested adding goal importance to TPB, noting that individuals prioritise certain goals over others. Research supports this, showing that when a pro-environmental goal, such as reducing carbon footprint, is seen as highly significant, people are more likely to act on it. Even with positive attitudes and norms, behaviours linked to high-priority goals are more likely to be carried out than those tied to lower-priority ones.

Research further suggests that individual goal orientations and contextual framing can influence the components of the Theory of Planned Behaviour (TPB). Keong and Hirst (2010) integrated goal orientation—an individual's general approach to setting and pursuing goals—into the TPB framework, confirming that the relationships between TPB variables remained unchanged while goal orientation traits played a role in shaping intention formation. In the environmental domain, Reyes and Mendiola (2021) linked TPB with goal-framing theory, demonstrating that the way in which sustainable behaviour is framed can alter the antecedents of TPB. Specifically, an environmentally framed goal strengthened pro-environmental attitudes, whereas a goal framed in terms of image or social considerations heightened perceived social norms. This suggests that the prominence of different goal frames influences the motivational pathway leading to intention—whether through personal conviction or social approval.

Implications for Pro-Environmental Intentions and Behaviour

Incorporating goal-setting mechanisms into the Theory of Planned Behaviour (TPB) provides greater clarity regarding how environmental intentions are formed and subsequently translated into action. Goals serve as an additional motivational layer that encourages individuals to act based on their attitudes and beliefs about control. For instance, explicitly setting a clear environmental goal (e.g. "reduce waste by 50%") can enhance attitudes towards recycling and maintain commitment even when faced with barriers. Consistent with the findings of Abraham and Sheeran (2003), integrating goal constructs—such as desires, the importance of goals, and goal orientation—alongside TPB variables enhances predictive validity.

2.6 The Knowledge Gaps and Summary

As discussed earlier in sections 2.2 and 2.3, research on recycling interventions has mainly focused on Western countries, especially in Europe and North America, while Chinese contexts remain underexplored. Despite significant waste management challenges in China, few studies have examined how social-norm nudges influence recycling behaviours there. This gap means current knowledge about household responses to recycling nudges primarily comes from Western settings, limiting understanding of how such interventions function within China’s unique cultural and policy environment.

Specifically, there is limited research in China on descriptive social-norm nudges using advanced methods like discrete choice experiments (DCEs) to measure household recycling preferences and willingness to pay (WTP). Unlike Western studies that demonstrate the effectiveness of social-norm cues, Chinese research often relies on surveys and theoretical models such as the Theory of Planned Behaviour. Without experimental evidence like Czajkowski et al.’s Polish study, Chinese policymakers lack clear data on how social norms might influence residents' financial support for recycling.

Another key gap is the lack of direct comparisons between voluntary and mandatory recycling policies in China. Previous studies typically examine each approach separately, leaving uncertainty about their relative effectiveness. The long-term impact of China’s mandatory policies remains unclear, and research rarely controls for cultural factors through within-country comparisons.

Finally, it remains unclear how effective social-norm nudges would be under voluntary versus mandatory recycling policies in China. Strict enforcement in mandatory systems might weaken the influence of social norms. Lin and Guan (2025) found heavy enforcement reduced residents’ long-term willingness to recycle by weakening social norms and personal attitudes. Few studies have compared normative nudges across these two policy types, leaving an important research gap.

As discussed in sections 2.4 and 2.5, models based on the Theory of Planned Behaviour (TPB) typically emphasise immediate predictors such as attitudes, subjective norms, and perceived behavioural control, but overlook broader personal goals or identity-based motivations. Scholars argue that integrating these higher-level life aspirations into TPB could provide deeper insights into individuals' environmental intentions. This represents a significant theoretical gap in environmental behaviour research.

Empirically, this gap is particularly evident in research on recycling preferences in China. Most Chinese studies rely on TPB frameworks, focusing mainly on direct factors like convenience, social norms, and attitudes, while rarely addressing long-term personal goals such as community welfare or personal growth. As a result, there is limited evidence on how broader life aspirations shape recycling behaviours, despite their potential explanatory power beyond traditional TPB predictors.

Methodologically, a notable gap exists regarding the limited application of advanced modelling techniques, such as the Hybrid Mixed Logit (HMXL). Unlike traditional models, HMXL combines observable factors (e.g. environmental knowledge and demographic characteristics) with latent psychological constructs (e.g. attitudes, subjective norms, personal goals). Using HMXL could more accurately capture how underlying psychological factors directly and indirectly influence recycling decisions, addressing measurement errors and offering richer insights into household recycling preferences.

Therefore, given these theoretical, empirical, and methodological gaps, Chapter 5 aims to expand existing Theory of Planned Behaviour (TPB) frameworks by incorporating personal life goals when studying recycling choices. Specifically, it investigates whether broader long-term life aspirations—such as achieving happiness, personal success, or benefiting future generations—directly influence individuals' recycling decisions or affect these indirectly through attitudes, perceived behavioural control, and subjective norms. Using the advanced Hybrid Mixed Logit (HMXL) model, this chapter analyses how integrating measurable decision-making factors and unobservable psychological motivations provides richer insights into household recycling behaviour within the Chinese context

In conclusion, this chapter reviews the literature on social norms, social norm nudges, the Theory of Planned Behaviour (TPB), goal theories, and pro-environmental behaviours from both economic and non-economic perspectives. It begins by examining previous research on social norms, nudges, economic penalties, mandatory policies, and their influence on pro-environmental behaviour. Numerous studies have explored how external factors, such as policies and nudges, shape environmental preferences and alter perceptions, yet there is still no universally accepted definition of the concept. This indicates a general desire to enhance environmental conditions, although the specific nature of this improvement varies across time and place. Additionally, the chapter reviews the TPB and its associated literature, alongside an exploration of goal theories. Researchers have attempted to extend the TPB framework by incorporating goal theory to better understand pro-environmental behaviour, particularly by examining the role of internal motivations. Various methods and practical applications have been proposed, but no clear consensus has been reached. As a result, further research is needed to refine and enhance the TPB model. The methodology used in this thesis is described in the subsequent chapter.

Chapter 3

Survey, Data Collection Methods and Methodology

3.1 Overview

This section outlines the research questions, the rationale for using DCE, the survey content, participant recruitment procedures, questionnaire development, and the design and implementation process. It also provides a general overview of the econometric models employed in the study. The questionnaires for the three cities were developed using a consistent logic and approach, allowing them to be treated as components of a single survey in the subsequent analysis. A summary of the survey design and implementation timeline is presented in Table 3.1.

Table 3. 1 Survey Design and Implementation Steps

Drafting research plan	(Completed Aug - Sep 2021)
Develop methodology	(Completed Oct - Nov 2021)
Develop questionnaire before interview	(Completed Dec - Feb 2022)
Research Ethics Application was approved	(on 1st April 2022)
One on one interviews	(Completed April - May 2022)
Revised questionnaire and experimental design	(Completed May - June 2022)
Pilot survey in China	(Complated July - Sep 2022)
Developed questionnaire and experimental design	(Completed Oct - Nov 2022)
Main survey	(Complated Dec - Mar 2023)

3.2 Thesis Objectives

Life can be likened to a canvas painted by countless decisions: from daily choices like meals to career paths and life ambitions, each decision shapes our unique life journey. When we aggregate the choices of all individuals around us, we form the societal structure we inhabit, collectively building the world as we perceive it. Clearly, choices are diverse and complex, influenced by factors such as habits, external pressures, personal beliefs, educational background, and income level. These varied and layered decisions ultimately sketch our distinct and multifaceted lives and societal landscape. The study of choices is well-established, with various theories and schools of thought aiming to understand the decisions made by economic agents. Central to choice analysis is exploring why and how choices are made at both individual and collective levels, potentially prompting search and learning to adapt in rapidly changing markets.

The neoclassical consumer choice model is based on the normative idea of 'rationality,' if consumers clearly understand their preferences, have full information, and make decisions that maximize their utility. It also presumes non-satiation, where consumers prefer more of a good to less. These core assumptions are central to microeconomic theory and widely examined in academic literature (Whinston and Green, 1995; Varian, 2014; Lancaster, 1966). However, in recent decades, growing empirical evidence has challenged the descriptive accuracy of economic theories on human behaviour. Researchers in decision-making, psychology, and behavioural economics have noted the predictive shortcomings of these theories, prompting significant re-evaluation of their validity (Karacuka and Zaman, 2012). Currently, the prevailing view in many fields is that economic theories of rational behaviour are normative rather than descriptively accurate. The Blackwell Handbook of Judgment and Decision Making provides extensive evidence to support this view, based on thorough experimentation on human decision-making, which contradicts the claim that economic theory is purely positive and grounded in undeniable facts (Sen, 1977; Soman, 2004). Environmental economists have criticised the homo economicus framework in standard microeconomics for its oversimplification and rigid assumptions, noting that consumers are often irrational and lack complete information when making decisions, making the model unrealistic in many respects (Max-Neef and Ekins, 1992). However, it is important to recognise that even with incomplete information, individuals can still make rational choices, including how they seek out and incorporate new information. They have highlighted the importance of factors such as social pressure and moral motivation in understanding economic behaviour and designing governance systems that align with societal values (Daly, 2015; Howarth and Wilson, 2006; Wilson and Howarth, 2002). The study of pro-environmental behaviour (PEB) has consequently become a major focus in ecological economics literature(Turaga et al., 2010; Czajkowski et al., 2017; Ojea and Loureiro, 2007; Owen and Videras, 2006).

One aim of my thesis is to explore whether people are inclined to invest more time and money into more thorough waste sorting and urban recycling programs in order to improve city environments. Additionally, it seeks to investigate the motivations behind these choices—whether they stem from internal factors, such as personal habits, short- or long-term goals, and values, or from external influences, such as changes in municipal recycling policies or social norms. To reiterate, the key objectives I address in this thesis:

1. Using the stated preference method and willingness to pay (WTP) as indicators of individual intent, I will compare the effects of mandatory waste sorting policies versus voluntary, encouraged policies on recycling preferences.

2. Examining how different types of social norm nudges impact household WTP for enhanced recycling efforts in Chinese cities and evaluating how well these nudges align with local waste sorting regulations.

3. Analysing whether factors from the Theory of Planned Behaviour (TPB) correlate with preference parameters for recycling.

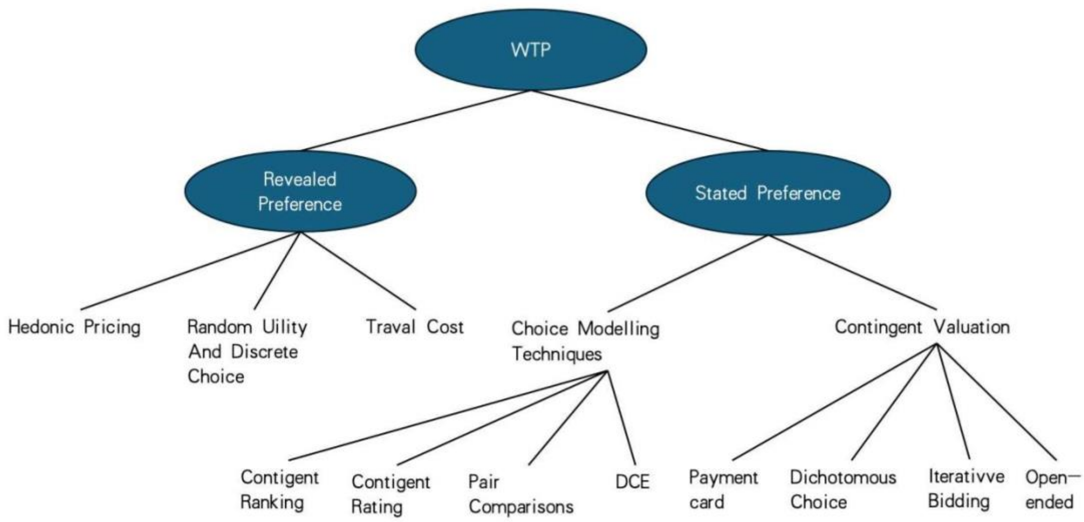
4. Investigating whether variables reflecting various self-reported life goals (such as contributing to future generations) are directly associated with recycling preferences, or if this relationship is mediated through TPB variables.

The core issue lies in understanding people's preferences for waste sorting. Currently, there is no market mechanism in China for residents to express their preferences for waste sorting. Consequently, the marginal benefits function of improved recycling can only be estimated through non-market valuation techniques.

3.3 Methodological Choices

Non-market valuation methods can be generally divided into revealed preference and stated preference approaches. In environmental economics, research on non-market goods is typically classified into revealed preference and stated preference approaches (Hanley et al., 2009). Refer to Figure 3.1 for a detailed breakdown. Let us provide a brief comparison of revealed preference and stated preference methods.

Figure 3. 1: Methods for Assessing Willingness to Pay. WTP is estimated via revealed and stated preferences,



Source: Adapted from Kjaer (2005) and Bateman and Großbritannien (2002)

3.3.1 Preferences: stated versus revealed

Methods for valuing environmental policy are traditionally classified as indirect and direct approaches. Indirect methods, such as the travel cost model, rely on consumers' actual choices to model behaviour, reflecting revealed preferences for both market and non-market goods. Revealed preference (RP) methods gather data by observing real market behaviour. In contrast, direct methods involve asking individuals what they would be willing to pay or accept for changes in environmental policies. These stated preference (SP) techniques rely on hypothetical scenarios where individuals indicate how they would behave, without actual behavioural changes(Adamowicz et al., 1994; De Corte et al., 2021). Unlike RP methods, SP approaches use data from experimentally controlled hypothetical settings rather than real-world market observations(Carson and Czajkowski, 2014; Hanley et al., 2019). The use of stated preference (SP) techniques for estimating environmental values has grown significantly over the past decades, particularly in non-market research where data is unavailable or desired market changes do not yet exist (Morrison et al., 1997; Boxall et al., 1996; Hanley et al., 2019; Basili et al., 2006). SP methods allow for the analysis of a broader range of attributes than those present in existing systems, with discrete choice experiments and contingent valuation being the most commonly used(Hanley and Czajkowski, 2019). In contrast, revealed preference (RP) methods, such as hedonic pricing, rely on real goods and services, while SP methods create combinations of goods or services.

As discussed in Section 2.3 of the literature, each approach has its own strengths and limitations. Revealed preference methods offer external validity as they rely on actual market choices where individuals have invested time and money. While RP avoids the criticism of relying on hypothetical behaviour, the behavioural models used are based on assumptions about preference structures, which may not always be testable (Adamowicz et al., 1994; Maxwell, 2001; Perman, 2003). Additionally, RP methods may face challenges from collinearity among attributes, which hinders the isolation of factors influencing choice—a key requirement in economic welfare analysis. Moreover, high data acquisition costs, non-quantifiable information, and the difficulty of controlling natural experiments due to unpredictable variations in human behaviour caused by idiosyncratic shocks further complicate their application. Lastly, RP methods may face limitations as changes in environmental quality can create scenarios beyond the current data range, requiring extrapolation beyond the model's estimation scope. Moreover, RP methods cannot capture non-use values. This contrasts with the aim of this study, which seeks to capture individuals' willingness to pay for waste sorting based on expected environmental improvements.

In contrast to RP methods, SP methods are often criticised for their hypothetical nature and reliance on stated rather than observed behaviour (Mitchell and Carson, 2013; Cummings, 1986; Hanley et al., 2019; Mendelsohn, 2019). Issues such as a lack of incentives for accurate responses or strategic behaviour are common concerns. Additionally, SP methods can be costly to implement, with significant challenges in designing suitable surveys. However, SP methods address gaps by providing insights that cannot be replicated in real-world settings. They remain the only practical approach for measuring non-use values and are frequently employed to capture values associated with environmental changes involving multiple attributes.

My thesis focuses on preferences for waste sorting behaviours, which lack market transaction data as these behaviours are typically driven by policies, habits, or social norms rather than explicit market prices. For example, individuals do not directly "pay" for waste sorting. Furthermore, policies on waste sorting often involve hypothetical or unimplemented scenarios, such as introducing new sorting systems, new collection methods, or new ending disposal plans, making stated preference methods like DCE more suitable for capturing preferences under these conditions. SP methods are also ideal for assessing non-market values, such as support for environmental protection or willingness to participate in waste sorting, which cannot be observed from market behaviour. Additionally, they capture subjective attitudes and complex motivations, such as convenience, social norms, or environmental awareness, that market data might overlook. Given the absence of data on actual purchasing behaviours in China, SP methods were deemed more appropriate for this study. These methods, which measure both use and non-use values, provide significant potential for generating rich insights into future policy interventions.

3.3.2 Contingent Valuation or Choice Modelling

As illustrated in Figure 3.1, SP methods are categorised into Contingent Valuation (CV) Methods (Carson and Mitchell, 1993; Hanley and Czajkowski, 2019; Mitchell and Carson, 2013) and Choice Modelling (CM) techniques, with particular emphasis on Discrete Choice Experiments (DCE) (Louviere et al., 2010; Hanley and Czajkowski, 2019). CV gained prominence in environmental economics in the mid-1970s (Randall et al., 1974). In contrast, DCE was developed in the 1980s (Louviere and Woodworth, 1983) and was first employed in environmental economics in the 1990s (Hanley et al., 1998). Contingent valuation surveys ask respondents whether they are willing to pay a specified amount for various policy changes. In contrast, choice modelling surveys assess willingness-to-pay for multiple policy attributes simultaneously. To illustrate the differences and applications of the Contingent Valuation (CV) and Discrete Choice Experiment (DCE) methods, consider an example where we aim to estimate individuals' willingness to pay (WTP) for increasing the waste recycling rate in their city. The CV method involves directly asking individuals their WTP for the policy. For instance, respondents might be asked if they would vote in favour of a proposed recycling policy in a referendum, which would involve an additional cost. In contrast, the DCE method, based on Lancaster's utility theory (1966), deconstructs the policy into a combination of attributes, such as the number of waste categories, collection frequency, bin distribution, and disposal methods (Czajkowski et al., 2017). Respondents are presented with various policy scenarios that combine these attributes at different levels and are asked to select their preferred option. The choice of method depends on the specific research or policy objectives. Boxall et al. (1996) suggest that contingent valuation surveys can be viewed as a form of choice modelling that evaluates the value of multiple attributes within a single valuation question.[12]

Discrete Choice Experiment surveys are well-suited for this study as they can estimate the marginal benefits of various attributes simultaneously. DCE is well-suited for scenarios involving multi-dimensional changes and trade-offs, as it allows for the separate valuation of individual attributes within a good or programme, even when these attributes are provided in combination. This capability is particularly valuable given that the exact structure of recycling policies in most Chinese cities has yet to be finalised. Policy parameters that can be adjusted include the number of collection points, levels of waste sorting, and the proportions of different waste disposal facilities. The marginal benefits of individual attributes can be used to estimate the overall benefits of various policy packages. A single choice modelling survey can achieve this by evaluating a range of policy options simultaneously. In contrast, contingent valuation would require dividing the sample into sub-groups, each assessing a different policy scenario. This makes the administration of a

[12] There is no consensus in the stated preference (SP) literature regarding the classification of SP methods. While Discrete Choice Experiments (DCEs) were initially proposed as an alternative to contingent valuation (CV), DCEs are simply an elicitation method within CV studies. Consequently, not all CV studies are DCEs (e.g., those using non-discrete choice formats), nor are all DCEs classified as CV. Typically, single-choice studies (e.g., yes/no responses to a policy at a cost or using payment cards) are referred to as CV, whereas studies involving multiple or alternative choices for a respondent are classified as DCEs.

contingent valuation survey more complex compared to a choice modelling approach(Morrison et al., 1998).

Despite its wide application in transport and marketing, experience with Discrete Choice Experiments (DCE) in environmental contexts remains limited, and several challenges persist. A primary disadvantage of DCE is the cognitive burden placed on respondents when ranking or choosing between bundles with multiple attributes and levels. Research shows that increased complexity can lead to random errors and inconsistent responses, with respondents relying on heuristics to simplify decisions rather than maximising utility(Ben-Akiva et al., 1992; Foster and Mourato, 1997). Furthermore, large numbers of choice sets may result in learning and fatigue effects, causing irrational responses (Tversky and Shafir, 1992). Pre-testing can help ensure that questionnaire designs minimise such fatigue. In addition, to estimate the total value of an environmental programme, CE assumes the value of the whole equals the sum of its parts. However, this assumption has been questioned, as unmeasured attributes or non-additive valuations may distort results. Comparative studies show DCE valuations of complete programmes may differ significantly from those derived via other methods, such as contingent valuation (CV) (Foster and Mourato, 1999; Gleave, 1999). Moreover, DCE struggles to value sequentially implemented multi-attribute programmes, which CV handles more effectively.

As with other stated preference methods, DCE outcomes are sensitive to study design. Factors such as attribute selection, level definition, and presentation format (e.g., text vs images) can influence welfare estimates. Changes in the number of choice tasks have been shown to significantly affect preference models, highlighting the need for careful design to ensure robust results. However, despite the shortcomings of DCE compared to CV surveys, its flexibility in estimating the marginal benefits of individual attributes makes it a more suitable approach in the context of this study. As shown in Figure 3.1, various Choice Modelling (CM) techniques are available, all based on the assumption that goods and services can be described by their attributes or characteristics. This study focuses on the value respondents assign to these attributes. CM techniques are divided into four categories:

paired comparisons, contingent ranking, contingent rating, and discrete choice experiments (DCE).

Discrete Choice Experiment (CE), which involves deciding whether to choose an option or not, aligns closely with my experimental design. It is widely preferred as it mirrors real-life decision-making processes and enables the estimation of willingness-to-pay (WTP) by focusing on alternatives that maximise perceived utility. DCE operates on the assumption that respondents select the option from a set of alternatives that offers the highest perceived utility. This requires decision-makers to implicitly trade off multiple attributes of the available options. Introduced by Louviere and Hensher (1982), DCE presents choices defined by their attributes or characteristics, allowing respondents to reveal the relative utility of each attribute and the disutility associated with higher prices(Hanley et al., 2001). Compared to contingent valuation methods, DCE is advantageous as it estimates the value of each attribute and provides insights into control programmes that alter multiple attributes simultaneously. As discussed, several alternative approaches are available, but this thesis adopts DCEs based on SP data. This method is chosen for its capability to estimate preferences and willingness-to-pay for attribute changes that are difficult to identify through market data. Relevant academic references include Bateman and Großbritannien (2002) and Louviere (2000), which provide detailed guidance on the use of choice experiments for environmental valuation.

Therefore, this study employs choice experiments to examine individual preferences for household recycling services. The Discrete Choice Experiment (DCE) approach collects and analyses choice data by simulating a hypothetical market through surveys. Participants are presented with several choice sets containing mutually exclusive options and are asked to choose their preferred alternative. Each alternative is defined by attributes with varying levels, allowing for implicit trade-offs between them. When cost or price is included as an attribute, marginal utility can be translated into willingness-to-pay (WTP) values for changes in attribute levels, which can then be combined to calculate welfare measures. These compensating variation measures are directly applicable in cost-benefit analyses (further details are provided in Chapter 4). As highlighted by Czajkowski et al. (2019) and Hoyos

(2010), choice experiments are extensively used in policy analysis addressing pro-environmental behaviours. Over the past decade, their application has grown significantly, establishing DCEs as a leading stated preference (SP) method for environmental valuation. While numerous stated preference studies, such as those by Basili et al. (2006) and Czajkowski et al. (2017), have explored recycling and waste management demand, This thesis explores whether individuals are willing to dedicate more time and money to comprehensive waste sorting and urban recycling programs to enhance city environments. It also examines the drivers behind these decisions, focusing on internal factors such as personal habits, goals, and values, as well as external influences like municipal recycling policies and social norms. Data were collected through a choice experiment involving households in these cities.

3.4 Survey objectives

Based on the main aims of the thesis presented in Section 3.2. The survey was developed with several key objectives: (1) to measure local citizens' knowledge and awareness of recycling; (2) to gather information on households' current waste sorting behaviours, including frequency, categories sorted, and level of effort; (1) measure the factors from the Theory of Planned Behaviour (TPB); (4) to design DCE choice cards that align with local conditions, ensuring an appropriate number of cards, alternatives, and attribute levels, while keeping the tasks understandable and manageable for respondents; (5) to measure different dimensions of long-term life goals, such as the pursuit of success, enjoyment, or environmentalism; (6) to create four scenarios with varying levels of descriptive social norms (no information, low, medium, or high), ensuring that the core questionnaire content is consistent across the three cities and scenarios, with randomised and balanced distribution of scenarios within each city to enable cross-city comparisons. In each scenario, ensuring that respondents are presented with one of four levels of descriptive social norms based on the treatment group to which they are assigned; (7) to collect socio-demographic and personality data for use as control variables in the analysis; and (8) to phrase questions concisely and maintain an effective balance between depth and breadth.

3.5 Survey Development Process

3.5.1 Initial survey development

The initial questionnaire was developed based on methodologies from previous studies, including Steg et al. (2014), Czajkowski et al. (2017), Czajkowski et al. (2014), Czajkowski et al. (2019). The attribute levels were designed following a comprehensive analysis of policy options under consideration in China at the time. To refine the questionnaire and design specific questions, consultations were held with three local experts from Zhengzhou, Shanghai, and Shijiazhuang, as well as three UK-based experts. The initial questionnaire consisted of five sections: (1) an introduction, (2) questions on environmental knowledges and awareness, current household waste collection practices and other pro-environmental behaviours, (3) items addressing long-term life goals and Theory of Planned Behaviour (TPB) factors, (4) an explanation of the attributes in the choice scenarios and the choice sets used to estimate preferences for various waste recycling systems, and (5) socio-demographic questions. To ensure consistency, internal and external factors influencing recycling behaviours were evaluated within the same respondents, reducing costs and improving efficiency. The data collected from sections 2, 4 and 5 primarily address two research objectives: using stated preference methods and willingness to pay (WTP) as indicators to compare the effects of mandatory versus voluntary recycling policies and examining the impact of different social norm nudges on household WTP for improved recycling efforts, while assessing their alignment with local waste sorting regulations. Meanwhile, data from sections 3, 4, and 5 focus on analysing whether factors from the Theory of Planned Behaviour (TPB) correlate with recycling preferences and exploring whether self-reported well-being goals, such as contributing to future generations, directly influence recycling preferences or whether this relationship is mediated through TPB variables.

The survey began by highlighting the significant rise in urban waste driven by China's rapid urbanisation and its environmental consequences. It introduced the Municipal Solid Waste (MSW) classification policy launched in 2017, outlining its specific goals. Conducted during Shanghai's role as a pilot city for this policy, the survey explained that the national government intended to refine the policy's nationwide implementation based on insights from pilot cities. Respondents were then assigned to one of three treatment groups and provided with information reflecting low, medium, or high levels of descriptive social norms (explained in the end of Chapter 3.5.1). At the end of the introductory section, participants were informed that the survey findings would be shared with local policymakers and could influence the development of MSW management strategies.

Section 2 of the survey focused on questions about respondents' environmental knowledge, recycling habits, and other eco-friendly behaviours (details provided in Chapter 4.3).

In Section 3, participants were asked to respond to statements related to the Theory of Planned Behaviour (TPB) and life goals by indicating their level of agreement or disagreement on a five-point Likert scale ("I definitely disagree" to "I definitely agree"). Examples include a TPB question: " Do you agree that people should care about is life and survival issues, not environmental issues such as improving solid waste classification?" and a life goal question: "Do you agree that your life Seeking to contribute to others in your local area or the surrounding world?" (details on the design of TPB and life goal questions are provided in Chapter 5.3).

In section 4, in our choice experiment, our initial design involved asking participants to choose from a range of possibilities for MSW classification and collection contracts, with four key attributes defining these contracts.

The first attribute pertained to the number of waste categories that participants would be required to sort their waste into before collection, with levels ranging from no sorting to sorting into 2, 3, 4, or 5 categories of waste. This attribute served as our primary measure of household recycling behaviour. The second attribute was the number of additional waste collection points available in the participant's living area, measured in square kilometres, with levels ranging from no classification bins to 1, 2, 3, 4, 5, or 6 classification bins in the living area. The third attribute pertained to the frequency of waste collections, with levels ranging from daily collection to collection 1, 2, 3, 4, 5, or 6 times a week. Finally, the fourth attribute was the additional cost of the MSW collection service, represented by a monthly bill that households needed to pay, with levels of 15, 45, 75, 105, or 150 Yuan.

As outlined in Chapter 3.3, the DCE approach was chosen for its ability to estimate preferences for specific attributes of recycling plans and to assess how factors such as social norms, environmental attitudes, and long-term life goals influence participants' utility. In the choice experiment, respondents were asked to select their preferred options for MSW classification, the number of collection points, and waste collection frequency from a range of possibilities, allowing us to analyse the effort levels associated with their recycling behaviours. In each choice scenario, the last option presented was an opt-out choice. In these scenarios, respondents were requested to select their most favoured contract from 4 available alternatives. Each respondent completed 6 choice tasks.

In section 5, the survey ended with questions regarding the socio-demographic characteristics of respondents. These variables include respondents' age, gender, location, education level, and household income. Please refer to Appendix A for further details regarding our choice experiment and questionnaire.

Information treatments

The survey provided participants with varying levels of descriptive social norm information, detailing the proportion of Shanghai residents engaged in recycling. Each participant, except those in the control group (treatment 4), received a single piece of information about others' recycling behaviours. The information was divided into three levels—low, medium, and high—based on their assigned treatment group, as outlined in Table 3.2. A randomized between-subjects experimental design was used to vary the magnitude of the social norm. The percentages of households participating in waste sorting in Shanghai were presented as 15% (2018), 75% (2019), and 95% (2020).

We opted to use social norm information based solely on Shanghai's practices to avoid the ethical issue of providing false information, described by Croson and Treich (2014) as "deceptive nudges." This decision was supported by data from sources such as the China Statistical Yearbook, China Environment Newspaper, and China Environment Protection Database. Shanghai was chosen as it was the first pilot city for China's mandatory waste sorting policy and the only city with readily available data on waste sorting participation rates. This approach ensured the ethical integrity of the study by relying on accurate and verifiable information. Each participant was assigned to only one of four evenly distributed treatment groups. Participants in the first three groups (T1, T2, T3) were presented with varying levels of descriptive social norms regarding recycling behaviour: low (15% of households in 2018), medium (75% in 2019), and high (95% in 2020). The fourth group served as a control group, experiencing the same process as the others but without any social norm information. Thus, each respondent was exposed to a single type of social norm-based nudge or received no nudge at all. (we explained this further in Chapter 4.3)

Table 3. 2: Treatment groups

Treatment	
Treatment 1	In 2018, 15% of all municipal waste collected from households in Shanghai, was sorted.
Treatment 2	In 2019, 75% of all municipal waste collected from households in Shanghai, was sorted.
Treatment 3	In 2020, 95% of all municipal waste collected from households in Shanghai, was sorted.
Treatment 4	No information of levels of sorting of waste provided.

To validate the survey instrument and the introduced changes, pre-testing was conducted through one-on-one interviews with 10 respondents in each city—Shanghai, Zhengzhou, and Shijiazhuang—amounting to 30 participants in total. Additionally, a pilot survey was carried out with 50 households in each city, involving 150 respondents overall. The pre-testing and pilot survey were conducted between February and March 2022, and the Research Ethics Application was approved on 1 April 2022.

Translation Procedure:

Given that most questions addressed straightforward concepts, such as life goals, sorting habits and individual differences, the translation process was relatively simple. During the questionnaire's development in English, we deliberately avoided expressions tied specifically to English cultural contexts, which could complicate translation. Instead, we prioritised the conceptual accuracy of each question, opting for direct translations where appropriate rather than free translations. Due to time and budget constraints, a formal assessment of translation quality was not feasible. However, following the recommendations of Harkness and Schoua-Glusberg (1998), three assessment methods were employed to ensure translation adequacy.

(i) *back translation, i.e. translating back into the original language.* ***(ii)*** *committee assessment, i.e. translation undertaken by a group of bilingual speakers and survey experts.* ***(iii)*** *comprehension assessment, i.e. checking that survey participants can properly explain and understand the meaning and concept of the translated materials*

3.5.2 Questionnaire Development Process

Our original plan, as contained in the ethics application approved by the committee, set out 4 distinct stages of the survey work in China. These stages were:

Stage 1 – conduct focus groups with residents of the 3 case study cities in China, to understand how people think about the recycling situation in their cities;

Stage 2 – conduct one-on-one cognitive interviews with 12 individual respondents in each city, to check the wording of our survey instrument;

Stage 3 – conduct a pilot survey test of the survey instrument, to allow us to estimate a model which can be used to improve the statistical efficiency of our experimental design;

Stage 4 – carry out the full survey.

Since recycling and waste sorting is an everyday feature of people's lives, they have a good understanding of the issues involved, especially as local governments in our case study cities have recently been promoting "greener" ways of sorting household waste. It therefore seems unlikely that these focus groups will be necessary from a survey design viewpoint, and we are also worried about how easy these will be to run on the web, because to consider the situation of COVID-19 that time in China and save cost, we had to collect the new self-stated data by using online household survey. We decided to move straight to Stage 2 (one-on-one cognitive interviews). Therefore, **our final plan only has three stages.**

Stage 1 *– conduct one-on-one cognitive interviews with 12 individual respondents in each city, to check the wording of our survey instrument;*

Stage 2 *– conduct a pilot survey test of the survey instrument, to allow us to estimate a model which can be used to improve the statistical efficiency of our experimental design;*

Stage 3 *– carry out the full survey.*

3.5.3 Data collection and survey administration

To overcome challenges posed by COVID-19 in China, as well as issues such as technological constraints, social norms, and language barriers, data collection was carried out entirely online across all three stages of the survey. This process was conducted between May 2022 and March 2023, ensuring efficiency and cost-effectiveness. The survey was administered through Wenjuanxing, a leading Chinese online survey platform comparable to Survey Monkey, which integrates with popular social media platforms such as WeChat, QQ, and Weibo. With 846 million monthly active users in 2019, WeChat is China's most widely used messaging app, QQ serves as a social network like MSN in the UK, and Weibo is the country's most popular microblogging site. Wenjuanxing's reputation for data quality and adherence to information protection standards is well-recognised, with its functionality comparable to Survey Monkey and Qualtrics. Several UK-based research groups have also used Wenjuanxing for studies in China, such as Dr. Keila Meginnis, who utilised the platform to distribute single-use survey links to randomly selected respondents from a panel of 2.6 million members, and Dr. Cotton, who employed the platform alongside Survey Monkey for comparative research (Cotton et al., 2021; Hinsley et al., 2022). Given its reliability and widespread use, Wenjuanxing was chosen to ensure a robust and efficient online survey process. We instructed the Wenjuanxing platform to strictly adhere to our sampling strategy for recruiting respondents online and to use our designed questionnaire for all three stages of the survey: the one-on-one interviews, the formal pilot, and the main survey. The main sample was designed to consist of 600 participants, randomly selected, with 200 respondents from each of the three cities: Shanghai, Zhengzhou, and Shijiazhuang.

3.5.4 Cognitive One on One Interviews

The primary aim of the cognitive interviews was to ensure that respondents understood the survey wording and the tasks they were required to complete. The full questionnaire was translated into Chinese for this purpose (details provided in the next section). Cognitive interviews were conducted with 30 respondents from the three case study cities in May 2022 (see Table 3.3 for participant profiles). The questionnaire and consent form were sent to participants via email.

Table 3. 3: Basic Profile of Cognitive Interviews Participants in Three Cities

AGE	GENDER	EDUCATION	AGE	GENDER	EDUCATION	AGE	GENDER	EDUCATION
39	M	4	29	F	5	34	F	5
20	F	2	35	M	4	22	F	4
45	F	4	41	F	4	32	M	5
25	M	4	34	F	5	25	M	2
30	M	3	22	F	4	44	M	5
40	M	2	25	F	3	23	M	3
30	F	4	23	M	5	50	M	4
62	M	3	22	F	4	22	M	3
32	F	4	42	F	3	20	F	4
29	M	5	55	M	3	57	F	2

(Education: 1. Junior high school and below; 2.Secondary; 3.Professional qualification of degree level;4. Undergraduate, University specialties; 5.Graduate and above.)

Sampling

Firstly, one on one cognitive interview questionnaire was administered via Wenjuanxing (WJX) platform to a sample of participants in China, during April 2022 and in the end of questionnaire we gave them the one on one cognitive interview invitation, then the contact details were asked.

Respondents gave their email or Wechat ID voluntarily. After receiving responses from local citizens in Shanghai, Zhengzhou and Shijiazhuang, we will randomly select 10 participants each city to do these one-on-one interviews, using the Wechat app (which works very well for a one-on-one conversation). These cognitive interviews will take place after respondents have completed the on-line questionnaire. The 20 minutes interview discussed whether people understand the information and tasks outlined in the questionnaire easily. Respondents will receive a small credit (<20 CNY =2 pounds) to their WJX account for completing the survey and participating in the interview. The consent form and participant information sheet (PIS) was provided. Respondents were told that I am making notes of the interview: these notes will be kept on a secure server.

During the interviews, participants were encouraged to "think aloud," sharing how they interpreted each question and identifying any terms or phrases they found confusing or difficult to understand. They were also invited to provide feedback on the overall quality of the questionnaire, including whether they found it engaging, straightforward, or challenging to complete.

Results and Changes made to Survey

The feedback from the one-on-one interviews was instrumental in refining the survey, leading to adjustments in formatting, wording, and the attributes included in the choice cards. Two key improvements were made to the questionnaire design. Firstly, in the Choice Experiment section, many respondents indicated that they did not intuitively understand "per square kilometre" and found the second attribute unclear and unappealing. Instead of increasing the number of bins per square kilometre, they preferred the option of adding bins closer to them. As a result, the second attribute was redesigned to specify the location of waste collection points, with options such as one point per floor, one per apartment block, or one shared between several blocks, accompanied by illustrative pictures to aid understanding. Secondly, as respondents expressed greater concern about urban waste processing facilities than the frequency of waste collection, the third attribute was revised to assess willingness to pay for city funds to develop advanced waste processing systems aimed at reducing environmental pollution. Finally, the choice cards were simplified by reducing the options from four to three, making the task more manageable for respondents.

In our revised choice cards, we made modifications to the choice cards to elicit participants' preferences regarding their selection of MSW classification and waste collection and disposal contracts from a range of options. The contracts included four attributes that participants had to consider when making their choices. These attributes were:

1. Method of waste sorting: Participants had to choose how many different categories they would be required to sort their waste into before it is collected. The levels for this attribute ranged from no sorting to sorting into 2, 4, or 7 categories of waste.

2. Waste collection plan: Participants had to choose how many waste collection points they would have in their living area. The levels for this attribute ranged from 1 waste collection point in each community to 1 waste collection point in each block or each floor.

3. Ending disposal plan: Participants had to choose the investment plan for ending waste disposal in their city. The levels for this attribute ranged from waste incineration to composting or recycling plans.

4. Cost: Finally, participants had to consider the additional cost of the MSW collection service, represented by a monthly bill that households needed to pay. The levels for this attribute ranged from 20 to 200 Yuan.[13]

We have included an example choice card in Figure. 3.2.

Overall, the interview outcomes suggested that respondents had a clear understanding of most questions, although changes to the phrasing of some questions and the choice cards (mainly those ones included in well-being scale) were necessary.

[13] At the time of our study 1 Chinese Yuan≈0.11Pound strling≈0.14 USD.

3.5.5 Pilot study

The pilot questionnaire was distributed through the Wenjuanxing platform in August 2022 to a sample of 153 participants across three cities: Shanghai, Zhengzhou, and Shijiazhuang, with approximately 50 respondents from each city. Participants received a small credit (<20

Figure 3. 2: Choice Card Before and After

Panel a: Initial Questionnaire Choice Card

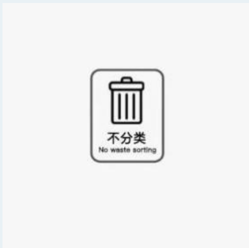
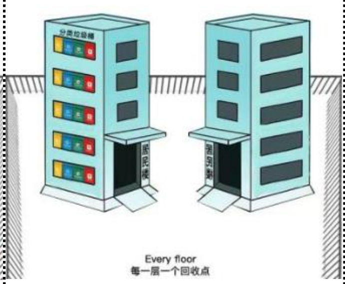
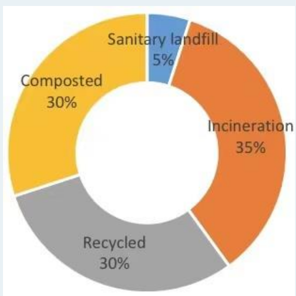
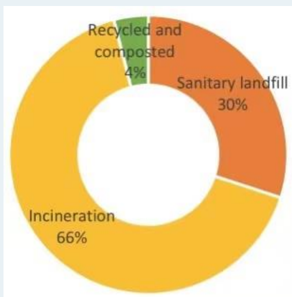
Situation1.	Option1	Option2	Option3	
Method of sorting in citizens	Sorting into 4 categories (recyclable, hazardous, wet, and dry waste)	Sorting into2 categories (recyclables, other)	None	
How many additional waste collection points in your living area (sq km)	3	5	2	Option 4 Current method of garbage collection
How many additional times for waste collections in your living area	2	1	2	
Additional Cost for month (YUAN)	75	45	15	
Your Choice	£	£	£	£

CNY, equivalent to £2) in their WJX account upon completing the survey. The consent form and Participant Information Sheet (PIS) were provided at the start of the questionnaire. The main socio-demographic characteristics of the pilot sample are detailed in Table 3.4.

Experimental Design for Pilot Study

The experimental design for the pilot study followed the Bayesian efficient approach recommended by Scarpa and Rose (2008). A subset of possible choice situations was selected to optimise the mean D-efficiency of a Multinomial Logit (MNL) model using Bayesian priors, improving the precision of parameter estimates in the DCE models. The design included 24 choice tasks, divided into four questionnaire blocks, with each respondent receiving six choice cards. All attributes were treated as dummy variables in the utility function, except for the additional monthly cost, which was treated as continuous. Bayesian priors were assumed to be normally distributed, with means derived from the MNL

Panel b: Final Questionnaire Choice Card

Situation1.	Option1	Option2	Option 3
Method of sorting in citizens			Existing situation – no changes, no additional costs to you
Waste collection plan			
Ending-disposal plan			
Additional Cost for month (YUAN)	200	60	
Your Choice	☐	☐	☐

model estimated on pilot survey data from the three sample areas (Zhengzhou, Shanghai, Shijiazhuang). However, as no comparable studies were found in China, priors based on earlier studies could not be used. Instead, the DCE pilot study was designed in Ngene using the D-error measure to achieve an efficient design for the MNL model, with near-zero priors applied to all attributes.

Table 3. 4: The Main Socio-demographic Characteristics of The Pilot Sample

	Percent
Male	44%
Age 18-30	52%
31-40	39%
41-50	7%
51 and above	2%
Education high school	2%
Secondary	3%
Professional qualification	11%
Under, university	74%
Graduate and above	10%
Income 3000(below)	2%
3001-6000	8%
6001-12000	28%
12001-20000	31%
20001-40000	25%
40001 above	6%
Shanghai	34%
Zhengzhou	33%
Shijiazhuang	33%

Result

To derive priors from the pilot data, I tested six different choice models: (1) conditional logit model (dummy coding), (2) conditional logit model (effects coding), (3) mixed logit model (dummy coding), (4) mixed logit model (effects coding), (5) mixed logit model ln(1) (dummy coding), and (6) mixed logit model ln(1) (effects coding). After analysing and comparing the results—evaluating coefficients, standard deviations, p-values, log-likelihood, probabilities, and AIC/BIC—we determined that Model 6 (mixed logit model ln(1) with effects coding) performed best. This model was subsequently used to obtain the priors. However, in this model, the attribute "sorting waste into two categories" was found to be statistically insignificant.

Changes Made to Survey

Based on feedback from the piloting process, some questions were rephrased slightly to enhance clarity, and two recycling behaviour questions were merged into a single question to reduce the length of the questionnaire. While the choice experiment offers valuable insights into participants' preferences for waste management contracts, it does not directly measure their actual behaviour. To address this, we added a general question asking participants to self-report their behaviour-intention gap, providing more comprehensive data on their actual recycling practices. This addition helps to better understand the relationship between recycling behaviour and internal and external factors, as well as to identify potential moderating influences.

3.6 Case study selection and description

Under the Shanghai MSW Management Regulation, enacted in June 2019, individuals who fail to comply with waste classification rules face fines of 50 to 200 yuan (Zheng et al., 2020). Initially, slogans promoting waste sorting were displayed throughout Shanghai, but by December 2019, these were replaced with posted guidelines and disposal instructions in residential communities. To enforce the regulation, Shanghai implemented a dual supervision system, ensuring unsorted waste is neither collected nor processed. Communities typically have 1–6 garbage collection rooms of varying sizes, with designated disposal times from 7–9 AM and 5–7 PM. Outside these hours, the rooms remain locked, and smart collection rooms can only be accessed with a card or QR code. Local volunteers oversee the disposal process, as reported by Xinhua Net. This enforcement campaign will continue until 2025, after which Shanghai plans to establish a comprehensive waste management system covering the full cycle of classification, collection, and disposal (Shanghai Municipal Development & Reform Commission, 2023). Despite years of effort, China's MSW classification policy has yet to be fully enforced in cities outside Shanghai, such as Zhengzhou and Shijiazhuang(Han and Zhang, 2017; Chu et al., 2023a; Chu et al., 2023b), where implementation remains limited to advocacy without effective supervision or enforcement mechanisms.

This research focuses on evaluating the status of waste classification and willingness to pay (WTP) for waste sorting in Shanghai, a pilot city with a mandatory policy, and compares it with two cities, Zhengzhou and Shijiazhuang, which follow advocative policies. The selection of Zhengzhou and Shijiazhuang is based on three key reasons. Firstly, both cities are major political and cultural hubs in North China and share similarities with Shanghai in terms of population size and area, ensuring comparability. Secondly, as provincial capitals of Henan and Hebei, they hold political significance and cultural structures that position them as influential models for other cities in China. Thirdly, Zhengzhou and Shijiazhuang adhere to the same national standard for MSW classification, "Classification and Evaluation Standard of MSW CJJ/T102-2004," as Shanghai. Furthermore, the 2022 Garbage Sorting Index Evaluation Report identifies their waste sorting performance as representative of 46 non-pilot cities. This study thus examines the differences in MSW classification effectiveness between mandatory and advocative policies by comparing these three cities.

3.7 Main survey

3.7.1 Sampling

The main survey questionnaire was administered to a sample of participants in China using the Wenjuanxing (WJX) platform in August 2022. The sample consisted of 600 respondents, with approximately 200 respondents from each of the three cities included in the study: Shanghai, Zhengzhou, and Shijiazhuang. Respondents were incentivized with a small credit of less than 20 CNY (equivalent to approximately 2 pounds) to their WJX account for completing the survey. At the beginning of the survey, participants were provided with a consent form and participant information sheet (PIS) to ensure their voluntary participation and informed consent. These measures were put in place to protect the rights and welfare of the participants and to ensure ethical and responsible conduct of the study.

The survey ultimately gathered 693 responses via an online platform, of which 13 were excluded due to incomplete information. The final sample consisted of 638 respondents, with approximately 210 participants from each of the three cities: Shanghai, Zhengzhou, and

Shijiazhuang. The sample was quota-controlled based on age and residency in the respective cities to ensure representativeness. Data quality was assessed to account for potential careless responses. In this study, we applied an ex-post screening method to identify and exclude careless responses, using survey completion time as a criterion. This approach, supported by Meade and Craig (2012)and Leiner (2019), considers completion time a reliable measure of response quality. We removed 45 respondents whose completion times were excessively short, defined as more than 1.5 times the interquartile range below the nearest quartile. While effective, this method is one of several approaches for detecting careless responses. As noted by Gao et al. (2016) and Lancsar and Louviere (2006), results derived from the filtered sample should be interpreted cautiously.

The main socio-demographic characteristics of the main survey

The main socio-demographic characteristics of the main survey sample are presented in Table 3.5 and the main socio-demographic characteristics of the main survey sample for each city are presented in Table 3.6

Table 3. 5: Basic Descriptive Statistics and Total vs. Sample Population

Total vs. Sample Population			
	Respondents	Percent	NBSC 2021 %
Gender	Mean: 1.532915 S.D. 0.508275		
1=Male	301	47.18	51.24
2=Female	334	52.35	48.67
3=Not to say	3	0.47	
Ages	Mean: 3.545455 S.D. 0.930357		
1=under 18	1	0.16	23.6
2=18-25	100	15.67	5.8
3=26-30	166	26.02	7
4=31-40	305	47.81	16
5=41-50	55	8.62	14.7
6=51-60	9	1.41	15.2
7=Over 60	2	0.31	16.7
Table 3.5 (continued)			

Education	Mean: 3.847962 S.D. 0.6484557		
1=Junior or lower	6	0.94	68.1
2=High school	27	4.23	15
3=College Diploma	73	11.44	
4=Undergraduate	484	75.86	13.6
5=Graduate and higher	48	7.52	3.3
Family income per month	Mean: 4.037618 S.D. 1.12479		Mean: 10760 (YUAN)=3
1=Under 3000	14	2.19	
2=3001-6000	44	6.9	
3=6001-12000	138	21.63	
4=12001-20000	188	29.47	
5=20000-40000	216	33.86	
6=40001 and above	38	5.96	
Regions			
1=Shanghai	217	34.01	
2=Zhengzhou	210	32.92	
3=Shijiazhuang	211	33.07	
Years of local residence	Mean: 4.346395 S.D. 0.9845997		
1=Within a year	8	1.25	
2=1 to 2 years	34	5.33	
3=2 to 5 years	87	13.64	
4=5 to 10 years	109	17.08	
5=More than 10 years	400	62.7	
Given social norm			
1=T1 (15%)	157	24.61	
2=T2 (70%)	161	25.24	
3=T3 (95%)	163	25.55	
4=T4 (control group)	157	24.61	
Total	638	100	

Our sample population was assessed in relation to four key parameters: gender, age, education, and income. We compared our sample to the official data provided by China's National Bureau of Statistics in 2021(NBSC 2021). Based on the availability and comparability of data, we performed Chi-square tests for age, gender, and education. The findings indicate that there are no statistically significant differences at a 95% confidence level (Pearson chi-squared = 3.6304) between the survey sample and the general population of China regarding gender. However, significant differences exist in the 99% confidence interval (Pearson chi-squared = 443.5449 and 2300) when it comes to five age groups and education levels between the survey sample and the overall population of China. As Table 3.5 demonstrates, the gender composition in our sample aligns quite closely with the actual gender distribution in China. On the other hand, the age group of 18-40 years old is over-represented in our sample, making our respondents notably younger than the overall Chinese populace[14]. In addition, there is a somewhat stronger parentage of undergraduate compared to actual undergraduate percentage, the education level of our sample is higher than that of the general population in China. Lastly, the mean income in our sample falls between 12,000 and 20,000 yuan, exceeding the estimated average monthly income for urban households (10,760 yuan)[15] in China. The possible reason for these differences may be attributed to the nature of our online survey. It's likely that the survey attracted a larger proportion of younger participants and individuals with higher levels of education. This might explain why we observed significant variations in the age groups and education levels between our survey sample and the broader population in China.

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[14] Given that our survey primarily targeted the age group of 18 to 60 years old, and only three out of the total 638 respondents fell outside my specified range, the representation of individuals below 18 and above 60 years old in the sample is too minimal to be considered. Therefore, our comparisons are confined to the sample demographic within the 18–60-year age range, aligning it with the broader Chinese population for a more representative understanding.

[15] According to the China Statistical Yearbook 2021 (http://www.stats.gov.cn/sj/tjgb/rkpcgb/;), the mean disposable income for urban households in China stood at 49283 yuan per capita per year, with the average household comprising 2.62 individuals in 2021. Therefore, the average family's monthly income approximates to 10760 yuan.

Table 3. 6: Total vs. Sample Population of Three Cites

Total vs. Sample Population for Three Cities						
	Shanghai (%)	Shanghai NBSC 2021 %	Zhengzhou (%)	ZhengzhouNBSC 2021 %	Shijiazhuang (%)	Shijiazhuang NBSC 2021 %
Gender	Mean: 1.502304 S.D. 0.5000587		Mean: 1.538095 S.D. 0.5264917		Mean: 1.559242 S.D. 0.4965434	
1=Male	108(49.8)	51.77	100(47.62)	50.15	93(44.08)	50.5
2=Female	109(50.2)	48.23	107(50.95)	49.85	118(55.92)	49.5
3=Not to say	0		3(1.43)		0	
Ages	Mean: 3.672811 S.D. 0.8253122		Mean: 3.385714 S.D. 1.004308		Mean: 3.57346 S.D. 0.9329658	
1=under 18	0	9.8(under14)	1(0.48)	19.2(under14)	0	19.3(under14)
2=18-25	19(8.76)	66.85(15-60 years old)	48(22.86)	67.5(15-60 years old)	33(15.64)	62.23(15-60 years old)
3=26-30	59(27.91)		53(25.24)		54(25.59)	
4=31-40	117(53.92)		91(43.33)		97(45.97)	
5=41-50	19(8.76)		12(5.71)		24(11.37)	
6=51-60	2(0.92)		4(1.90)		3(1.42)	
7=Over 60	1(0.46)	23.38	1(0.48)	13.2	0	18.47
Education	Mean: 3.917051 S.D. 0.5938491		Mean: 3.757143 S.D. 0.69912		Mean: 3.867299 S.D. 0.639561	
1=Junior or lower	2(0.92)	47	2(0.95)	53	2(0.95)	63
2=High school	7(3.23)	19	13(6.19)	18	7(3.32)	17
3=College Diploma	15(6.91)		32(15.24)		26(12.32)	
4=Undergraduate	176(81.11)	34	150(71.43)	29	158(74.88)	20

5=Graduate and higher	17(7.83)		13(6.19)		18(8.53)	
Family income per month	Mean: 4.460829 S.D. 0.8423045	Mean:15391(YUAN)=4	Mean: 3.752381 S.D. 1.169452	Mean :9647(YUAN)=3	Mean: 3.886256 S.D. 1.202979	Mean:8289(YUAN)=3
1=Under 3000	1(0.46)		5(2.38)		8(3.79)	
2=3001-6000	1(0.46)		27(12.86)		16(7.58)	
3=6001-12000	27(12.44)		56(26.67)		55(26.07)	
4=12001-20000	70(32.26)		58(27.62)		60(28.44)	
5=20000-40000	104(47.93)		55(26.19)		57(27.01)	
6=40001 and above	14(6.45)		9(4.29)		15(7.11)	
Years of local residence	Mean: 4.474654 S.D. 0.8590843		Mean: 4.133333 S.D. 1.142969		Mean: 1.502304 S.D. 0.9845997	
1=Within a year	1(0.46)		6(2.86)		1(0.47)	
2=1 to 2 years	8(3.69)		19(9.05)		7(3.32)	
3=2 to 5 years	23(10.6)		32(15.24)		32(15.17)	
4=5 to 10 years	40(18.43)		37(17.62)		32(15.17)	
5=More than 10 years	145(66.82)		116(55.24)		139(65.88)	
Total	217		210		211	

In addition, when comparing the main socio-demographic characteristics of the main survey sample for each city. We also used Chi-square tests for gender and education for each cities. The findings indicate that there are no statistically significant differences at a 95% confidence level (Pearson chi-squared = 0.295 (Shanghai), 0.309 (Zhengzhou) and 3.203 (Shijiazhuang)) between the survey sample for each city and the actual percentages in the three surveyed cities regarding gender. Therefore, the gender makeup within the sample from each of the three cities adheres closely to the actual gender ratios in these locations.

However, significant differences exist in the 99% confidence interval (Pearson chi-squared = 298.209 (Shanghai), 278.883 (Zhengzhou) and 556.804 (Shijiazhuang)) when it comes to three education levels between the survey sample for each city and the actual percentages in the three surveyed cities. Table 3.6 illustrates a trend of our sample having a relatively higher proportion of individuals with undergraduate or higher education compared to the actual percentages in the three surveyed cities. However, the average family income brackets of our sample (12,001-20,000 yuan, 6,001-12,000 yuan, and 6,001-12,000 yuan) align with the estimated average monthly family income for the respective cities (15,391 yuan, 9,647 yuan, and 8,289 yuan)[16].

Additionally, we conducted a one-way ANOVA analysis to examine the variations in income and education levels across three different cities. Our results indicate statistically significant differences, with significance levels better than 1%, in both income and education among these three cities. Our sample indicates that participants from Shanghai possess a greater extent of higher education (undergraduate, graduate, and beyond) and higher income (12,001 yuan and above) than their counterparts in Zhengzhou and Shijiazhuang, which mirrors the reality of these cities.

In summary, our sample appears to include a higher proportion of younger participants and individuals with higher education levels, likely due to the nature of the online survey, and

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[16] According to the Shanghai City Bureau of Statistics 2021; Zhengzhou City Bureau of Statistics 2021; Shijiazhuang City Bureau of Statistics 2021 (https://tjj.sh.gov.cn/7renpu/index.html; https://tjj.zhengzhou.gov.cn/tjsj/index_2.jhtml; https://www.sjz.gov.cn/col/1605834487975/index.html;), the mean disposable income for urban households in Shanghai, Zhengzhou, Shijiazhuang stood at 79610 yuan, 41049 yuan and 35266 yuan per capita per year, with the average household comprising 2.32, 2.82, 2.82 individuals respectively in 2021. Therefore, the average family's monthly income approximates to 15,391 yuan, 9,647 yuan, and 8,289 yuan.

perhaps also the survey topic—maybe younger people are more interested in recycling than older individuals, making them more likely to respond to the survey. This may explain the significant differences in age and education levels observed between our sample and the general population in China. Additionally, the sample reflects regional disparities, with participants from Shanghai showing higher levels of education (undergraduate and postgraduate degrees) and higher incomes (12,001 yuan and above) compared to respondents from Zhengzhou and Shijiazhuang, aligning with the socio-economic realities of these cities.

3.8 Methodological Approach

This chapter outlines the primary techniques used to estimate the statistical findings and provides details on the variables analysed in the two core chapters of this thesis (Chapters 4 and 5), with further discussion presented in the respective sections of those chapters. Section 3.8.1 introduces Discrete Choice Experiments (DCEs), while Section 3.8.2 explores their variations and theoretical foundations within consumer theory.

3.8.1 Discrete Choice Models

The theoretical foundation of Discrete Choice Experiments (DCE) was developed by Lancaster (1966), who proposed that consumers derive utility from the specific attributes of goods rather than solely from the goods themselves. This approach is particularly effective for analysing goods or services that are complex and described by multiple attributes, such as a pro-behavioural experiment (PBE) program. Econometrically, Choice Experiments rely on discrete choice analysis (McFadden, 1974), which is grounded in the Random Utility Model (RUM). This framework links a deterministic model with a statistical representation of human behaviour (Thurstone, 1994), reflecting the assumption that consumers aim to maximise their utility based on both observed and unobserved factors in the data.

As previously discussed, Discrete Choice Experiments (DCEs), when implemented as surveys, present respondents with a series of hypothetical scenarios requiring them to choose between a limited number of mutually exclusive alternatives. They are a quantitative research method commonly used to evaluate trade-offs and preference strengths for both use and non-use values. Originally developed by Louviere and Hensher (1982) and Louviere and Woodworth (1983), DCEs draw on advances from multiple fields, including axiomatic conjoint measurement and information integration theory in psychology, random utility theory in economics, and discrete multivariate models for contingency tables and experimental design in statistics Lancsar and Louviere (2008). The first environmental application of a DCE was by Adamowicz et al. (1994). Over the past decade, DCEs have grown significantly in use and are now a widely adopted stated preference (SP) method for environmental valuation. Unlike traditional consumer behaviour theory, which assumes goods are the direct source of utility and overlooks their intrinsic properties, Lancaster (1966) proposed a new approach where utility is derived from the attributes or characteristics of goods, or combinations of goods. He argued that goods possess multiple characteristics in fixed proportions, and it is these characteristics, rather than the goods themselves, that influence consumer preferences. This theory is based on three key assumptions: (1) utility arises from the characteristics of goods, not the goods themselves; (2) each good has multiple characteristics, many of which are shared with other goods; and (3) combinations of goods may exhibit unique characteristics distinct from those of the individual goods.

Random Utility Theory (RUT)

Choice analysis relies on data that captures individuals' preferences for discrete, mutually exclusive alternatives, typically presented in categorical form, such as waste sorting methods, environmental awareness levels, or participation in recycling. Given the categorical nature of this data, traditional OLS regression models cannot accurately capture the underlying data-generating process. In such cases, the dependent variable is often a binary variable. For instance, in my analysis, a question might ask, "Are you willing to pay more to support a more efficient recycling system?" Responses are summarised as "yes" or "no," while independent variables may include personal characteristics and other environmental factors. The primary focus of model development is to explore heterogeneity in the factors influencing respondents' decision-making processes. Random Utility Theory (RUT) posits that choices are driven by the attributes of a policy or project (the deterministic component) along with a random component. This stochastic element accounts for gaps between theoretical predictions and observed choices, arising from incomplete information or variability in individual recycling or environmental preferences. Mathematically, the Random Utility Model (RUM) can be formalised as an equation that represents the utility of an individual as the sum of two components: a systematic (deterministic) component and a random (stochastic) component. This framework captures the decision-making process by combining observable factors with unobserved variations. The equation is presented as follows: **Equation (3-1)**

$$U_{ijt} = X_{ijt} + \varepsilon_{ijt}$$

In this context, U_{ijt} denotes the utility of individual i for alternative j in choice situation t. This utility is composed of a deterministic, observable component X_{ijt}, which depends on explanatory variables and unknown parameters β, and an unobserved random component ε_{ijt} treated as a random variable, which accounts for uncertainty—stemming either from respondents not fully understanding the ramifications of their choices or from the analyst's inability to capture all relevant factors (Bhat, 2008). As with any utility function, the individual aims to select the alternative that maximises their utility. The probability of alternative j being chosen can be determined using the following equation, which captures the likelihood of this option being selected based on the utility derived from it: **Equation (3-2)**

$$Pr(ijt) = Pr(\varepsilon_{ijt} - \varepsilon_{ikt} > X_{ikt} - X_{ijt}), \forall k \neq j$$

This formula represents the probability that the difference in the random components is less than the difference in the deterministic components, indicating that only the differences in utility truly matter. It reflects the likelihood of alternative j being chosen over any other alternative k, where $k \neq j$. Given the nature of the data, individuals choose from multiple mutually exclusive options (multinomial choices), selecting the one they believe offers the highest utility. This decision is subjective and influenced by respondents' attitudes and characteristics. The models discussed in this section are chosen based on the data's nature.

As noted by Train and Weeks (2005), accounting for both preference and scale heterogeneity introduces correlations among observed attributes, which must be appropriately addressed. In this study, four modelling techniques are employed to investigate respondents' preferences and facilitate comparison. First, a Conditional Logit (CL) model is used. Next, a Mixed Logit (ML) model is applied to account for the data's nature and unobserved preference heterogeneity among respondents. Latent Class Analysis (LCA) is then utilised to estimate class membership based on respondents' willingness-to-pay (WTP) for different levels of recycling policy options. Finally, a Hybrid Choice Model is adopted to integrate measurable characteristics of decision-makers with unobservable factors, such as attitudes towards recycling and life goal tendencies. The following sections outline each model to highlight their theoretical implications and their application in the data analysis chapters.

3.8.2 Conditional Logit (CL) Model

Both Multinomial Logit (MNL) and Conditional Logit (CL) models are used to analyse an individual's choice among a set of J alternatives. The key difference lies in the focus of analysis: the MNL model centres on the individual as the unit of analysis, using their characteristics as explanatory variables, whereas the CL model focuses on the alternatives available to each individual, with the explanatory variables being the attributes of those alternatives. The Conditional Logit (CL) model, an extension of the Multinomial Logit (MNL) model, is characterised by its use of fixed-effects logistic regression, disregarding random effects or data non-independence. It is particularly suitable for modelling choice behaviour when the explanatory variables include attributes of the available alternatives. We begin by introducing the Multinomial Logit (MNL) model as a foundation for the extension we aim to explore. Let U_{ijt} represent the utility of individual i in choice situation t for alternative j. Since choices are driven by random utilities, the relationship can be expressed using the standard utility equation same as above: **Equation (3-1).**

$$U_{ijt} = X_{ijt} + \varepsilon_{ijt}$$

First, let us define Y_i as the choice made from j alternatives, we assume rationality, where respondents aim to maximise their perceived utility within the limits of their expenditure constraints. When a person has q choices, we define a latent variable Y_i^* to represent the level of indirect utility from the i's choice. Therefore, Y_i defined as follows: **Equation (3-3)**[17]

$$Y_i = \begin{cases} = 1, & if \;\; Y_i^* max(Y_1^*, Y_2^*, \dots Y_q^*) \\ = 0, & otherwise \end{cases}$$

If the probability density function is defined, it represents the likelihood of a specific outcome or choice being observed, based on the distribution of the underlying random components in the utility model. The corresponding mathematical expression is presented below: **Equation (3-4)**

$$f(\varepsilon) = \exp(-\varepsilon - \exp(-\varepsilon))$$

Where ε represents the unobserved random component. This equation defines the probability density function of a standard Gumbel distribution (as known as the Type I Extreme Value (Gumbel) distribution).

According to Train (2009), the probability of choosing alternative j can be derived from the model and is expressed mathematically as follows: **Equation (3-5)**

$$Pr_{ij} = \frac{\exp(X_{ijt})}{\Sigma \exp(X_{ijt})}, \qquad j = 1,2,..J$$

This forms the basis of the Multinomial Logit (MNL) model, providing a framework for analysing choice behaviour by linking utility maximisation with the probability of selecting a particular alternative.

The expected utilities are based on the individual's characteristics. So,

[17] See full proof in (Maddala, 1983).

Equation (3-6)

$$X_{ijt} = x'_{ijt}\beta_j$$

where, β_j j represents the utilities of various choices. As a result, the necessary quantities are substituted directly into the formula without requiring approximations. While MNL models offer clear advantages, alternative specifications are considered due to their limitations, particularly the assumption of no preference heterogeneity among respondents and the restrictive Independence from Irrelevant Alternatives (IIA) property, which can lead to unrealistic predictions. The IIA axiom, introduced by Luce (1959), underpins the derivation of the logit formula, with Marschak (1960) demonstrating that it implies Random Utility Maximisation (RUM). The IIA states that the ratio of probabilities of choosing between two alternatives (provided both have non-zero probabilities) is unaffected by the inclusion or exclusion of additional options in the choice set (Louviere et al., 2010). However, the utility maximisation approach has limitations, as errors in decision-making can arise due to imperfect information, optimisation challenges, and the inability to measure all relevant variables precisely.

Building on Thurstone's work, McFadden (1974) proposed treating utility as a random function and suggested modelling expected utilities based on the characteristics of the alternatives (Thurstone, 1927; Thurstone, 1928). Let m_j represent a vector of characteristics for the j-th alternative and ϕ denote the corresponding vector of case-specific coefficients. This approach leads to the formulation of the Conditional Logit model, expressed as follows:

Equation (3-7)

$$X_{ijt} = m_j'\phi$$

This model is crable to a log-linear model, where the main effect is represented by the covariates m_j. Such models are typically applied when the number of available choices is substantial. By combining the two models described above, a more generalised framework can be developed. For instance, consider a scenario where *N* respondents are faced with q choices.

Y_{ij}^{*} denotes the indirect utility for the i-th respondent making the j-th choice;

Y_{ij} equals 1 if individual i chooses alternative j, and $Y_{ij} = 0$ otherwise. Therefore, we have:

Equation (3-8)

$$Y_{nj}^{*} = x'_i\beta_j + m'_j\phi + \varepsilon_{ij}$$

In this model, x_i represents individual-specific variables, while m_j denotes the n-th respondent's vector of attribute values for the j-th alternative associated with individual i. This framework accounts for both individual characteristics and the attributes of the available choices.

The probability of choice is thereby defined as: **Equation (3-9)**

$$Pr_{nj} = Pr\ (Y_{nj} = 1) = \frac{exp\ (x_i'\beta_j + m_j'\phi)}{\sum_{k=1}^{q} exp\ (x_i'\beta_k + m_k'\phi)}$$

Where $Pr_{\,nj}$ represents the probability that individual n chooses option j, the variables x_i are the individual-specific characteristics, such as age, income, or education. Each alternative has its own set of coefficients, β_j which show how these personal characteristics influence the attractiveness of different alternatives. The variables m_j are attributes of each alternative, while ϕ represents coefficients that reflect general preferences for these attributes, assumed to be consistent across all individuals and alternatives. When calculating the probability that individual i selects alternative j, we assume the random error terms ε_{ij} follow a Type I Extreme Value (Gumbel) distribution and are independent and identically distributed across both alternatives and individuals. Because of this assumption, when deriving the probability, these random terms are integrated out.

The independence from irrelevant alternatives (IIA) property, while simplifying estimation, imposes restrictive and often unrealistic assumptions on consumer behaviour. Another limitation of the conditional logit model is its inability to account for preference heterogeneity, as the β coefficients in Equation (6) are assumed to be fixed across the population. To address this, the mixed logit model is commonly used, allowing the β coefficients to vary among individuals, thereby accommodating preference heterogeneity.

The assumption of fixed β coefficients in the conditional logit model can be relaxed to account for preference heterogeneity, resulting in the mixed logit or random parameters logit model (Revelt and Train, 1998). This approach assumes that model parameters are randomly distributed across the population, capturing preference heterogeneity by estimating the mean and standard deviations of these parameters.

3.8.3 Mixed logit Model (ML)

The mixed logit (ML) model, as outlined by McFadden and Train (2000), is detailed below for econometric estimation. In this model, certain parameters, including alternative-specific constants (ASCs), are treated as random variables to account for unobserved heterogeneity among individuals. These random parameters can follow various distributions based on theoretical considerations and empirical data; for instance, normal or log-normal distributions are commonly used. The utility of individual i selecting alternative j in choice situation t is represented by **Equation (3-10)**

$$U_{ijt} = \beta_i x_{ijt} + \varepsilon_{ijt}$$

where β_i represents the coefficient vector for observed variables specific to individual i, x_{ijt} denotes the observed variables associated with individual i and alternative j *in situation* t, and ε_{ijt} is the unobserved utility component for individual i choosing alternative j *in situation* t.

In the Mixed Logit model, the probability of choice can be defined as:

Equation (3-11)

$$Pr(Y_{it} = j) = \frac{exp(X_{ijt})}{\Sigma_{T=1}^{ijt} exp(X_{ijt})}$$

When, **Equation (3-12)**

$$X_{ijt} = x'_{ijt}\beta_j + \alpha_j$$

The model is expressed as:

Equation (3-13)

$$\beta_{ig} = \beta_g + \Delta_g w_i + \xi\pi_{ig}$$

Equation (3-14)

$$\alpha_{ij} = \alpha_j + \Delta_j w_i + \xi\pi_{ij}$$

The model includes x_{ijt}, representing g attributes of alternative j for individual i in choice situation t. Additionally, w_i denotes a set of q characteristics specific to individual i. The term π_{ig} is a vector of g random variables with a mean of zero, unit variance, and no covariance. The alternative-specific constant (ASC) is given by α_j, while π_{ij} captures heterogeneity in choice-specific constants, assuming a normal distribution. In addition, the coefficient β_g represents the population mean for the g-attribute, while the individual-specific preference parameter β varies across respondents. The choice-specific constants α fluctuate around their means rather than not fixed for all individuals. The distributions of α_{ij} and β_{ig} allow for heterogeneity, influenced by w_i with weights Δ_j and Δ_g. In other words, Δ_j and Δ_g measure how strongly individual characteristics m_i affect the average values of these parameters, thus showing how personal factors shift respondents' preferences to different attributes.

In the mixed logit model, the parameter ξ represents the scale or standard deviation of the random preference variation among individuals. Specifically, it controls how strongly random terms (π_{ig} and π_{ij}) influence individual-specific utility parameters. A larger value of ξ indicates greater unobserved heterogeneity in preferences, while a value of zero reduces the model to a simpler fixed-coefficient model without random variation.

These models were designed to address unobserved differences in preferences by allowing coefficients to vary rather than remain fixed. Various parametric distributions can be used, though research often assumes normally distributed coefficients, with price or monetary attributes typically kept constant..

3.8.4 Willingness to Pay (WTP)

To assess the value respondents place on different attributes, we estimate their Willingness to Pay (WTP). Marginal WTP is calculated to determine the importance of a one-unit change in an attribute, allowing us to evaluate respondents' WTP accordingly. WTP estimates for marginal changes are derived for all attributes using the specified formula.

Equation (15)

$$WTP = \frac{-\beta_{ATTRIBUTES}}{\beta_{COSTS}}$$

For mixed logit model, the individual-specific preference parameter β and the choice-specific constants α are not fixed across all respondents but vary around their means. The distributions of α_{ij} and β_{ig} have means that can exhibit heterogeneity influenced by w_i, with weights Δ_g and Δ_j respectively (Sheremet et al., 2017). The Krinsky and Robb (1986) method is employed to calculate confidence intervals for these parameters. Research has shown that willingness-to-pay (WTP) estimates can be influenced by unobserved factors. Hole and Kolstad (2012) and Train and Weeks (2005) found that personal experience affects respondents' preferences, which in turn impacts WTP estimates. A different method is to estimate models in the WTP space. They also suggested that learning can influence both the average and variance of random taste parameters, thereby affecting WTP calculations.

In this research, I estimate models both in preference space and directly in willingness-to-pay (WTP) space, subsequently comparing the outcomes of these two approaches. Estimating in WTP space allows for direct interpretation of attribute coefficients as marginal WTP, relaxing the assumption of fixed price coefficients. Daly et al. (2012) and Carson and Czajkowski (2014) have discussed the benefits of this approach. The discussion regarding the superiority of these methods continues. Balcombe et al. (2009) and Daly et al. (2012) reported that WTP space estimates tend to be more stable and reasonable. Similarly, Sonnier et al. (2007) and Train and Weeks (2005) found that models in preference space fit the data better but produced less reasonable WTP distributions than models in WTP space. Conversely, Hole and Kolstad (2012) observed that models estimated in preference space provided a somewhat better fit while delivering more realistic WTP estimates. Given these mixed findings, I have chosen to estimate WTP in both preference and WTP spaces to comprehensively compare the results. In addition, we also calculated individual-level willingness to pay (WTP) as a comparison to the previous two results (detailed in Section 4.2).

3.8.5 Latent class

The Latent Class Model (LCM) emerged in the mid-20th century within the social sciences, introduced by Paul F. Lazarsfeld to identify unobserved subgroups in survey samples. Their research on latent structure analysis laid the groundwork for this approach by introducing a discrete, unobservable variable that accounts for patterns in respondents' answers. Lazarsfeld (1968) developed Latent Class Analysis (LCA), which classifies individuals into distinct latent groups based on their observed responses. Collins and Lanza (2009) later defined LCA as a "mixture model that assumes the presence of an unobserved categorical variable dividing a population into latent classes." Practically, LCM treats unobserved heterogeneity as a discrete distribution, meaning that each latent class represents a distinct subgroup with its own behavioural or statistical characteristics. Goodman (1974) made a significant contribution by formalising the maximum likelihood estimation for Latent Class Models (LCM) and demonstrating how to apply these models to data. Other researchers, such as Andersen (1982), further refined the methods and expanded their application. The main goal of Latent Class Analysis (LCA) is to classify individuals into distinct groups based on observed data and to identify the key variables that most effectively define these groups. This approach helps researchers in understanding the differences between classes and their characteristics. The theory behind LCA suggests that individual behaviour is shaped by both observable factors and unobserved heterogeneity. By uncovering hidden subgroups within categorical data, LCA provides valuable insights into patterns that may not be immediately apparent. Over time, its applications have expanded across various fields.

Unlike continuous models, Latent Class Analysis (LCA) uses categorical latent variables to classify individuals into distinct groups, such as purchasing habits, behavioural patterns, education levels, or health conditions. Each respondent is assigned to one of several mutually exclusive and exhaustive latent classes. This approach is particularly effective when the population consists of clearly defined segments and is well-suited for capturing multi-modal or discrete heterogeneity. LCA is also valuable for policy design and stakeholder communication, as it helps identify and target specific groups more effectively(Greene and Hensher, 2003; Sagebiel, 2017).

When the Multinomial Logit (MNL) model fails to account for heterogeneity, the latent class model offers a semi-parametric alternative by avoiding strict assumptions about parameter distributions across individuals (Uebersax, 1999).

In economics and choice modelling, Boxall and Adamowicz (2002) introduced latent class modelling (LCM) to environmental economics. Using a latent class logit model within a recreational demand context, they identified distinct consumer segments with varying preferences. Their findings showed that incorporating latent classes resulted in significantly different welfare estimates for policy changes when compared to a model that assumes a homogeneous population. This study highlighted the policy relevance of LCM, as recognising different user segments allows policymakers to create more equitable and effective interventions or compensation schemes tailored to each group. For example, in studies on household recycling behaviour, Latent Class Models (LCM) have been used to explain differences in individuals' recycling decisions. Czajkowski, Hanley, and Nyborg (2014) Czajkowski et al. (2017) conducted a choice experiment in Poland on waste management and identified three distinct groups of recyclers with different motivations, ranging from moral responsibility to cost-saving. Their findings provide valuable insights for designing more targeted and effective recycling policies.

In this thesis, we have been assuming a continuous distribution of coefficients in the mixed logit model so far. However, it's also possible for the coefficients to be discrete, leading to the latent class model. Let's consider decision maker $i,$ who chooses among J alternatives in each of T choice situations, where $i = 1, 2, \cdots, N.$ Each alternative j available to this decision-maker at choice occasion t is described by a set of K attributes, represented as a row vector x_{ijt}. We define y_{ijt} as a binary indicator, set equal to *1* if alternative j is chosen, and 0 otherwise. In the context of the conditional logit model (clogit in Stata), the joint likelihood of her T choices is given by: **Equation (3-16)**

$$P_i(\beta) = \prod_{t=1}^{T} \prod_{j=1}^{J} \left(\frac{exp\,(x_{ijt}\beta)}{\sum_{l=1}^{J} 1 + exp\,(x_{ilt}\beta)} \right)^{y_{ijt}}$$

where β represents a column vector consisting of K coefficients, which can be understood as the marginal utilities associated with the respective attributes in x_{ijt}. where x_{ijt} is a set of attributes describing alternative j in choice situation t for person i. β is a vector of coefficients representing how these attributes influence the choice. y_{ijt} equals 1 if individual i chooses alternative j at occasion t, and 0 otherwise.

The Latent Class Conditional Logit (LCL) model extends the conditional logit model by introducing discrete representation of unobserved preference variations among decision makers. Specifically, it is assumed that there are Q distinct types or "classes" of decision makers, each class q chooses according to its own conditional logit model, characterised by a specific vector of utility coefficient β_q. In this model, the specific class to which an individual belongs remains unknown to the analyst, regardless of whether the individual is aware of it. Consequently, class membership stays uncertain. To address this, two key parameters are estimated:

1. Class Membership Probabilities – These denote the likelihood that an individual belongs to a particular latent class, similar to factor scores.
2. Conditional Response Probabilities – These describe the probability of individuals in a given class responding differently to observed variables.

Lanza and Cooper (2016) emphasise these aspects of LCA in their research. Bhat (1997) and Swait (1994) were among the first to apply LCA to discrete choice analysis, utilising it to investigate how individuals select from multiple alternatives. Suppose that the probability of decision maker i belonging to class q is determined by a fractional multinomial logit specification given by:

Equation (3-17)

$$\pi_{iq}(\Phi) = \frac{exp(z_i'\gamma_q)}{1+\sum_{l=1}^{Q-1} exp(z_i'\gamma_l)}$$

Where, z_i represents a row vector of decision maker $i's$ characteristics, including the constant regressor, such as 1. γ_q is a column vector of membership model coefficients for class q, with the γ_Q normalized to *0* for identification purposes. And $\Phi = (\gamma_1, \gamma_2, \cdots, \gamma_{Q-1})$ denotes a collection of the $Q - 1$ identified membership coefficient vectors. Here, the symbol l is simply an index used for summation. It indicates that the probabilities are summed across all categories from l up to $Q - 1$, except for a baseline category.

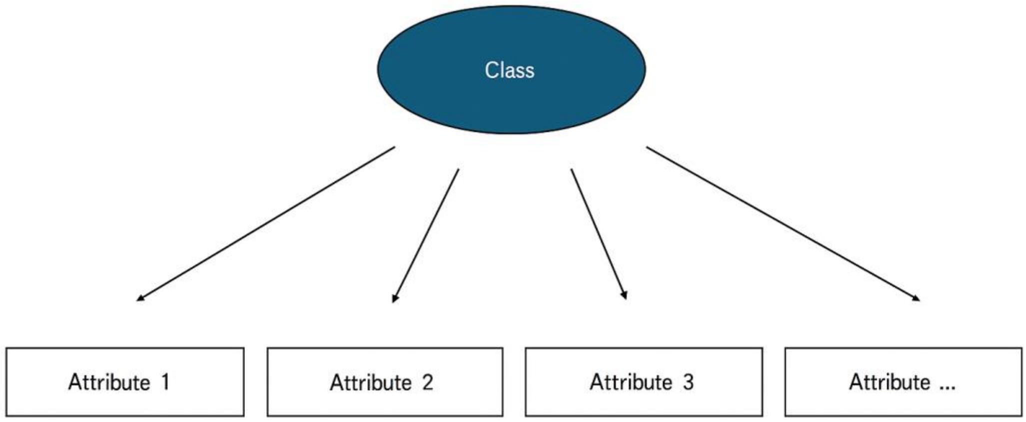
In the LCL model, the joint likelihood of decision maker i's choices can be expressed as follows:

Equation (3-18)

$$H_i(A, \Phi) = \sum_{q=1}^{Q} \pi_{iq}(\Phi) P_i(\beta_q)$$

Where A represent a set consisting of Q vectors of utility coefficients, denoted as $(\beta_1, \beta_2, \cdots, \beta_Q)$. Each $P_i(\beta_q)$ is derived by applying **Equation (3-16)** at the point where $\beta = \beta_q$. This formula can be optimized either through conventional techniques or via the EM algorithm. In Stata, gllamm employs the direct approach (Rabe-Hesketh and Skrondal, 2017), while the lclogit command utilizes the indirect method involving the EM algorithm (Pacifico and Yoo, 2013). When estimating the model, we cannot determine with certainty which observation belongs to which class, which is why the term latent is used. Each class is defined to represent a specific behavioural pattern and can be seen as a probabilistic decision rule. Latent Class Analysis (LCA) has various applications, particularly in understanding heterogeneity to improve the targeting of interventions, campaigns, and marketing strategies.

Figure 3.3: Latent Class model diagram.



In Figure 3.3, the class is a discrete latent variable, meaning that each respondent belongs to one group or another, which shapes their response patterns. LCA identifies these response patterns and classifies individuals into distinct latent subgroups based on their shared characteristics.

The latent class conditional logit (LCL) model extends the conditional logit model by accounting for unobserved differences in preferences among decision makers. It assumes decision makers belong to one of several distinct groups, or 'classes', each with its own set of preferences described by specific utility coefficients (β_q). The probability of an individual belonging to a particular class is determined by their observable characteristics. Overall choice probabilities are calculated by combining class-specific choice probabilities with these class-membership probabilities. The resulting likelihood for each decision maker's set of choices is obtained by summing across all possible classes, and the sample likelihood is computed by aggregating these individual likelihoods.

3.8.6 Hybrid Choice model

Hybrid Choice Models (HCM), also called Integrated Choice and Latent Variable (ICLV) models, build on traditional discrete choice models by incorporating psychological factors like attitudes and perceptions into decision-making. This approach emerged in the early 2000s. Ben-Akiva et al. (2002) develop an integrated framework that combined random utility theory with structural equations for latent variables. Their work showed that linking choice models with psychological factors improved predictive accuracy compared to models relying only on simple attitude proxies. At the same time, Walker and Ben-Akiva (2002) introduced the Generalized Random Utility Model, which provided a theoretical basis for connecting unobservable influences, such as attitudes, with decision-making under utility maximisation. These early contributions established HCM as a powerful tool for capturing variations in preferences that go beyond what traditional socio-demographic factors can explain.

Hybrid choice models comprise three main components: structural equations, measurement equations, and a discrete choice model. This approach simultaneously identifies the connections between latent psychological factors (e.g., attitudes, behavioural intentions) and their influence on decision-making within the choice model. Additionally, it incorporates observable characteristics, such as socio-demographic and contextual factors, to explain variations in these latent traits. By combining these elements, hybrid choice models offer a comprehensive framework to understand individual preferences and the underlying factors driving heterogeneity in decision-making across various contexts.

Structural equations are formulated to define the latent variable (LV), typically assumed to be linear in the parameters with a normally distributed error term. The LV is a function of certain socio-demographic variables X_i, expressed as **Equation (3-17)**:

$$LV = \Psi' X_i + \xi_i$$

with a coefficient vector Ψ', which is $p * 1$ (number of latent variables) and X_i is $p * 1$ socioeconomic vectors, and an error term ξ_i, which is assumed to follow a multivariate normal distribution.

Measurement Component

Psychological factors influencing individual behaviour often cannot be measured directly, unlike characteristics such as age and gender. Researchers must instead use various indicator questions in a survey, with responses expected to be determined by latent variables that indicate psychological traits or beliefs.

The set of measurement equations link the latent variable (LV) to the responses to indicator I.

Equation (3-18)

$$I_i^* = \rho' LV_i + \eta_i$$

Where ρ' is a vector of coefficient (is $m * 1$ – number of indicators) indicating the effect of the LV on the indicator, and η_i is a vector of error terms assumed to come from a multivariate normal distribution with zero means and an identity covariance matrix. Likert-type indicators have an intrinsic ordering of responses and are thus modelled as ordered logits, which include threshold parameters to be estimated.

Equation (3-19)

$$f(x) = \begin{cases} i_1, & if -\infty < \rho LV_i < \tau_1 \\ i_2 &, \ if\ \tau_1 < \rho LV_i < \tau_1 + \delta_i \\ & \ldots\ldots \\ i_k, & if\ \tau_{(k-1)} < \rho LV_i < +\infty \end{cases}$$

Where $\tau_1 \ldots \tau_{k-1}$ are the threshold parameters of the k classes to be estimated, and δ_i is the width of the class.

The final component of HMXL is a choice model based on Random Utility Theory (RUM). RUM assumes that an individual's utility depends on the characteristics of the alternative and a stochastic unobserved component. The utility U that an individual i obtains from an alternative j in choice situation t is given by the following **Equation (3-1)**:

$$U_{ijt} = \beta_i' X_{ijt} + \varepsilon_{ijt}$$

where the utility expression is a function of alternative attributes X_{ijt}, the associated coefficients β_i, and a stochastic component ε_{ijt} which accounts for factors not observed by the econometrician that affect individuals, utility and choices. Note that β_i are individual-specific, thus allowing for heterogeneous preferences among respondents, leading to a hybrid mixed logit model (HMXL).

In the HMXL models, it is assumed that the random parameters β_i depend on latent variables LV_i, which capture unobservable factors influencing decision-making. These latent variables are linked to underlying traits or preferences, and their relationship with the random parameters is expressed through a specific functional form, as shown in **Equation (3-20)**:

$$\beta_i = \Lambda' \boldsymbol{LV_i} + \beta_i^*$$

Since Ψ is a matrix of coefficients to be estimated and β_i^* follows a multivariate normal distribution with a mean vector and covariance matrix that need to be estimated. Λ is a matrix $(attributes * LVs)$, which has a number of columns equal to the number of latent variables and a number of rows equal to the number of attributes. Consequently, the conditional probability of individual *i*'s choices is expressed as: **Equation (3-21)**

$$Pr(y_i|X_i, \beta_i^*, LV_i, \Lambda) = \prod_{t=1}^{T_i} \frac{exp(\beta_i' X_{ijt})}{\sum_{k=1}^{C} exp(\beta_i' X_{ikt})}$$

This study applies the Hybrid Choice Model (HCM) framework to incorporate latent variables into preference analysis, using observable indicators to represent underlying factors. A structural equation model is first developed to estimate relationships among latent variables and the influence of related observable factors. Subsequently, these latent variables, along with sociodemographic characteristics and their observable indicators, are integrated into a mixed Logit model to evaluate their effects on stated preferences. Observable indicators are measured using a Likert scale ranging from "strongly agree" or "strongly support" to "strongly disagree" or "strongly oppose," with a numerical scale of 1 to 5.

Recent studies have addressed issues such as endogeneity and measurement errors in Hybrid Choice Models (HCM). Budziński and Czajkowski (2022) emphasise that including attitude indicators in a choice model without accounting for potential correlations with unobserved factors can lead to biased results. To tackle this, they propose enhancing the model by allowing error terms in the latent variable and choice components to be correlated or by introducing additional latent factors. Simulation tests confirm that these adjustments help recover true preference parameters, rendering HCM estimates more reliable. Overall, advancements in estimation methods and formal validation tests have strengthened the accuracy and practical use of HCM in real-world contexts.

In recent years, environmental behavioural economists have utilised Hybrid Choice Models (HCM) to enhance benefit estimates in stated preference studies. Faccioli et al. (2020) employed HCM in a choice experiment focused on peatland restoration, discovering that individuals with stronger pro-environmental attitudes and a deeper connection to their locality were willing to pay more for restoration efforts. This approach effectively linked general environmental beliefs to economic values. Similarly, Boyce et al. (2019) incorporated stable personality traits into choice models for public environmental goods and noted consistent effects across multiple surveys. Their findings indicated that personality differences played a significant role in explaining variations in preferences and could even predict how individuals might respond to new environmental policies. These studies lead to better-fitting models and more credible welfare estimates, providing policymakers with insight into the levers that can drive behaviour change.

3.9 Summary

To summarise, the preceding discussion confirms that DCEs are an appropriate method for examining preferences related to recycling in this study. Additionally, I detailed the step-by-step process, from designing the DCE questionnaire, conducting one-on-one interviews, and running the pilot study, to completing the main survey. The results revealed key socio-demographic characteristics, including a higher proportion of younger and more highly educated participants, likely influenced by the online survey format. These characteristics account for differences in age and education levels compared to the general Chinese population. Regional disparities were also observed, with respondents from Shanghai demonstrating higher education levels and incomes compared to those in Zhengzhou and Shijiazhuang, aligning with the socio-economic context of these cities.

To analyse recycling preferences, the study applies established econometric techniques, beginning with the foundational Multinomial Logit (MNL) model. Recognising its limitations, more advanced approaches, such as the Random Parameter Logit model, Latent Class Analysis, and Hybrid Choice Models, were employed to better capture preference heterogeneity and psychological factors influencing recycling behaviours.

The data collected and the models developed will be used in subsequent chapters to address four core objectives: (1) comparing the effects of mandatory versus voluntary waste sorting policies on recycling preferences using stated preference methods and willingness to pay (WTP) as indicators; (2) assessing the impact of social norm nudges on household WTP for improved recycling efforts and their alignment with local waste regulations; (3) examining the relationship between Theory of Planned Behaviour (TPB) factors and recycling preferences; and (4) investigating whether self-reported well-being goals, such as contributing to future generations, influence recycling preferences directly or through mediation by TPB variables. These analyses will provide valuable insights into the drivers of recycling behaviour and inform policy design.

Appendix A-1

Questionnaire (Final version)

Participation Information Sheet

CHINA RECYCLING SURVEY

Purpose of survey

This survey will be launched to investigate what people across Shanghai, Zhengzhou, Shijiazhuang know about the current solid waste management and what are their current recycling behaviours. In addition, new solid waste management measures are being proposed across these three cities and we would like to know your advice and choice on the new management. Result from the survey can provide more information to local government to decide how best to improve local domestic waste regulation.

By taking a few minutes of your time, you will get involved in shaping the future of new municipal solid waste management options in China and add greatly to our understanding of what is important to you.

Funding

Funding new solid waste management regulations in Shanghai, Zhengzhou, Shijiazhuang involves a cost to households. Therefore, it is important that citizens from all cities give their suggestions. Results from the survey will be shared with interested policy makers responsible for developing new solid waste management plans.

Protecting your confidentiality

The participants data will be secured and will be putted on a password protected computer system and the data collected will only be accessible to the researchers involved in this study and will be used for research purposes only. The survey are truly anonymous.

Rights of participants

You are totally voluntary and you can withdraw at any time you want, In addtion, you are free to skip any question you choose without giving reason and there is no consequences to you.

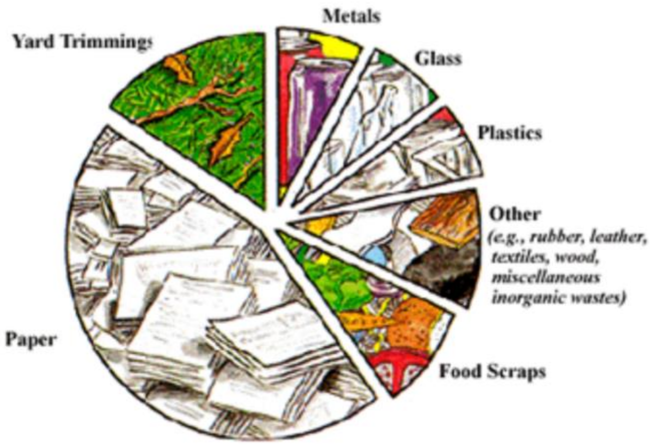
The questionnaire should take no longer than 15 minutes to complete. You don't necessarily need to know about the topic to complete this questionnaire. There is no right or wrong answer. You can just follow your heart. Thank you for your participation.

ENVIRONMENT ISSUES IN CHINA

According to China Statistical Yearbook (2001-2017), for 297 cities and 399 counties in China, the total MSW amount increased from 32 million tonnes in 1980 to 217 million tonnes in 2017. Development of China has brought about an unprecedented increase in the amount of municipal solid waste (MSW). The rapid growth of MSW brings heavy burdens to sustainable development, as China faces environmental pollution.

WHAT IS MUNICIPAL SOLID WASTE?

Municipal solid waste (MSW) is a waste type consisting of everyday items that are used then threw away by domestic householders.



WHAT PROBLEMS CAN MUNICIPAL SOLID WASTES CAUSE?

Since, in China, the traditional ways are to incinerate or landfill solid waste, leading to serious environmental problems. Landfills may cause many serious environment issues. Landfills can cause contamination of groundwater or aquifers and contamination of soil.

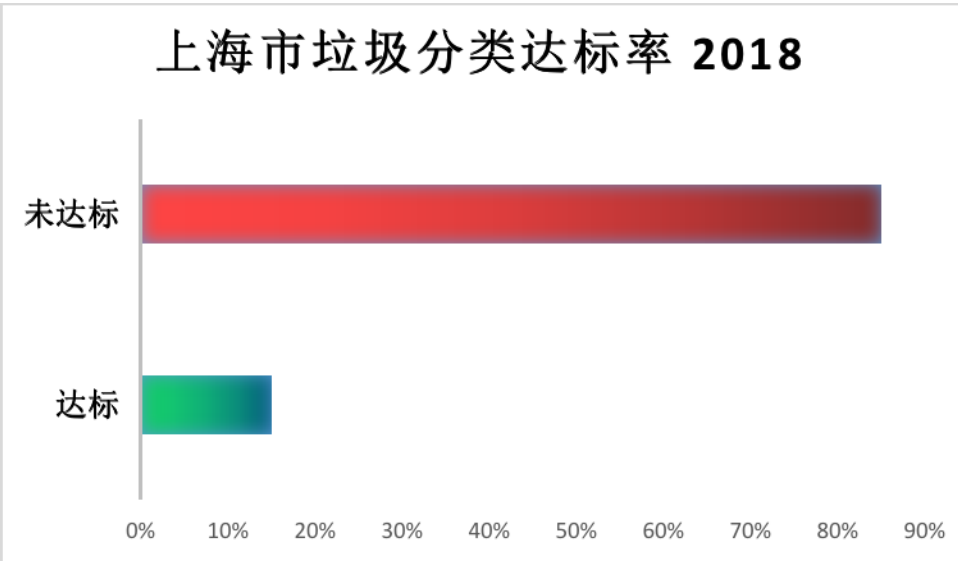
In addition, Incineration will cause local environment pollution by producing a number of outputs (the ash and flue gas). Flue gases might contain air pollutants such as dioxins, furans, sulphur dioxide, heavy metals and hydrochloric acid. In China, incineration is one of the main reason for foggy and haze weather in the most northern cities such as (Beijing, Shijiazhuang, Shanghai).

TREATMENT

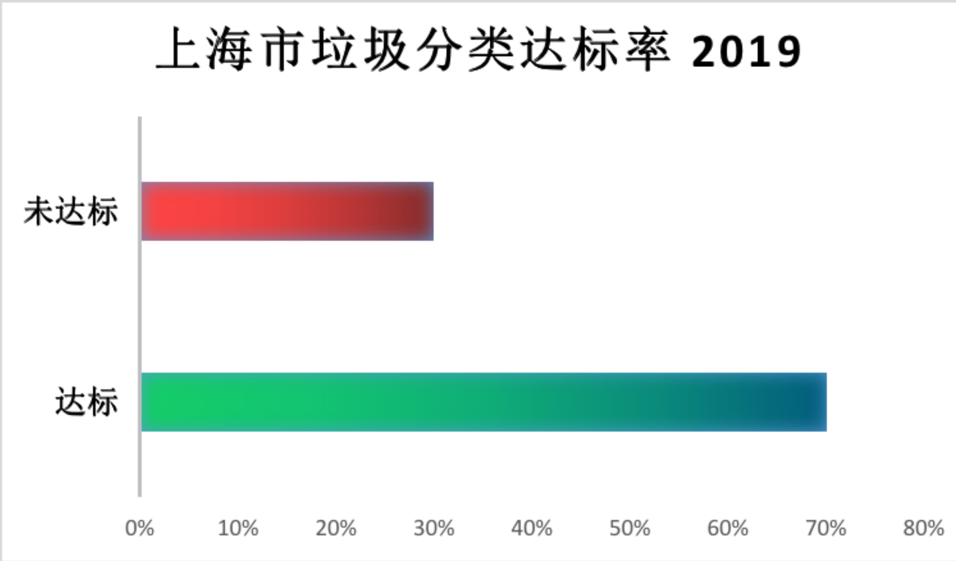
Therefore, to promote sustainable development, the Chinese government pledged that the country should achieve a utilization rate of 30% in household MSW recycling by 2021, and 46 cities should pilot the mandatory classification of household waste (China Environment News Paper, 2019). Better management of MSW might be an effective way to deal with the waste dilemma. Shanghai was selected as one of the first pilot cities for MSW waste sorting. As the Shanghai Municipal Solid Waste management regulation was published on July 2019,

Q2 Please answer the following questions

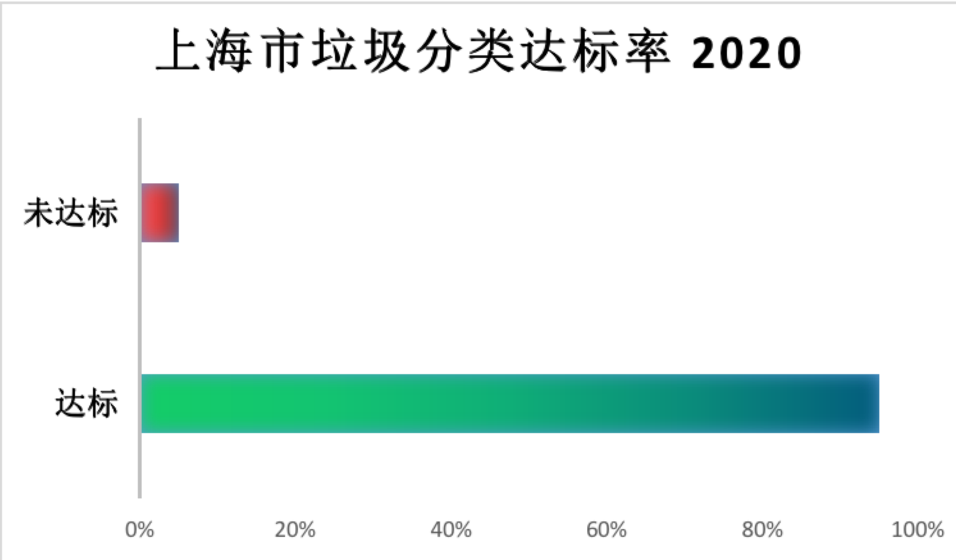
TREATMENT 1



TREATMENT 2



TREATMENT 3



TREATMENT 4

NO INFORMATION

PART A

1. Environment awareness and Knowledge

We would first like to know your environment awareness and knowledge.

3. How much of what you just read ABOVE did you know beforehand?

	Part 1 ENVIRONMENT ISSUES IN CHINA; Part 2 WHAT PROBLEMS CAN MUNICIPAL SOLID WASTES CAUSE?; Part 3 TREATMENT
1	I never heard before.
2	I knew a general idea of environmental issues or problems or treatments in China.
3	I knew most of issues, problems and treatments, also I knew some numbers and details.
4	I knew everything
5	I knew much more

4. Do you have involvement in following green activities?

Using recycled paper bag Driving electric vehicle or riding bicycle E-waste recycling, old for new services Donating secondhand clothes	
None of it	1
One of these behaviours	2
Two of these behaviours	3
Three of these behaviours	4
Four of these behaviours	5
More than that	6

5. Have you heard of global warming, plastic pollution, PM 2.5, soil contamination previously?

None of it	1
One of these issues	2
Two of these issues	3
Three of these issues	4
Four of these issues	5
More than that	6

6. Which of a following photo best describes the collection point sanitation of your current living area?

Option 1

Option 2

Option 3

Option 4

Option 5

2. Recycling Behaviour

We would like to know your past and current recycling behaviour.

7. Please indicate your current numbers of sorting category.

No sorting (mixed disposal)	1
(2 categories)	2
(4 categories)	3
(more than 4 categories)	4
	5

8. selling recyclable wastes after classification (separate recyclables and sell them to recyclable material collectors, and dispose of the rest into trash cans)

(A) , YES

(B) , NO

9. How long have you kept following the disposal way you selected above?

(A). Within or one year

(B). Two or three years

(C). Four or five years

(D). More than five years

10. Do you have high adherence level to separation and disposable of recyclable materials?

(1 = Strongly Adherence, 2 = Adherence 3 = Moderately, 4 = NON-Adherence, and 5 = Strongly NON-Adherence)

3. Theory of planed behaviour questions

Personal attitude and belief toward recycling

11. Please give your response to the following statements. (1 = Strongly Agree, 2 = Agree 3 = Moderately, 4 = Disagree, and 5 = Strongly Disagree)

A	Do you agree that people should care most about is life and survival issues, not environmental issues such as improving solid waste disposal?	1	2	3	4	5
B	Do you agree that people need to participate in waste classification in order to save resources and protect environment for human being and future generations?	1	2	3	4	5
C	Do you agree that recycling is waste of your time. If You are working full time and do not have the time to recycle?	1	2	3	4	5

Subjective norm

12. To what extent do you agree or disagree with the following statements (1 = Strongly Agree, 2 = Agree 3 = Moderately, 4 = Disagree, and 5 = Strongly Disagree)

A	Do you agree that your family and friends expect you to engage in recycling behaviours?	1	2	3	4	5
B	Do you agree that most people would approve of your recycling behaviours?	1	2	3	4	5
C	Do you agree that the local government have responsibility to waste classification and recycling and have nothing to do with residents?	1	2	3	4	5

Perceived behavioral control

13. Please indicate your answer to the following statements. (1 = Strongly Agree, 2 = Agree 3 = Moderately, 4 = Disagree, and 5 = Strongly Disagree)

A	Do you agree that it is very inconvenient when you classify your house wastes?	1	2	3	4	5
B	Do you agree that it is a piece of cake to remember how to sort waste?	1	2	3	4	5
C	Do you agree that there are plenty of opportunities to recycle in your normal life?	1	2	3	4	5

PART 2

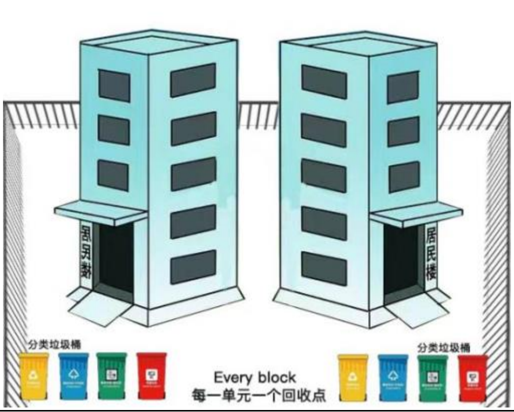
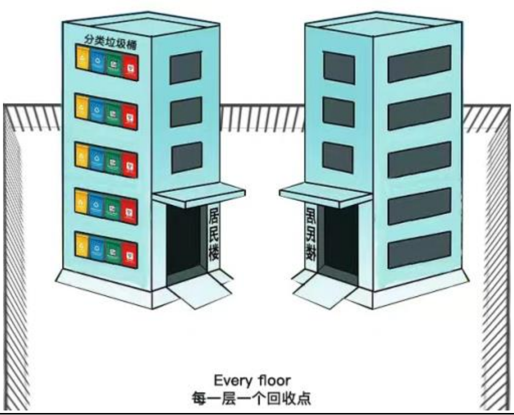
CHOICE EXPERIMENT

In our choice experiment, we ask participants which MSW classification, collection plan and ending disposal plan they will select from a range of possibilities. The status of these four attributes can be described as follows:

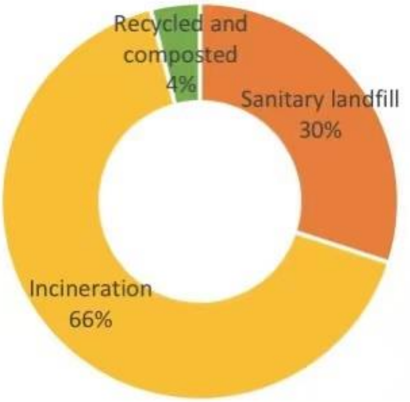
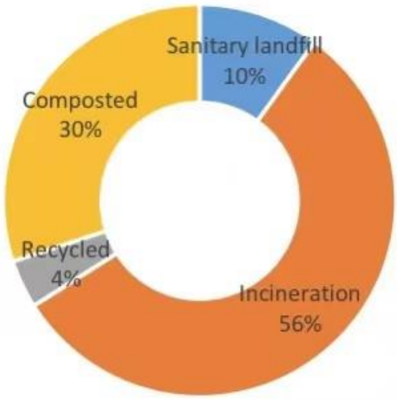
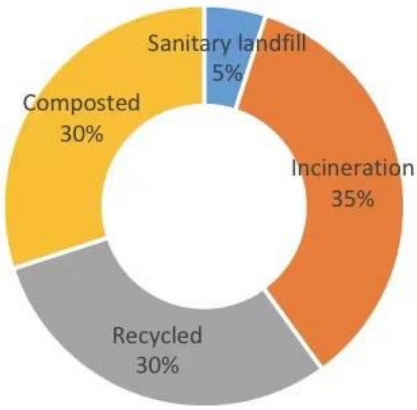
First attribute: Behaviour taken

Method of sorting in household	Description of attribute level
	**You may decide to take this plan to sort wastes into 2 categories**
	**You can also decide to take this better plan to sort wastes into 4 categories**
	**You can also decide to take this best plan to sort wastes into 7 categories**
	**You may decide to take this plan to not sort wastes**

Second attribute: Waste collection plan

Waste collection plan	Description of attribute level
	You may decide to take this plan to put one waste collection point in every community and collect every day
	You can also decide to take this better plan build one waste collection point in every block of the building you live and collect every day
	You can also decide to take this best plan to build one waste collection point in each floor of the building you live and collect every day

Third attribute: Ending-disposal plan

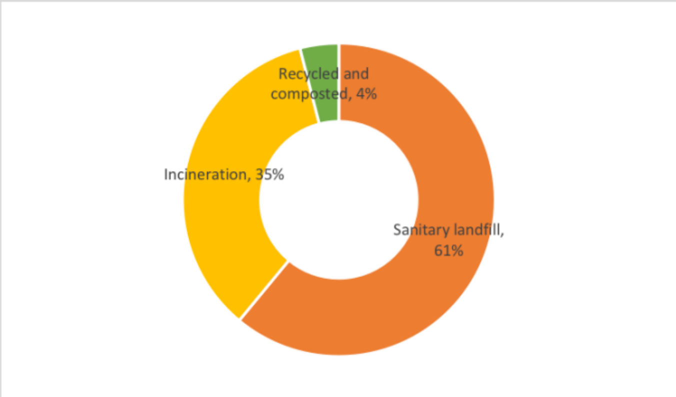
Ending-disposal plan	Description of attribute level
	**You may decide to take this plan to build more incineration power plants as an alternative to landfills. (In 2032, 60% of the total MSW will be disposed by incineration)**
	**You can also decide to take this better plan by developing composting to divert organic waste from landfills and incinerators. (in 2032, 30% of the total MSW will be disposed by composting)**
	**You can also decide to take this best plan to build more recycling plants to divert metal, paper, glass, plastic waste from landfills and incinerators**

Information of Third attribute

Current situation

At current stage, landfilling is still the main method for the disposal of MSW in China (Figure 1). In 2020, almost 35% of the total MSW was disposed of by incineration, with 61% sent to landfill and only 4.4% recycled (National Bureau of Statistics of China, 2021). .

Current situation: Disposal method for MSW in 2020 (Figure 4)



The end of treatment for MSW leads to a huge waste of potential materials, increases the consumption of resources, and brings negative impacts on the environment. If MSW is well managed, it results in a large resource pool for electricity production and steam for heating.

We designed three alternative better ending-disposal plans.

The ending-disposal plan A (waste-to-energy)

Since 1995, China has introduced incineration plants as an alternative to landfills. The first garbage power plant was built in Shenzhen during the "8th Five-Year Plan". China's incinerators follow the model of "waste-to-energy (WTE)", in which the captured heat is converted to electricity for generating power supply. However, the operation of incineration plants has encountered limitations due to the high emissions of dioxin and the difficulty of disposing of incineration residue, which impact the environment and public health.

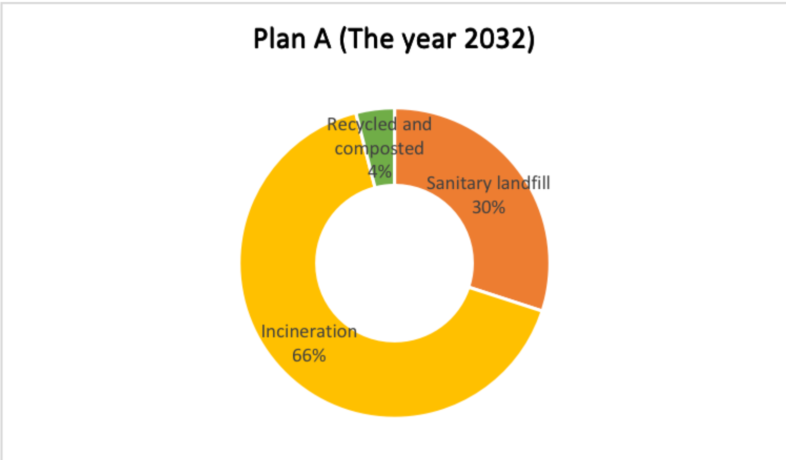
To deal with the problem, this plan will upgrade current incineration power plants and build more plants in China. The plant does two things to eliminate the gas. First, it raises the temperature of the furnace to 800C, the critical point when dioxin automatically decomposes. Second, it uses active carbons to assimilate dioxin in the fumes.

As compared with that of developed countries (e.g., over 80% in Japan), it is evident that incineration for MSW treatment in China needs to keep developing.

The Shanghai Jiangqiao MSW incineration plant (Picture 1),

This is one of the largest incineration plants in China treating approximately 10% of municipal waste generated in Shanghai. The facility includes three incinerators each with a capacity of 500 metric tons per day and two 12.5 MW turbine generators. The technology and main equipment are from Europe. The pollution level of the exhaust gas emitted by the plant is no higher than required environmental levels in the European Union (EU).

In plan A, incineration will be the main method for the disposal of MSW (Figure 2). in 2032, 60% of the total MSW will be disposed by incineration.



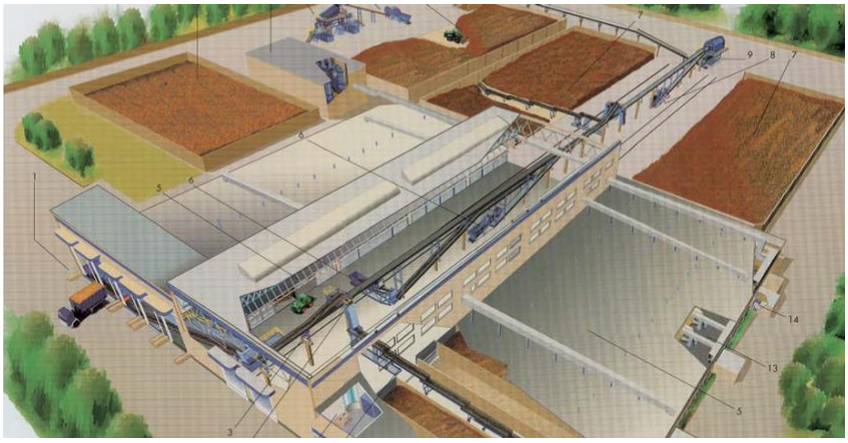
The ending-disposal plan B (waste-to-energy)

Centralized composting has been adopted in many regions worldwide to divert organic waste (e.g., green waste, kitchen waste, etc.) from landfills and incinerators.

Composting is a method of waste recycling based on the biological degradation of organic matter under aerobic conditions, producing stabilized and sanitized compost products. Diverting municipal solid waste (MSW) organic material from landfills by composting has many environmental benefits, such as reducing greenhouse gas emissions (USEPA, 2015), decreasing leachate quantities once discarded in landfills (Adhikari et al., 2009), and increasing the calorific value of feedstock to generate more energy.

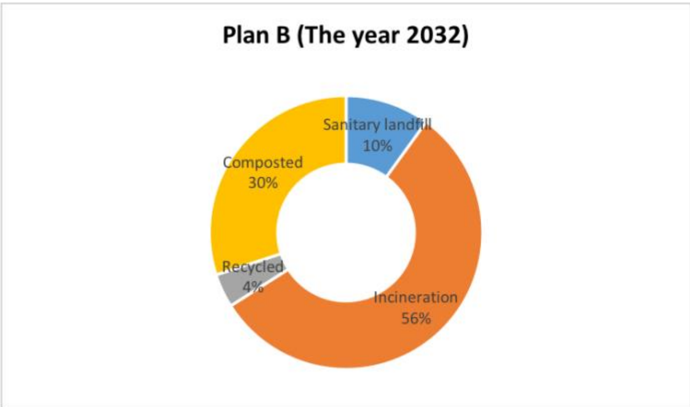
As mentioned above, less than 4% was composted, the poor quality of compost derived from MSW in China may partially be ascribed to inefficient separation/sorting of the mixed waste.

Nangong Garbage Composting Plant (Picture 2)



Nangong Garbage Composting Plant, which opened 11 years ago in 1998 as Beijing's first garbage composting plant, will be reconstructed and expanded to enable its daily garbage disposal capacity to reach 1,000 tons.
Nangong Composting Plant saves 13 mu of land used for landfill every year and has saved a total of 140 mu of land over the 11 years since it opened.

In plan B, composting will be adopted to divert organic waste (e.g., green waste, kitchen waste, etc.) from landfills and incinerators (Figure 3). in 2032, 30% of the total MSW will be disposed by composting.



The ending-disposal plan C (Recycle)

Recycling is the process of collecting waste materials and processing them into new products. Turning the trashed wastes into useful products is beneficial for both the community and the environment. This plan will be not only beneficial for the environment but also can conserve natural resources. As shown above, China MSW recycling is very low.

For example, the recovery rate of glass packaging containers in China is indeed too low. Some scholars estimated that the recycling rate of waste glass in China was only 13%, far below the world average (50%).

Glass recycling flow chart (Picture 3)

The glass bottle with more energy consumption is recycled, this recycling method can save 800 kg of quartz sand, 130 kg of caustic soda, 130 kg of limestone and 140 litres of heavy oil for every 1 ton of glass packaging.

For example

In 2020, the recycling rate of plastic products in China dropped down to 17.6 percent. Despite the rising environmental concerns in China, the recycling rate of plastic products remained relatively low.

Plastic recycling flow chart (Picture 3)

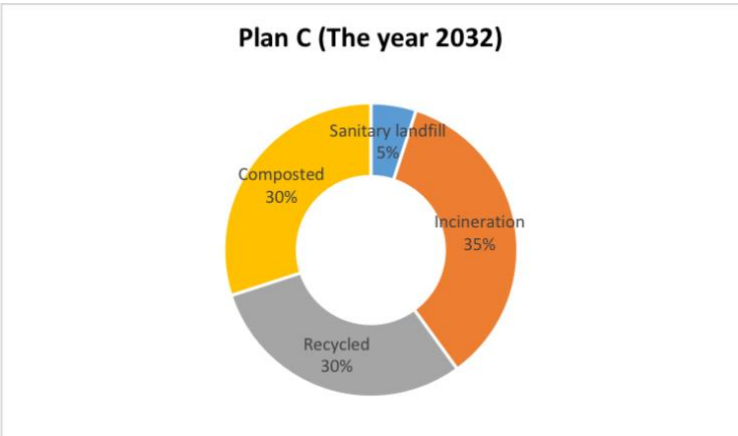
One ton of recycled plastic saves 5,774 Kwh of energy, 16.3 barrels of oil, 98 million BTU's of energy, and 30 cubic yards of landfill space.

For example

The recycling of paper is the process by which waste paper is turned into new paper products. It has a number of important benefits: It saves waste paper from occupying homes of people and producing methane as it breaks down.

One ton (2000 pounds) of recycled paper can save 17 trees, 380 gallons of oil, three cubic yards of landfill space, 4000 kilowatts of energy, and 7000 gallons of water. This represents a 64% energy savings, a 58% water savings, and 60 pounds less of air pollution!

In plan C, recycling will be adopted to divert metal, paper, glass, plastic waste from landfills and incinerators (Figure 4). in 2032, 30% of the total MSW will be disposed by recycling.



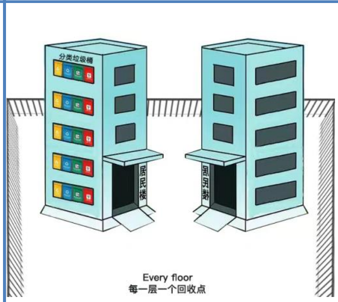
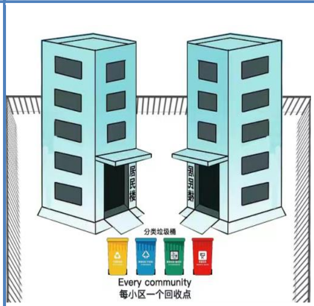
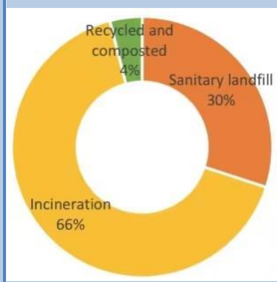
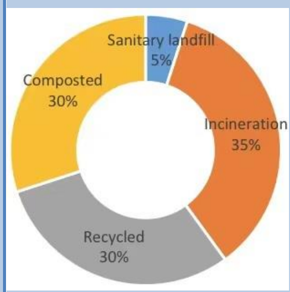
Fourth attribute: Additional cost for month

Additional cost for month	Description of attribute level
20YUAN	You can pay 20 YUAN per month
40YUAN	You can pay 40 YUAN per month
60YUAN	You can pay 60 YUAN per month
80YUAN	You can pay 80 YUAN per month
100YUAN	You can pay 100 YUAN per month
200YUAN	You can pay 200 YUAN per month
	Note: Any changes from your current situation would need to be funded by taxpayers.

On the following pages you will be presented with 4 choice cards like the one below:

- **Choose the option you most prefer on each choice card.**
- **There are no wrong or right answers. We are just interested in your opinion.**
- **Option 1, 2, 3 are two alternative future management options and will incur additional costs to you, each year, for 3 years.**
- **Option 4 is the same on each choice card and it never involves a payment. It describes the situation that could result in the future when there is no further change from current management.**

<table>
<tr><th>Situation1.</th><th>Option1</th><th>Option2</th><th rowspan="5">Option 3

Current method of garbage collection and disposal</th></tr>
<tr><td>Method of sorting in citizens</td><td>
</td><td>
</td></tr>
<tr><td>Waste collection plan</td><td>
</td><td>
</td></tr>
<tr><td>Ending-disposal plan</td><td>
</td><td>
</td></tr>
<tr><td>Additional Cost for month (YUAN)</td><td>40</td><td>200</td></tr>
<tr><td>Your Choice</td><td>£</td><td>£</td><td>£</td></tr>
</table>

15. Currently, how many collection points in your living area or community?

Every floor of the building you live	1
Every block of the building you live	2
Every community	3

Reasons for choices (Question 14, 15)

16. Which of the management aspects were important when you made your choice among the alternatives on the choice cards?

A. Method of sorting in citizens
B. How many classification bins in your living area
C. End disposal plan
D. Cost for month

17. To what degree do you typically make decision spend money or approach your activities with each of the following intentions. (1 = Strongly Agree, 2 = Agree 3 = Moderately, 4 = Disagree, and 5 = Strongly Disagree)

A	Seeking pleasure?	1	2	3	4	5
B	Seeking to do what you believe in?	1	2	3	4	5
C	Seeking to pursue excellence or a personal ideal?	1	2	3	4	5
D	Seeking to contribute to others in your local area or the surrounding world?	1	2	3	4	5
E	Seeking to have lots of money and nice possessions?	1	2	3	4	5
F	Seeking to have high status and prestige?	1	2	3	4	5
G	Seeking enjoyment?	1	2	3	4	5
H	Seeking to be popular and have an attractive social image?	1	2	3	4	5
I	Seeking to benefit future generations	1	2	3	4	5
J	Seeking to prevent harm to the local environment and wildlife	1	2	3	4	5
K	Seeking to benefit my household	1	2	3	4	5
L	Other (please state below)					

PART 3

Well-being

We would like to know your well-beings .

Please imagine a ladder with steps numbered from zero at the bottom to 10 at the top.

The top of the ladder represents the best possible life for you and the bottom of the ladder represents the worst possible life for you.

18. On which step of the ladder would you say you personally feel you stand at this time? (ladder-present)

0 (Worst possible life) / 1 / 2 / 3 / 4 / 5 / 6 / 7 / 8 / 9 / 10 (Best possible life)

19.On which step do you think you will stand about five years from now? (ladder-future)

0 (Worst possible life) / 1 / 2 / 3 / 4 / 5 / 6 / 7 / 8 / 9 / 10 (Best possible life)

20.To what extent are you satisfied with environment condition in your living area? (Strongly disagree 1 2 3 4 5 6 7 8 9 10 Strongly agree)

21.To what extent do you feel optimistic about local environment condition in the future? (Strongly disagree 1 2 3 4 5 6 7 8 9 10 Strongly agree)

22.All hings considered, *how happy did you feel at this moment?* 0 (extremely unhappy) / 1 / 2 / 3 / 4 / 5 / 6 / 7 / 8 / 9 / 10 (extremely happy).

23. Overall, to what extent do you feel that your life is centered around a set of core beliefs that give meaning to your life (Strongly disagree 1 2 3 4 5 6 7 8 9 10 Strongly agree)

24. *Overall, to what extent do you feel that your environment protection behaviour is something worth investing a great deal of effort in?* (Strongly disagree 1 2 3 4 5 6 7 8 9 10 Strongly agree)

25.To what extent do you feel that you get intensely involved in many of the thing you do every day? (Strongly disagree 1 2 3 4 5 6 7 8 9 10 Strongly agree)

26.How often did you experience the following feelings when you are sorting your waste properly during A LOT OF THE DAY ? How about Enjoyment?

(Never enjoy) / 1 / 2 / 3 / 4 / 5 / 6 / 7 / 8 / 9 / 10 (always enjoy)

27.To what extent would you say you did what you want to do in your life, such as reading, study, go gym, recycling etc)
(I did nothing 1 2 3 4 5 6 7 8 9 10 I did everything I want to do)

PART 4

The basic information of respondents

We will now ask you a few questions about yourself.

Q.1 Gender: male o, Female o , Other o, Prefer not to say o

Q.2 What age are you? _________ age

Q.3 Which of the below best describes your education level?

Junior high school and below	1
Secondary	2
Professional qualification of degree level	3
Undergraduate, University specialties	4
Graduate and above	5

Q.4 Please give answers that how many family members are there in your family, including you:

AGE	NO. OF PEOPLE
a) Below 10	
b) Between 10-18	
c) Between 18-60	
d) Over 60	

Q.5 Which of the following best describes your current occupation (multiple choice)?

Full-time job	1
Part-time job	2
Unemployed	3
Retired	4
Student	5
Home maker	6
Other	7

Q.6 Which of the following best describes your total <u>family monthly income</u> before deduction of tax.

A) Less than 5000 YUAN	1
B) 5000 – 10000 YUAN	2
C) 10000 –15000 YUAN	3
D) 15000-20000 YUAN	4
E) 20000-40000 YUAN	5
F) 40000 YUAN AND ABOVE	6
G) Refused	7

Q.7 Which of the following best describes your length of residence time where you currently live?

Within one year	1
One-two years	2
Two-five years	3
Five-ten years	4
Ten years and above	5

Q.8 Which of the following city is your habitation area?

(1) Zhengzhou,
(2) Shanghai,
(3) Shijiazhuang,

Other (please state)

Q.9 Please add any other comments you might have about this interview.

Thank you for your participation.

Chapter 4

Investigating the Effect of Social Norm Nudges on Willingness to Pay for Recycling in China

4.1 Abstract

With China's rapid urbanisation, the country has been facing a growing municipal solid waste (MSW) disposal problem. In response, various regions have introduced different waste classification policies and targets. The question arises: have these policies been effective? Moreover, increasing attention is being paid to nudges as a supplement to local environmental policy. However, to serve as an effective policy instrument, nudges must produce consistent and foreseeable effects on specific behaviours. This study utilises the choice experiment approach to collect data at the individual level from residents of three Chinese cities, comparing Zhengzhou and Shijiazhuang, which are currently under advocative policies, with Shanghai, where a mandatory policy is in place (detailed in introduction). Two main research objectives are addressed: first, RO1 investigates whether Shanghai's mandatory recycling policy results in higher willingness-to-pay (WTP) for recycling compared to the voluntary policies in Zhengzhou and Shijiazhuang (H1); second, RO2 explores how social norm nudges affect households' WTP, specifically assessing whether stronger social norms increase WTP (H2), if the policy context (mandatory vs. voluntary) and geographical proximity influence their effectiveness (H3), and whether individuals' past recycling behaviour moderates responses to social norm nudges (H4). The empirical setting of the study involves examining choices related to household waste contracts and recycling actions. It specifically evaluates the households willingness to pay (WTP) for waste collection contracts that demand more recycling effort by the household. To assess the impact of a specific nudge – the communication of a descriptive social norm – a randomized experiment was implemented. The experiment varies two dimensions of the social norm: the varying proportion of city residents participating in recycling and the geographic closeness. For the econometric analysis, we applied a mixed logit (ML) model,

incorporating interaction terms between varying levels of waste sorting policies and social norm nudges. Additionally, respondents' self-reported past recycling behaviours were analysed to determine whether prior recycling habits influence the effectiveness of social norm nudges. Results indicate that Shanghai's mandatory recycling policy significantly boosts residents' WTP by increasing compliance costs, enhancing moral responsibility, building habits, and improving recycling facilities, supporting H1. For RO2, moderate social norm nudges effectively enhance WTP, but excessive nudging reduces motivation (H2). Neither geographical proximity nor policy type strengthens the effect of social norms (H3). Finally, past recycling experience matters: residents less involved in recycling initially respond positively to moderate social norms but negatively to overly strong cues (H4).

4.2 Introduction

Background and motivations

Developing a sustainable waste management framework remains a significant challenge for many governments, especially in rapidly urbanizing developing countries with limited investment funds (Zhang and Wang, 2020; Xu et al., 2018; Suocheng et al., 2001). As the world's largest developing nation, China is experiencing rapid urbanization and industrialization. According to National Bureau of Statistics of China (2023), China's permanent population urbanization rate has continuously risen,[18] exceeding 66.16% by the end of 2023, more than tripling since 1980. The increase in urban population has led to an unprecedented rise in municipal waste generation (Zhang et al., 2010; Li et al., 2016; Liu, 2008). The China Statistical Yearbook (2023) reveals a sharp rise in municipal solid waste (MSW) production, with the total volume in 297 cities and 399 counties surging from 32 million tonnes in 1980 to 244 million tonnes in 2022. Despite the high environmental cost of landfills in terms of water, soil pollution, and greenhouse gas emissions, they remain the primary method for waste disposal (Zhang et al., 2016; Briguglio, 2017).

An effective strategy for reducing landfill waste is to improve the separation at the source into recyclable or compostable materials from non-recyclable/non-compostable material, where sorting at the household level proves to be more economically efficient than centralized approaches. This approach is especially beneficial for specific types of waste that become hard to recycle when combined (Czajkowski et al., 2019). Broad public participation is deemed crucial in addressing the solid waste crisis (Briguglio, 2017; Zhang et al., 2020; Varotto and Spagnolli, 2017). In 2000, Shanghai led as one of the first among eight cities in China to trial separate waste collection (Tai et al., 2011). By 2003, the government had categorized municipal solid waste (MSW) into recyclables, hazardous, and other waste, and in 2007, the Ministry of Construction released the "Measures for the Management of MSW," explicitly requiring that waste in areas subject to classification policies be placed in

[18] Permanent immigrants are individuals granted official authorization to update their registration from their origin to their new location. In contrast, temporary migrants haven't altered their registration status, despite residing in a different place for durations ranging from a few days to several years or more (Goldstein, 1990).

designated containers or at collection points according to sorting criteria. Despite these efforts, sorting rates in key cities remained below 15% up to 2008. As discussed in Chapter 1, in 2017, China initiated a mandatory municipal solid waste (MSW) classification policy, targeting a 30% household recycling rate by 2021 across 46 cities. Despite 17 years of primarily advocatory MSW policies, practical sorting outcomes remained limited. In July 2019, Shanghai implemented the Municipal Solid Waste Management Regulation, becoming a pilot city for enforced waste sorting. By 2021, over 95% of Shanghai residents participated in waste sorting, marking significant success. However, mandatory policies require substantial regulatory resources and administrative efforts, potentially leading to public resistance. Currently, cities like Zhengzhou and Shijiazhuang continue with advocatory policies, lacking effective supervision and enforcement mechanisms. China's waste sorting policies fall into two categories: advocative and mandatory. Under advocative policies, such as those in Zhengzhou and Shijiazhuang, residents receive guidance on proper waste categorisation, but enforcement relies on social pressure rather than financial penalties. In contrast, Shanghai has adopted a stricter mandatory approach, with active monitoring and fines for non-compliance, a system set to continue until 2025. The key distinction between these policies lies in the degree of oversight and the application of economic penalties, further explored in Section 4.3. This raises the question of which approach is more effective in encouraging residents to recycle. Additionally, environmental policy research suggests that one measure can shape public attitudes towards related initiatives. Given that waste management involves sorting, collection, and disposal, it is important to assess whether China's classification policy influences public commitment to the earlier and later stages of recycling.

In fact, rather than depending on command-and-control policy mechanisms, which often face substantial critique, numerous alternative approaches exist that can effectively encourage individuals to engage in recycling activities. A widely recognized strategy involves the use of financial incentives, based on incentive theory, which examines the influence of relative pricing on behaviour (Lu and Wang, 2022; Abbott et al., 2013). These researches commonly recognise that pricing incentives, like 'pay as you throw' schemes, and alterations in waste collection systems affecting recycling efforts, significantly influence people’s recycling behaviour, a concept supported by various studies (Fehr and Falk, 2002; Callan and Thomas, 1997; Jenkins, 1993; Hong and Adams, 1999; Hong, 1999; Sidique et al., 2010; Viscusi et al., 2011). However, apart from the high costs of implementation and supervision, these financial incentives can sometimes lead to unintended consequences, negatively impacting the adoption of desired behaviours. The “over justification effect” theory (Deci et al., 1999) is often cited by researchers to describe this paradox, emphasizing how external rewards may undermine intrinsic motivations like personal norms, known as the “crowding-out effect” (Ariely et al., 2009; Gneezy and Rustichini, 2000; Zhang and Wang, 2020; Varotto and Spagnolli, 2017).

Economic incentives are often contrasted with “nudging” strategies. Leveraging insights from behavioural economics, the concept of “green nudges,” introduced by Thaler and Sunstein (2008), is increasingly being integrated into environmental policies to subtly encourage individuals to engage in more eco-friendly behaviours (Alpizar and Gsottbauer, 2015; Schubert, 2017; Carlsson et al., 2019). A nudge can be defined as an element of choice architecture that predictably modifies people's behaviour without restricting any choices or significantly altering their economic incentives (Sugden, 2009; Raihani, 2013). Policymakers are integrating the psycho-social aspects of preferences, including intrinsic motivations such as altruistic preferences and extrinsic motivations like social norms into the design of environmental policies, as identified by Chetty (2015), Nyborg et al. (2016) and others like Frey (2013) and Van den Bergh (2008). Lately, waste management studies have shifted focus to investigating behavioural policy interventions like nudges, recognized for their political acceptability and lower costs of implementation (Swim et al., 2011; Kirakozian, 2016; Chakravarty and Mishra, 2019; Hanley and Czajkowski, 2019). Additionally, it's highlighted that nudges could be integrated with economic incentives to enhance their impact on promoting pro-environmental behaviours (Sudarshan, 2017; Fanghella et al., 2021; Drews et al., 2020).

A key example of a nudge involves sharing social norms—what the majority of people do and/or approve of (Farrow et al., 2017). Numerous experimental studies, including those by Fischbacher et al. (2001), Krupka and Weber (2009), and Croson et al. (2005), have consistently found that individuals tend to increase their contributions to public goods when they observe others doing the same. Croson and Treich (2014) emphasize the significance of socio-psychological factors in influencing behaviours, particularly in the context of environmental public goods. They highlight that the way choices are framed can be crucially important. This framing often includes people's perceptions and beliefs about the behaviours of others, essentially concerning social norms. Accordingly, social norm nudges foster desired pro-environmental behaviours by highlighting their frequency and acceptance among the population (Constantino et al., 2022). However, Given the varied evidence on the effectiveness of social norm nudges in promoting pro-environmental behaviours, it's crucial to explore the factors influencing the effectiveness of these nudges and their adaptability to different decision-making contexts for recycling policy development (Czajkowski et al., 2019). Moreover, assessing the compatibility of social norm nudges with existing local waste management policy is equally important.

Objectives

So far, employing nudges for MSW management has been infrequent (Carlsson et al., 2019), and the bulk of studies investigating causal relationships have mainly focused on Western societies. Therefore, it is good opportunity to choose China as our study areas. We conducted a stated preference (SP) study comparing Zhengzhou and Shijiazhuang, which are currently under advocative policies, with Shanghai, where mandatory waste sorting is enforced. This study aims to explore the relationships between past recycling behaviours, social norm nudges, local mandatory or advocative waste sorting policies, and the willingness to financially support recycling initiatives in China.

Two main research objectives guide the analysis:

RO1 tests whether households under mandatory recycling policies (Shanghai) exhibit higher WTP for recycling compared to those under voluntary policies (Zhengzhou and Shijiazhuang) (Hypothesis 1).

RO2 examines how social norm nudges affect households' recycling-related WTP, specifically investigating whether stronger social norms increase WTP (H2), if their

effectiveness differs under mandatory versus voluntary policies (H3), and whether individuals' past recycling experience moderates responses to these nudges (H4).
To achieve these objectives, we employed a randomised experimental design where participants received varying levels of information about others' recycling behaviours (social norms). Participants' stated WTP for improved recycling standards served as a measure of their recycling intentions. Econometric analysis utilised a Mixed Logit (ML) model, incorporating interactions between policy types and social norm nudges. Additionally, self-reported previous recycling behaviours were analysed to assess their impact on the effectiveness of social norm interventions.

Our research makes several contributions. To our knowledge, this research is pioneering in China for using the stated preference method and WTP as indicators of individuals' intentions to compare the impact of mandatory waste sorting policies on these intentions against the effects of advocative policies. Furthermore, this study is the first to investigate potential spillover effects of such policies on intentions concerning waste collection and disposal within the recycling process. Moreover, this is first study in enhancing the understanding of social norm nudges and pro-environmental behaviours by exploring how the WTP for increased recycling in households is influenced by the type of social norm nudge implemented within the context of Chinese cities, and assessing the compatibility of this nudge with existing local waste sorting policies. If governments aim to increase the use of social norm-based nudges in conjunction with pricing strategies and infrastructure enhancements to attain recycling targets (or any environmental policy objectives), the implementation of our experimental insights becomes important.

In subsequent sections, the paper first provides a summary of existing literature on the impact of mandatory policy, social norms and social norm nudges on pro-environmental behaviours in Section 2. Section 3 details the design of the empirical study and the econometric methods employed. In Section 4, results from a mixed logit model. Finally, Section 5 offers a discussion and concludes the findings.

Behavioural mechanisms and hypotheses

Behavioural mechanisms: (mandatory policy vs advocated policy)

From the discussion in Chapter 2.2 and 2,3, we identify four potential mechanisms through which Shanghai's mandatory policy influences household waste sorting: deterrence, the crowding-out effect, modification of social norms, and formation of better habits. For our study:

Deterrence

In Shanghai (area with mandatory policies), the threat of financial penalties ranging from 50 to 200 Yuan, equivalent to fines for traffic violations, has heightened the cost of non-compliance with waste separation mandates. The city processed 19,446 waste sorting violations in the policy's first year, with over 700,000 volunteers monitoring compliance. This widespread supervision and the potential for immediate punishment or warnings under the watchful eyes of volunteers during designated disposal times have significantly increased the likelihood of enforcement, further details of which are discussed in Section 3. This setup also ensures that residents' concerns over their reputation encourage adherence to sorting regulations, making evasion of these mandates practically impossible (Vollaard and van Soest, 2024).

Crowding-out effect

Gneezy et al. (2011) suggest that extrinsic incentives like fines and warnings, as previously mentioned, can convert behaviours motivated internally into transactional exchanges, potentially diminishing intrinsic motivation for waste sorting.

Modification of social norms

Shanghai's mandatory waste sorting policy potentially reshaped social norms around waste separation. Initially, the policy received extensive promotion on social media and through slogans across the city, alongside guidelines and disposal instructions placed near community bins. The official endorsement of injunctive norms for household waste sorting increases the moral cost of non-compliance, driven by the negative consequences of social disapproval. Lane et al. (2023) highlight that emphasizing the illegality of incorrect waste separation and the possibility of fines further reinforced these standards, transforming what might have been seen as voluntary into a compulsory practice.

Formation of better habit

Finally, while the crackdown in Shanghai is scheduled to continue until 2025, our choice experiments were conducted during the crackdown period in 2023. Since the policy has been in place for two and a half years from 2019 to the point of our experiment, we believe it has been sufficient for some individuals to form new habits. These new habits reduce the effort required to engage in the behaviour.

Upgrade of waste sorting tools

In addition to upgrading and increasing the number of waste sorting bins in streets and communities, the purchase of household waste sorting receptacles has also improved. This enhancement in waste separation tools for households and public areas keeps the cost of waste separation low and makes the process more convenient, encouraging waste separation practices.

Therefore, in Shanghai, responses to the waste sorting policy might include deterrence, a crowding-out effect, social norm modification, formation of new habits, and upgrading of waste sorting tools. In contrast, in Zhengzhou and Shijiazhuang, which implement advocative policies, the responses might include social norm modification and upgrading of waste sorting tools, since the only difference between the advocative and mandatory policies lies in the level of supervision and the enforcement of economic penalties.

Thus, drawing from the reviewed literature and the behavioural mechanisms discussed, this study proposes the following hypotheses corresponding to our two research objectives:

RO1: tests whether households under mandatory recycling policies (Shanghai) exhibit higher WTP for recycling compared to those under voluntary policies (Zhengzhou and Shijiazhuang).

H1: A mandatory policy (Shanghai) has a greater impact on individuals' WTP for higher levels of waste sorting compared to an advocative policy (Zhengzhou and Shijiazhuang).

Behavioural mechanisms: (Descriptive social norms)

To simply test whether the implementation of a new nudge, specifically a descriptive social norm, can increase the chances of achieving the existing policy objectives. We vary two dimensions of the social norm: its absolute level and the geographical proximity. Based on the literature reviewed above, we identify three potential mechanisms influencing short-term effects of a social norm-based nudge on waste separation:

Size of the social norm

Household utility is likely influenced by social norms, as these norms dictate the level of respect or sanctions we receive from that of a relevant interest group, depending on how well they adhere to them (Czajkowski et al., 2017; Hanley and Czajkowski, 2019). The communication of the absolute level of social norms shapes beliefs about average peer waste sorting levels, influencing waste sorting decisions. If a significant gap exists between an individual's behaviour and the norm, social approval may motivate improvements. However, if behaviour meets or exceeds norms, motivation may wane. Thus, the effect of a nudge depends on the absolute size of the norm, determining the gap between current behaviour and the norm. If the perceived benefits of social approval outweigh the cost of adjusting waste sorting behaviour, individuals are likely to align with the norm. Given the discussions above, we propose:

RO2: examines how social norm nudges affect households' recycling-related WTP, specifically exploring three behavioural mechanisms H2, H3 and H4:

H2. higher absolute values of the social norm are positively related to willingness to pay for enhanced household-level sorting efforts.

Geographic proximity

Our study sampled residents from Shanghai, Zhengzhou, and Shijiazhuang to explore the impact of changes in Shanghai's city-norm on these cities, testing the geographic proximity effect, further detailed in Section 3. Masclet et al. (2003) suggest that a geographic proximity effect occurs because individuals conforming to certain behaviours—and who might sanction non-conformity—are more likely to be those living nearby rather than farther away, even if the latter belong to a relevant peer group. This leads to hypothesis 3:

H3. Higher levels of social norm potentially have a more pronounced effect on the willingness to pay for recycling in Shanghai (a geographically proximate city that supplied the data to generate social norm values) compared to Shijiazhuang and Zhengzhou.

Waste separation habit

As discussed, the impact of a nudge depends on the gap between an individual's current behaviour and their perceived norm. The larger this gap, the stronger the individual's motivation to enhance their willingness to pay for future separation efforts. However, a larger gap may also mean that more effort is required to conform. Nonetheless, established habits can reduce the perceived effort needed, as discussed in Chapter 5.2. Consequently, the impact of a social norm nudge is shaped by individuals' preferences and the costs they encounter, which are in turn influenced by their previous recycling habit (Czajkowski et al., 2019). Our final hypothesis is:

H4. The efficacy of a social norm nudge on willingness to pay for future recycling efforts is moderated by an individual's prior recycling habit.

Our hypotheses are tested using a study implemented in Zhengzhou, Shijiazhuang and Shanghai (described in more detail in the following section), where the characteristics of household waste systems make construction of credible stated preference scenarios possible.

4.3 Survey Design and Methodology

In this chapter, we employ the method of choice experiments to estimate individual preferences regarding household recycling. According to Hanley and Czajkowski (2019), choice experiments have been widely used in policy analysis with respect to a range of pro-environmental behaviours. There are many stated preference studies examining the demand for recycling and waste management, as exemplified by Basili et al. (2006) and Czajkowski et al. (2017); but here we use the method to show how variations in a descriptive social norm between three Chinese cities shape personal preferences for recycling services. Our choice experiment sampled Chinese households in Shanghai, Zhengzhou and Shijiazhuang. As discussed in Chapter 3, in order to achieve our research objective, we developed an initial questionnaire based on previous surveys conducted by Steg et al. (2014) and Czajkowski et al. (2014, 2017, 2019). The survey encompassed four main sections: (1) an introduction, (2) questions regarding current household waste collection practices and other pro-environmental behaviours, (3) an explanation of attributes in the choice scenarios, and the choice sets for estimating preferences for different waste recycling systems, and (4) questions of socio-demographic factors.

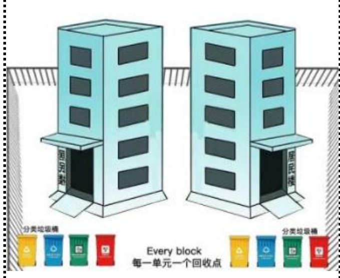
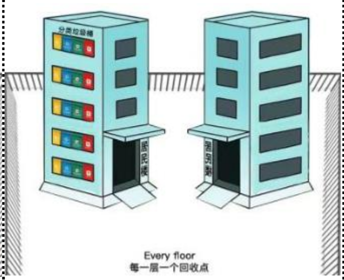
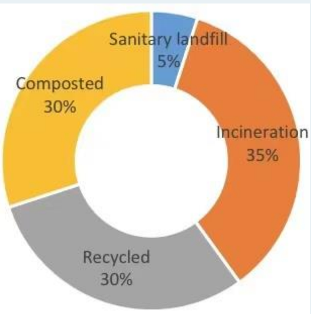
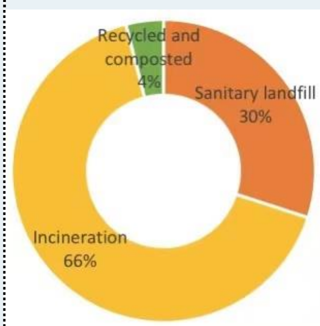
At the start, the survey outlined the significant increase in urban waste caused by China's rapid urbanization and its environmental impact and pollution. It briefly introduced the current response policy, the MSW classification policy launched in 2017, along with its specific goals. As the survey took place during the period when Shanghai was one of the first pilot cities for China's MSW classification policy, the national government planned to adjust the subsequent nationwide implementation of the policy and goals based on the experiences and outcomes from the pilot cities. Consequently, at the end of the first section, subjects were informed about the survey's potential impact – that the findings would be shared with local policy makers and could influence the development of municipal solid waste management policies under consideration. Subsequently, it was structured to ask about respondents' environment knowledge, their recycling habits, and other eco-friendly behaviours.

In our choice experiment, attributes and their levels were chosen based on a comprehensive analysis of policy options being considered at the time in China. This policy innovation required cities to achieve designated recycling targets through the creation and management of an integrated system for waste recycling, collection, and disposal accessible to all residents. Cities had the freedom to select various waste sorting, collection, and disposal systems. The fees charged to households based on the system implemented. The choice cards elicited participants' preferences regarding their selection of waste sorting and waste collection and disposal contracts from a range of options. The contracts included four attributes that participants had to consider when making their choices:

- *Method of waste sorting: Participants selected from no sorting of wastes generated in the household, to sorting into 2, 4, or 7 waste categories. This serves as the primary indicator of their anticipated recycling behaviour following social norm information.*

- *Waste collection plan: Participants had to choose how many waste collection points they would prefer to have in their living area/apartment block. The levels for this attribute ranged from waste collection point in each community to waste collection point in each block or each floor of each apartment block.*

Figure 4. 1: Example of Choice Cards (Based on Figure 3.2)

Situation1.	Option1	Option2	
Method of sorting in citizens			Option 3 I would not choose any
Waste collection plan			
Ending-disposal plan			
Additional Cost for month (YUAN)	200	60	
Your Choice	☐	☐	☐

- *Final disposal plan: Participants had to choose the investment plan for completing the waste management plan in their city. The levels for this attribute ranged from waste incineration to composting or recycling plans.*

- *Cost: Finally, participants had to consider the additional cost of the MSW collection service, represented by a monthly bill that households needed to pay. The levels for this attribute ranged from 20 to 200 Yuan*[19].

In each choice scenario, the last option presented was an opt-out choice. Figure 4.1 illustrates a sample choice card. In these scenarios, respondents were requested to select their most favoured contract from three available alternatives. Each respondent completed 6 choice tasks. The survey ended with questions regarding the socio-demographic characteristics of respondents. These variables include respondents' age, gender, location, education level, and household income.

Table 4. 1 Treatment Groups (Main Sample)

	Treatment	Number of subjects
Treatment 1	In 2018, 7% of all municipal waste collected from households in Shanghai, was sorted.	157
Treatment 2	In 2019, 46% of all municipal waste collected from households in Shanghai, was sorted.	161
Treatment 3	In 2020, 79% of all municipal waste collected from households in Shanghai, was sorted.	163
Treatment 4	No information of levels of sorting of waste provide	157

4.3.1 Information treatments

The survey presented participants with varying degrees of a descriptive social norm, specifically informing them about the proportion of Shanghai residents engaged in recycling.[20] Each participant received only one piece of information about others' recycling

[19] At the time of our study 1 Chinese Yuan≈0.11Pound strling≈0.14 USD.

[20] We chose to use only social norm information based on practice in Shanghai as we tried to avoid the unethical practice of providing false information to subjects, a concern highlighted by Croson and Treich (2014) as "deceptive nudges". This decision was also informed by our findings from sources such as the China Statistical Yearbook, China Environment Newspaper, and China Environment Protection Database. Shanghai

behaviour, except for those in the control group (treatment 4), who did not receive any such information. This information was categorized into three levels of the norm – low, medium, or high – based on the participant's assigned treatment group, as shown in Table 4.1. A randomized experimental design was employed to adjust the magnitude of the social norm in a between-subjects design. The social norm information presented the percentage of households (15%, 75%, and 95% for 2018, 2019, and 2020, respectively) reported to have participated in waste sorting activities in Shanghai during these years. This approach was chosen to avoid the ethical concerns of misleading participants with false information, often referred to as "deceptive nudges" (Croson and Treich, 2014). Each participant was assigned to only one of four evenly distributed treatment groups. Participants in the first three groups (T1, T2, T3) were presented with varying levels of descriptive social norms regarding recycling behaviour: low (15% of households in 2018), medium (75% in 2019), and high (95% in 2020).The fourth group served as a control group, experiencing the same process as the others but without any social norm information. Thus, each respondent was exposed to a single type of social norm-based nudge or received no nudge at all. As noted in our literature review, Shanghai implements a mandatory waste sorting policy, while Zhengzhou and Shijiazhuang adopt advocative policies. This variation offers us an opportunity to test hypothesis H1 by comparing the WTP for waste sorting across the three cities. The treatments T1, T2, and T3 each represented different proportions of Shanghai residents participating in recycling: 15% in 2018 for T1, 75% in 2019 for T2, and 95% in 2020 for T3, with T4 receiving no nudge. This design enables the testing of hypothesis H2 by collectively analysing the data from all three cities. Since the survey presented all participants with a descriptive social norm specific to Shanghai, by comparing how changes in the size of the Shanghai city-norm affect these cities, allow us to test the geographic proximity effect, referred to as hypothesis H3. Finally, we analyse how the impact of a given nudge differs based on individuals' reported previous recycling actions, facilitating an examination of Hypothesis H4.

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was selected because it is first pilot city for mandatory waste sorting policy in China, and it is the only city where data on the participation percentage in waste sorting is readily available.

4.3.2. Case study selection and description

In our case, according to the Shanghai MSW Management Regulation enacted in June 2019, individuals who fail to comply with domestic waste classification rules face fines ranging from 50 to 200 yuan (Zheng et al., 2014; Liu and Zheng, 2023). Initially, Shanghai's streets were adorned with slogans promoting waste sorting. By the end of December, these were replaced by posted guidelines and disposal instructions within communities. To enforce this regulation, Shanghai has established a dual supervision mechanism where waste that is not sorted will neither be collected nor disposed of. Communities in Shanghai have 1-6 garbage collection rooms of varying sizes, with designated disposal times from 7-9 AM and 5-7 PM. Outside these hours, the rooms are locked, and some smart garbage rooms only open with a card or QR code during these times. Local volunteers supervise the disposal process, as reported by Xinhua Net.[21] The aforementioned crackdown is set to continue until 2025, after which a comprehensive and enduring management mechanism for domestic waste sorting, along with a full-cycle classification, collection, and disposal system, will be established (Shanghai Municipal Development & Reform Commission, 2023). Despite years of efforts, China's MSW classification policy, except for Shanghai (as discussed in 4.2), has not been fully enforced in 46 cities such as Zhengzhou and Shijiazhuang (Han and Zhang, 2017; Chu et al., 2023a). These cities remain in the advocacy phase, lacking effective supervision and enforcement mechanisms.

The research primarily evaluates the status of waste classification and the willingness to pay for waste sorting in the Shanghai area (a pilot region with a mandatory policy). The study

[21] To address individual violations, most volunteers used photo postings to display residents' waste disposal actions, highlighting both compliant and non-compliant sorting.

As of May 23, 2023, according to data from the Shanghai Greening and City Appearance Bureau, over 710,000 volunteers have registered for waste sorting, establishing a three-tier volunteer system at the city, district, and town levels. Shanghai has significantly intensified its waste sorting enforcement efforts. From January 1 to June 25, 2019, municipal law enforcement conducted over 13,900 inspections, handling 1,224 violations, advising 13,739 individuals, and mandating 7,822 corrective actions. In the latter half of 2019, there were 5,546 cases of waste sorting violations processed, involving 5,085 institutions and 461 individuals, with 232 violations reported to the credit system. The enforcement of mandatory policies led to a noticeable decrease in penalties in the second half of the year, as reported by Xinhua Net. (http://www.xinhuanet.com/politics/2020-01/07/c_1125428529.htm).

selects two cities, Zhengzhou and Shijiazhuang, which implement advocative policies, for comparison against Shanghai, based on three main reasons. Firstly, Zhengzhou and Shijiazhuang are prominent political and cultural centres in North China. As central cities and megacities, they share similarities in population size and area, offering a high degree of commonality and comparability. Secondly, they enjoy political prominence as the capitals of Henan and Hebei provinces, respectively, and share cultural structures that make them exemplary models for other cities in China to emulate. Thirdly, both cities adhere to the same MSW classification standards as Shanghai, following the national standard “Classification and evaluation standard of MSW CJJ/T102-2004”. Additionally, according to the Garbage Sorting Index Evaluation Report 2022, their waste sorting performance is representative of 46 cities, excluding the pilot city, Shanghai. Therefore, the study chooses these three cities to compare the effects of mandatory and advocative policies on MSW classification effectiveness. The questionnaire development and experimental design for the pilot study are comprehensively explained in Chapter 3.

The main survey was conducted in August 2022, gathering 693 responses through an online platform. Among these, 13 had to be excluded for incomplete information. For the rest of the sample, the data quality depends on careless responses.[22] The final sample consisted of 638 respondents, with approximately 210 respondents from each of the three cities included in the study: Shanghai, Zhengzhou, and Shijiazhuang. The sample was quota-controlled with respect to, age and being a resident of the respective city.

[22] In our study, we employed an ex post screening method to filter out careless responses, based on the total time taken to complete the survey. This method is supported by research from Meade and Craig (2012) and Leiner (2019), who suggest completion time as a reliable indicator of response quality. We excluded 45 respondents whose completion times were excessively short, defined as being more than 1.5 times the interquartile range away from the nearest quartile. While effective, this screening method is one among several for addressing careless responses, and as noted by Gao et al. (2016) and Lancsar and Louviere (2006), findings based on this filtered sample should be interpreted with caution.

4.3.3. Econometric Approach

Mixed logit model

We employed the mixed logit (ML) model for econometric estimation (McFadden and Train, 2000). In our analysis, we introduced interactions between different levels of waste sorting attributes and three treatment variables: T1-15%, T2-75%, and T3-95% relative to T4, the control group. All parameters, including alternative specific constants (ASC) and cost, were modelled as random. Typically, parameters followed normal distributions, except for cost, which was modelled with a negative log-normal distribution. Individual i's utility from choosing alternative j in situation t can be expressed by **Equation (4-1)**:

$$U_{ijt} = \beta_i X_{ijt} + \varepsilon_{ijt}$$

where β_i represents the coefficient vector for observed variables specific to individual i, X_{ijt} denotes the observed variables associated with individual i and alternative j in situation t, and ε_{ijt} is the unobserved utility component for individual i choosing alternative j in situation t.

In the Mixed Logit model, individual-specific coefficients (β) vary across a population with density $f(\beta|\theta)$. This density function depends on the mean and covariance of the population's preference parameters (θ). The parameters β_i represent individual-specific taste parameters that reflect the marginal utilities of choice attributes, capturing heterogeneous preferences among respondents. These parameters follow a multivariate (parametric) distribution $\beta_i \sim f(b, \Sigma)$,where b is a mean vector and Σ is a variance-covariance matrix. To account for preference variations due to information treatments, the model adapts to $\beta_i \sim f(b + \delta z_i, \Sigma)$, with z being a binary indicator for treatment effects and δ representing a vector of estimated attribute-specific effects (Hanley and Czajkowski, 2019).

Assuming the probability of respondent i choosing alternative k in situation t, conditional on β_i, can be expressed by **Equation (4-2)**:

$$L_{ijt}(\beta_i) = \frac{e^{\beta_i' x_{ikt}}}{\Sigma_j e^{\beta_i' x_{ijt}}}$$

This is the conditional logit equation (McFadden, 1974). The probability of the observed sequence of choices for a respondent, given their specific coefficient vector β_n is given by **Equation (4-3)**:

$$S_i(\beta_i) = \prod_{t=1}^{T} L_{ij(i,t)t}\,(\beta_i)$$

where $j(i,t)$ represents the alternative chosen by individual i on choice situation $t.$ Since β_i is unconditional on $\beta,$ and the utility is linear in parameters, the integral of $L_{ik}(\beta_i)$ across all possible values of β'_n results in the unconditional probability of choice. The unconditional probability of the observed sequence of choices is derived by integrating the conditional probability across the distribution of β coefficients is given by **Equation (4-4)**:

$$P_i(\theta) = \int S_i(\beta) f(\beta|\theta) d\beta$$

The probability is essentially an average of the standard logit formula, with β evaluated at various values specified by the density function $f(\beta|\theta)$. In model specifications, both individual-specific and alternative-specific variables can be incorporated. The log likelihood of the simulated form can be written as **Equation (4-5)**:

$$SLL(\theta) = \Sigma_{i=1}^{N} \ln\left(\frac{1}{R}\Sigma_{r=1}^{R} S_i(\beta^r)\right)$$

Where R denoted the log likelihood is calculated across multiple replications, and β^r is derived from rth draw from the distribution $f\ (\beta|\theta)$ (Hole, 2007). **Equation (4-5)** is the simulated log likelihood (SLL) for the mixed logit model. Because the unconditional choice probabilities can't be calculated exactly, simulation is used to approximate them. In short, the mixed logit model accounts for individual-specific variation in preferences by assuming random parameters. To estimate this model, the unconditional choice probability for each respondent is obtained by averaging conditional probabilities over numerous simulated draws of these random parameters. The model's overall likelihood is then approximated by summing the logarithms of these averaged probabilities across all respondents, yielding the simulated log likelihood.

Individual level WTP

In the mixed logit model, individual-level coefficients are estimated through the expected value of β, which is conditional on a specific response pattern y_i and a set of alternatives characterized by x_i is given by **Equation (4-6)**:

$$E[\beta|y_i x_i] = \frac{\int \beta \prod_{t=1}^{T} \prod_{j=1}^{J} [\frac{exp(x'_{ijt}\beta)}{\sum_{j=1}^{J} exp(x'_{ijt}\beta)}]^{y_{ijt}} f(\beta|\theta) d\beta}{\int \prod_{t=1}^{T} \prod_{j=1}^{J} [\frac{exp(x'_{ijt}\beta)}{\sum_{j=1}^{J} exp(x'_{ijt}\beta)}]^{y_{ijt}} f(\beta|\theta) d\beta}$$

The numerator calculates a weighted average of the random parameters β, with weights given by the probability of observing the individual's actual choices under each value of β. The denominator integrates the probabilities of observing these choices across all possible values of β, effectively normalising the expression. Intuitively, this formula provides the most likely average value of an individual's utility parameters, given the choices they made. This concept represents the conditional mean of the coefficient distribution for a subgroup of individuals facing identical alternatives and making similar choices. Revelt and Train (2000) recommend approximating $E[\beta|y_i x_i]$ using simulation, which can be executed through the mixlbeta command after a mixed logit model is estimated with mixlogit using Stata 18 (StataCorp LLC, College Station, TX, USA). We then used the 'centile' command in Stata to produce the consumer WTP percentiles (Hole, 2007 and 2013). Lastly, we utilised the 'kdensity' command to generate the WTP density graph at individual level WTP.

4.4 Data Analysis and Main Result

4.4.1 Optimal fitting model[23]

According to the literatures, three different mixed logit models and three distinct methods to calculate WTP were adopted in this study, with only the best-fit model and WTP method selected for hypothesis testing. Table 4.2 outlines the choice modelling results, aggregating data without treatment differentiation. ModelM1, in the first column, assumes normal distributions for parameters except cost, which is log-normally distributed and estimated within preference space. Model M2, in the second column, employs a fixed cost coefficient, serving as a benchmark for WTP calculations. The third column presents the WTP values measured under ModelM1 in the WTP space[24], allowing for comparative analysis across models. In these models, parameters uncorrelated to specific attribute levels indicate a preference shift for that attribute relative to a baseline, and all use 2000 Halton draws for computation.

[23] Our results begin with the baseline model - the conditional logit model, and we compared two versions of the conditional logit model, each with a different set of variables interacting with the ASC variable. However, after we tested the Independence of Irrelevant Alternatives (IIA) assumption, a fundamental aspect of the conditional logit model, employing the Hausman test (Hausman and McFadden, 1984). Our conditional logit model led to the rejection of the null hypothesis, which proposed that the IIA holds. This outcome signals a need for a model that loosens this assumption, such as the mixed logit model or the latent class model.

[24] In the third column, since in the WTP space we encountered convergence issues with the inclusion of interaction terms, and it only achieved convergence at a low level of simulation draws (default 50 Halton draws). As a result, we decided to present the results in Table 5.2.1 for the poor model in the WTP space Model M6 (2000 Halton draws) for WTP comparison in WTP section.

Table 4. 2: Estimation results of The Mixed Logit Models

Variables	Model M1 (LN COST)	ModelM2 (FIXED COST)	Model M1 (WTP SPACE)
	Coefficient	**Coefficient**	**Coefficient**
Non-random parameters			
Monthly cost per household		.-0.0046536***(0.0006748)	
Random parameters			
Sort in 7 categories (vs. no in-home sorting)	2.15*** (0.14)	2.00*** (0.13)	562.44*** (89.91)
Sort in 4 categories (vs. no in-home sorting)	2.39*** (0.153481)	2.26*** (0.14)	610.68*** (90.52)
Sort in 2 categories (vs. no in-home sorting)	1.49*** (0.12)	1.42*** (0.1306)	388.89*** (52.71)
Waste collection point in every block (vs. collection point in every community)	0.21** (0.09)	0.24*** (0.08)	61.67*** (22.57)
Waste collection point in every floor (vs. collection point in every community)	0.09 (0.10)	0.10 (0.09)	3.96 (21.98)
Disposal plan-composting (vs. incineration)	0.28*** (0.08)	0.29*** (0.08)	61.29*** (20.55)
Disposal plan-recycling plants (vs. incineration)	1.01*** (0.11)	0.92*** (0.10)	205.86***(35.70
asc	3.09*** (0.37)	3.10*** (0.35)	1269.81*** (246.01
Transferred ln (Monthly cost per household)	.-0.0099*** (0.001)		.-0.0099*** (0.001)
SD			
Sort in 7 categories (vs. no in-home sorting)	1.46*** (0.14)	1.30*** (0.13)	.-309.52*** (57.51)
Sort in 4 categories (vs. no in-home sorting)	0.45 (0.28)	.-0.49*** (0.25)	49.01* (25.15)
Sort in 2 categories (vs. no in-home sorting)	0.80*** (0.19)	0.88*** (0.17)	.-139.10***(38.46)
Waste collection point in every block (vs. collection point in every community)	0.12 (0.54)	0.09 (0.45)	25.17(26.08)
Waste collection point in every floor (vs. collection point in every community)	1.02*** (0.14)	0.98*** (0.13)	153.72*** (42.48)

Table 4.2 (continued)

Disposal plan-composting (vs. incineration)	0.64***(0.1)	0.75*** (0.12)	.-153.80*** (39.76)
Disposal plan-recycling plants (vs. incineration)	0.89*** (0.15	.-0.72*** (0.15)	136.38*** (40.75)
asc	2.62*** (0.32)	3.002*** (0.28)	1053.74*** (185.59)
Monthly cost per household			
Transferred ln (Monthly cost per household)	0.07***(0.03)		0.07*** (0.03)
LL at constant(s) only	.-2757.44	.-2793.22	.-2778.36
AIC	5550.89	5620.46	5592.73
BIC	5683.17	5745.38	5725.01
pseudo R2	0.34	0.32	0.33
n (observations)	11484	11484	11484
r (respondents)	638	638	638

Notes: Standard errors are in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

For Models M1, M2, and Model M1 in WTP space, attribute levels mostly align with expectations and show significant differences from baselines, except for the insignificant preference for recycling points on every floor. This indicates a general positive attitude towards higher waste sorting, accessible recycling facilities upgrading and sustainable waste management methods. The significant and positive Alternative Specific Constant (ASC) suggests that opting out is less preferred. The cost coefficient[25] is negatively correlated across all models, indicating an increased likelihood of opting out with rising costs. Lastly, the table shows significant varied preferences across attributes, with the exception of recycling points on each block and sorting into 4 categories in Model M1. Model M1 (ln cost) demonstrates enhanced performance as indicated by log-likelihood, AIC, BIC, and Pseudo R2 values.

[25] Consider the lognormal coefficients. Coefficient βk (cost) adheres to a lognormal distribution if the natural logarithm of βk (cost) showcases a normal distribution. We express the lognormal distribution in relation to the integral normal distribution. In other words, we compute parameters such as mean and standard deviation that depict the mean and variance of the natural logarithm of the coefficient: lnβk follows a normal distribution N(mean, sd). The mean and variance of βk are subsequently derived from the calculated estimates of mean and sd. The median is exp(mean), the mean is exp(mean + sd/2), and the variance is exp(2mean + sd) [exp(sd) − 1] (Train, 2003 Chapter 6).

Table 4.3 illustrates the WTP distributions derived from both Model 2 (fixed cost) and Model 1 (lognormal cost) in preference-space. Additionally, for Model 2[26], we only used the classical delta method to compute the WTP estimates. Contrastingly, for Model 1, we employed three distinct methods[27] - the delta method, non-parametric bootstrap procedures, and individual level parameters - for the purpose of comparison. We juxtaposed all WTP outcomes from Models M1 and M2 with Model M1 in the WTP space to provide a comprehensive analysis.

Table 4.3 mirrors the results found in Table 4.2 across all WTP outcomes. Compared to waste collection points and the final disposal plan, the sorting attribute garnered the greatest willingness to pay from participants, and sorting waste into 4 and 7 categories was the most favoured, leading to the highest willingness to pay. This is likely due to the fact that China's promoted waste sorting policy is divided into these four categories. In addition, we have chosen to use individual level parameters for WTP calculations in subsequent analyses due to their closer alignment with Model 1 in the WTP space results and narrower confidence intervals[28] compared to other methods.

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[26] Additionally, we implemented the delta method, non-parametric bootstrap procedures by resampling observations 1000 times, and individual level parameters to derive WTP estimates for Model M2, and we obtained nearly identical results. However, due to space constraints in the paper, we only presented the results calculated using the classical delta method for comparison.

[27] We also attempted to compute the median WTP estimates using the delta method and non-parametric bootstrap procedures for Model M1. However, these attempts produced extremely large, and therefore implausible, WTP values along with excessively broad confidence intervals. As a result, to maintain clarity and robustness in our findings, we opted to utilise mean WTP estimates in the paper.

[28] Given our assumption of log-normal costs, to prevent extreme WTP (willingness-to-pay) values when a respondent's calculated cost coefficient is near zero, we calculate the conditional mean coefficients for each individual in the sample. We then determine the ratio of these conditional means and interpret the mean and variance of these ratios among individuals as indicative of the population's overall WTP. Essentially, this approach trades off reduced sample dispersion for more reliable estimates of average values.

Table 4. 3: Estimation results of WTP

	ModelM2 fixed cost (Delta)	ModelM1 ln cost (Delta)	Mode1 ln cost (non-parameter bootstrap)	Model1 ln cost (individual level WTP)	Model 1 in WTP SPACE
Sort in 7 categories (vs. no in-home sorting)	431*** [313 550]	216*** [157, 275]	216*** [30, 402]	779*** [736, 821]	562. *** [386, 738]
Sort in 4 categories (vs. no in-home sorting)	486*** [367, 604]	240*** [177, 305]	241*** [351, 446]	866 *** [827, 906]	611*** [433, 788]
Sort in 2 categories (vs. no in-home sorting)	306*** [240, 372]	149 *** [106, 193]	149*** [25, 274]	567*** [536, 598]	389*** [286, 492]
Waste collection point in every block (vs. collection point in every community)	53*** [18, 89]	21** [2, 40]	21 [-29, 72]	77*** [74, 81]	62*** [17, 106]
Waste collection point in every floor (vs. collection point in every community)	22 [-18, 63]	9 [-12, 29]	9 [-14, 31]	22 [5, 38]	4 [-39, 47]
Disposal plan-composting (vs. incineration)	62*** [29, 95]	29*** [12, 47]	29 [-45, 103]	125*** [114, 136]	61*** [21, 102]

Notes: Significance levels: *** p<0.01 ** p<0.05 * p<0.1.95% confidence intervals are in brackets. Parameter estimates represent WTP expressed in Chinese Yuan per month per household.

4.4.2. H1. the effect of local policies

We hypothesized that a mandatory policy (Shanghai) has a greater impact on individuals' WTP for higher levels of waste sorting compared to an advocative policy (Zhengzhou and Shijiazhuang). Given that we randomly selected an equal number of participants from three cities. The data was then segmented based on Model M1, creating three distinct models referred to as Model M3 (C1, C2, C3) for Shanghai, Zhengzhou, and Shijiazhuang. Drawing on past studies (Kasilingam and Krishna, 2022), acknowledges the substantial influence of socioeconomic factors on individuals' WTP. Each city-specific model was estimated independently, following a "backward" method, each incorporating a selection of significant variables age and gender interacting with ASC.[29]

In preference space, Table 4.4 indicates that in all three cities, participants significantly favor any level of waste sorting compared to the baseline of no sorting. Shanghai's coefficients for 4 and 7 category waste sorting are higher than Zhengzhou and Shijiazhuang's. In addition, most waste disposal plan attributes align with expectations and significantly differ from baselines, except Zhengzhou's insignificant preference for composting. Shanghai shows a stronger preference for composting and recycling plans than the other cities. Finally, only Shanghai's participants significantly prefer any waste collection plan level over the baseline of having a collection point in every community. However, given that the scales of these coefficients might differ, it's crucial to calculate WTP values for different attribute levels, addressing potential scale-related shortcomings effectively. The log-likelihood ratio test showed significant differences in parameter estimates among the cities, highlighting unique variations in preferences across city pairings. The computation of -2LL, which is twice the difference of the log-likelihood of the pooled model (both Shanghai and Zhengzhou respondents) and the sum of the log-likelihood of Shanghai and Zhengzhou, resulted in a

[29] To examine interactions between the Alternative-Specific Constant (ASC) and socio-demographic variables (such as age, gender, education, income and location) for respondents in each city, we employed a "backward" method for model specification, starting with a comprehensive model encompassing all potential ASC interactions with respondent characteristics. Through iterative refinement, less significant parameters were progressively eliminated, refining the model to retain only significant or policy-relevant coefficients. Main effects were kept in the model regardless of their significance levels.

value of 43.4572. Specifically, it was computed as -2 * (-1834.2726 – (-947.6729 -864.7211)) = 43.4572. This calculated -2LL value (43.4572) exceeded the critical chi-square value (31.45) at 20 degrees of freedom, at the 5% significance level. Hence, the null hypothesis, which assumes parameter equality between Shanghai and Zhengzhou, was rejected. Furthermore, analogous procedures were conducted for each pair of city combinations. (Shanghai vs Zhengzhou: 43; Shanghai vs Shijiazhuang: 80; Zhengzhou vs Shijiazhuang: 146)

For willingness to pay, Figure 4.2 reveals Shanghai participants exhibit higher WTP for sorting waste into 4 and 7 categories across all treatments compared to Zhengzhou and Shijiazhuang. Furthermore, Table 4.5 illustrates Shanghai participants' higher WTP for all waste collection and disposal plans versus the baseline across treatments, in contrast to Zhengzhou and Shijiazhuang.

Table 4. 4: Estimation results of the Mixed Logit Model M3 for Three Cities

Variables	Model M3C1 (Shanghai)	Model M3C2 (Zhengzhou)	Model M3C2 (Shijiazhuang)
	Coefficient	**Coefficient**	**Coefficient**
Non-random parameters			
Gender_ASC	.-0.73 (0.62)	0.06 (0.62)	.-2.43*** (0.86)
Age_ASC	.-0.64* (0.38)	0.19 (0.34)	.-0.75** (0.37)
Random parameters			
Sort in 7 categories (vs. no in-home sorting)	2.66*** (0.33)	1.65*** (0.28)	2.04*** (0.29)
Sort in 4 categories (vs. no in-home sorting)	3.10*** (0.50)	2.23*** (0.21)	2.45*** (0.28)
Sort in 2 categories (vs. no in-home sorting)	1.29*** (0.29)	1.72*** (0.23)	1.45*** (0.28)
Waste collection point in every block (vs. collection point in every community)	0.40** (0.18)	0.23 (0.28)	.-0.19 (0.22)
Waste collection point in every floor (vs. collection point in every community)	0.51* (0.28)	0.12 (0.37)	.-0.23 (0.15)

Table 4.4 (continued)

Disposal plan-composting (vs. incineration)	0.57***	0.01	0.42***
	(0.22)	(0.15)	(0.16)
Disposal plan-recycling plants (vs.	1.45***	0.73***	1.11***
incineration)	(0.29)	(0.22)	(0.19)
ASC	5.78***	3.19*	10.46***
	(2.01)	(1.79)	(2.58)
Transferred ln (Monthly cost per household)	.-0.02***	.-0.01***	.-0.01***
	(0.004)	(0.001)	(0.002)
SD			
Sort in 7 categories (vs. no in-home sorting)	2.04***	1.32***	0.93***
	(0.35)	(0.24)	(0.30)
Sort in 4 categories (vs. no in-home sorting)	.-2.29***	.-0.27	.-0.049
	(0.71)	(0.46)	(0.33)
Sort in 2 categories (vs. no in-home sorting)	.-0.28***	.-0.004	1.54***
	(0.71)	(0.59)	(0.28)
Waste collection point in every block (vs.	0.59	0.10	1.00***
collection point in every community)	(0.36)	(0.48)	(0.29)
Waste collection point in every floor (vs.	1.82	0.80***	0.79***
collection point in every community)	(0.41)	(0.24)	(0.23)
Disposal plan-composting (vs. incineration)	0.94***	0.45*	0.88***
	(0.34)	(0.27)	(0.25)
Disposal plan-recycling plants (vs.	1.38***	.-0.40	0.98***
incineration)	(0.37)	(0.37)	(0.23)
ASC	.-2.38***	2.71***	3.18***
	(0.65)	(0.76)	(0.63)
Transferred ln (Monthly cost per household)	.0.17***	0.01**	0.009***
	(0.11)	(0.005)	(0.003)
LL at constant(s) only	.-947.67	.-864.87	.-847.22
AIC	1935.34	1769.74	1834.45
BIC	2060.75	1894.49	1959.29
pseudo R2	0.34	0.37	0.39
n (observations)	3906	3780	3798
r (respondents)	217	210	211

Notes: Standard errors are in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

Therefore, we have obtained evidence that fails to reject our hypothesis H1, showing that compared to the advocative policy in Zhengzhou and Shijiazhuang, Shanghai's mandatory policy significantly boosts individuals' willingness to pay (WTP) for higher levels of waste sorting, such as sorting into 4 or 7 categories. Additionally, evidence suggests the mandatory policy produces a positive spillover effect on individuals' WTP towards the waste collection and waste disposal stages of the recycling process. However, this result, encompassing all treatments, suggest the observed impact may also stem from the nudge effect. Specifically, information on recycling behaviours of a certain percentage of individuals within the respondent's own city (Shanghai) yields a greater influence than similar data from a different city (Zhengzhou and Shijiazhuang). We will discuss this effect in H3 part.

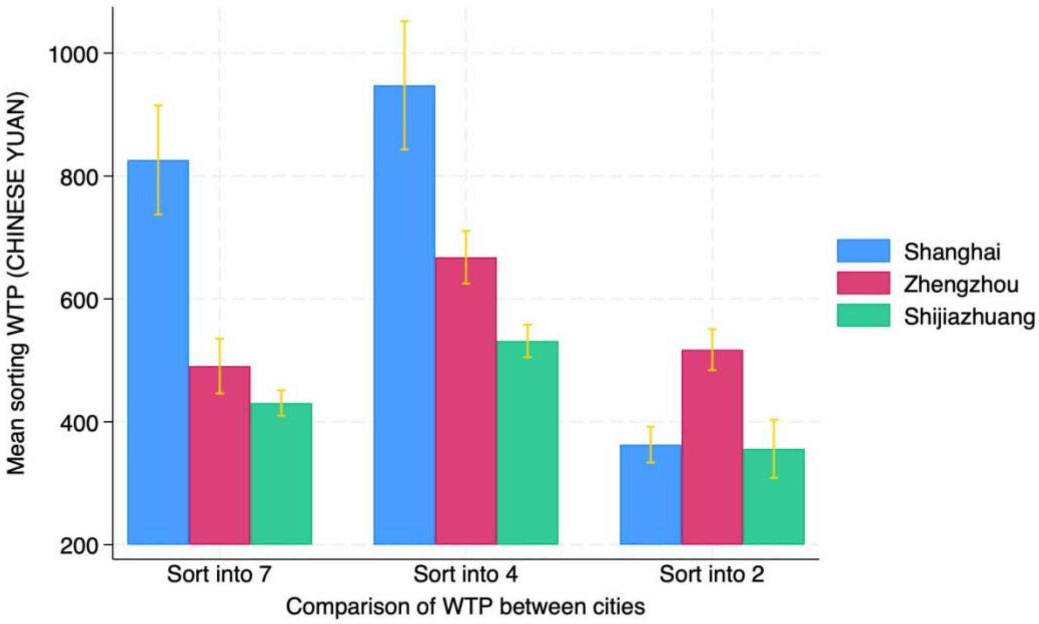
Table 4. 5: Estimation results of Individual Level WTP for Each Cities (Model M3)

	Respondents	WTP	Std. dev.	95% conf. interval	
ModelM3C1 (SHANGHAI)					
Sort in 7 categories (vs. no in-home sorting)	217	826	664	738	915
Sort in 4 categories (vs. no in-home sorting)	217	947	780	844	1051
Sort in 2 categories (vs. no in-home sorting)	217	362	217	334	392
Waste collection point in every block (vs. collection point in every community)	217	118	89	107	131
Waste collection point in every floor (vs. collection point in every community)	217	127	333	83	171
Disposal plan-composting (vs. incineration)	217	179	164	158	201
Disposal plan-recycling plants (vs. incineration)	217	393	266	358	428
ModelM3C2 (ZHENGZHOU)					
Sort in 7 categories (vs. no in-home sorting)	210	490	327	446	535
Sort in 4 categories (vs. no in-home sorting)	210	667	316	625	710
Sort in 2 categories (vs. no in-home sorting)	210	517	244	484	550
Waste collection point in every block (vs. collection point in every community)	210	71	35	67	77
Waste collection point in every floor (vs. collection point in every community)	210	31	117	16	47
Disposal plan-composting (vs. incineration)	210	12	51	5	19
Disposal plan-recycling plants (vs. incineration)	210	217	101	204	231
ModelM3C3 (SHIJIAZHUANG)					
Sort in 7 categories (vs. no in-home sorting)	211	430	152	410	451

Table 4.4 (continued)

Sort in 4 categories (vs. no in-home sorting)	211	531	194	505	558
Sort in 2 categories (vs. no in-home sorting)	211	356	349	309	403
Waste collection point in every block (vs. collection point in every community)	211	-32	105	-46	-18
Waste collection point in every floor (vs. collection point in every community)	211	-46	87	-58	-35
Disposal plan-composting (vs. incineration)	211	99	107	84	114
Disposal plan-recycling plants (vs. incineration)	211	246.	156	226	268

Figure 4. 2: Mean monthly WTP for waste sorting by city (with 95% CI). Shanghai shows highest WTP across all sorting levels.



Parameter estimates represent WTP expressed in Chinese Yuan per month per household.

4.4.3 H2. The absolute size of the social norm

Our hypothesis posits that increased absolute social norm values enhance the willingness to pay for better household sorting. We divided participants into four groups and consolidated the data into Model M4, following Model M1's framework in Section 2. This model introduces interactions between various information interventions and waste sorting attributes to examine how absolute social norm values affect preferences for improved household sorting efforts.[30]

In preference space, Table 4.6 illustrates how varying social norms (T1, T2 or T3) affect waste sorting preferences relative to a control group (T4). The results indicate that T1 and T2 significantly enhances the preference for sorting into four categories over no sorting. In contrast, the highest recycling norm (T3) significantly reduces the preference for sorting into four categories. Full version in Appendix A1

Table 4. 6: Estimation results of The Mixed Logit Model M4 (Interaction terms between Waste Sorting Levels and Treatments)

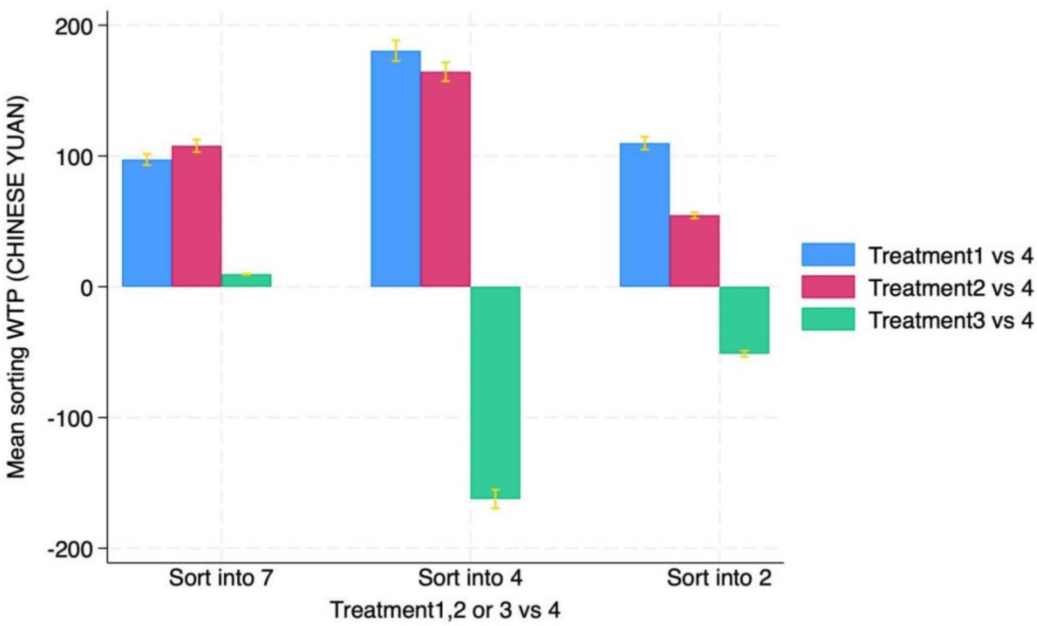
choice	Coefficient	Std. err.
Non-random parameters		
Interaction		
Sort7(vs. no in-home sorting)_T1vs.T4	0.30	0.31
Sort4(vs. no in-home sorting)_T1vs.T4	0.56**	0.28
Sort2(vs. no in-home sorting)_T1vs.T4	0.34	0.29
Sort7(vs. no in-home sorting)_T2vs.T4	0.33	0.31
Sort4(vs. no in-home sorting)_T2vs.T4	0.51*	0.28
Sort2(vs. no in-home sorting)_T2vs.T4	0.17	0.29
Sort7(vs. no in-home sorting)_T3vs.T4	0.033	0.29
Sort4(vs. no in-home sorting)_T3vs.T4	.-0.51**	0.26
Sort2(vs. no in-home sorting)_T3vs.T4	-0.16	0.28
LL at constant(s) only	.-2747.01	
AIC	5548.03	
BIC	5746.44	
pseudo R2	.35	
n (observations)	11484	
r (respondents)	638	
Notes: *** p<0.01 ** p<0.05 * p<0.1.		

[30] In contrast to the variable attributes' coefficients, which are randomized, interaction terms are characterized by fixed coefficients. Other methodologies, such as incorporating scale heterogeneity, could potentially account for noticeable interpersonal variations in respondent decision-making. However, this study specifically employs treatment and demographic interactions within attribute data, as this approach is more adept at generating context-specific insights. In addition, when considering attribute interactions in our model, the focus remains exclusively on these interactions themselves, as they do not affect the values of coefficients without such interactions. Consequently, the discussion is limited solely to the examination and analysis of these interactions.

For willingness to pay, individual-level parameters were employed to compute the WTP for interaction terms, demonstrating how much more individuals in T1, T2 or T3 are willing to pay for enhanced sorting levels over no sorting, in comparison to T4. Figure 4.3 shows that respondents in T1 and T2 had a positive WTP for all sorting levels over no sorting compared to T4, with the highest WTP values observed for sorting into four categories (181 and 164 yuan, respectively). However, for respondents in T3, the WTP for sorting into 2 and 4 categories over no sorting is negative compared to T4. Full version in Appendix A2

In addition, Figure 4.4 reveals significant preference heterogeneity for recycling within our dataset. From Panels A and B, as the levels of social norms increase, respondents show greater variation in their preferences for higher levels of sorting (such as dividing waste into four or seven categories). We will revisit the analysis of this heterogeneity in our discussion.

Figure 4. 3: WTP differences by treatment and sorting level (95% CI). Medium (T1) and low (T2) norm levels increase WTP, while the highest norm level (T3) shows a negative effect.

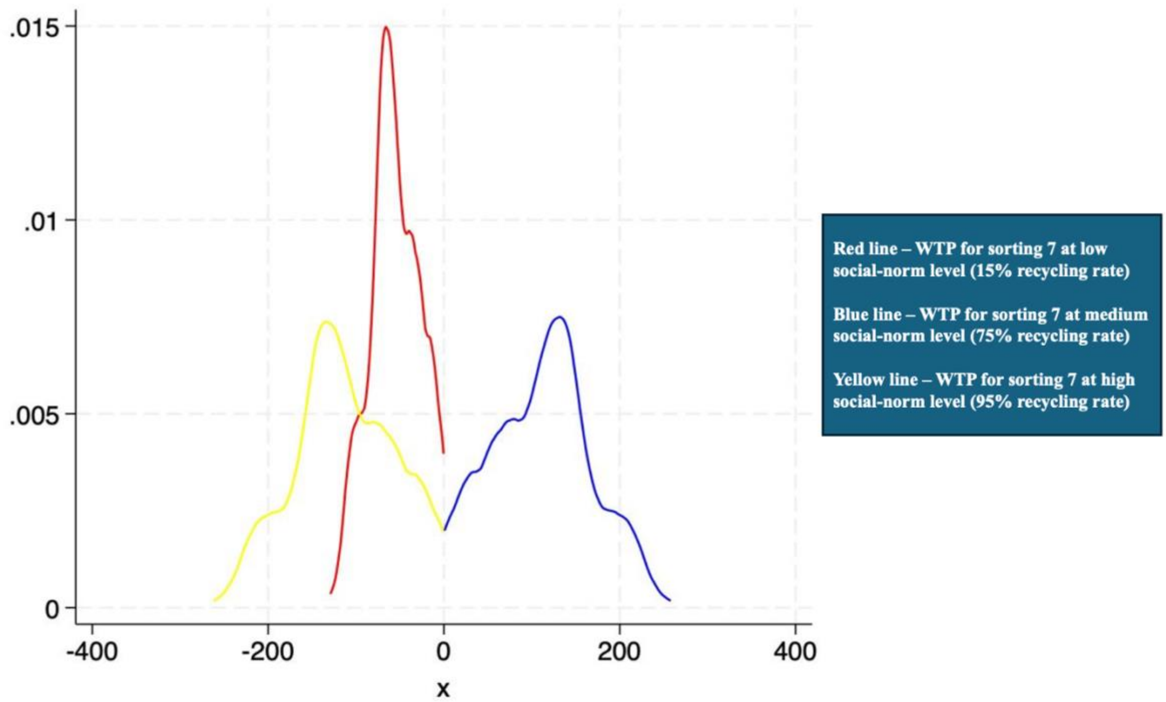


Parameter estimates represent WTP expressed in Chinese Yuan per month per household.

Thus, we first uncover evidence that refutes our Hypothesis H1. Contrary to what we assumed, higher levels of the absolute size of the social norm actually lead to an increased WTP for better household sorting. We observed positive and statistically significant effects from the information intervention on WTP for sorting waste into four categories, particularly when presenting information that 15% and 75% of people in Shanghai engaged in waste sorting. Surprisingly, the impact did not increase with the absolute size of the norm; rather, the effects were relatively similar across these levels. In addition, if the descriptive social norm information given to participants regarding waste recycling is excessively high - in this instance, 95% of people recycling in Shanghai - their enthusiasm may be suppressed.

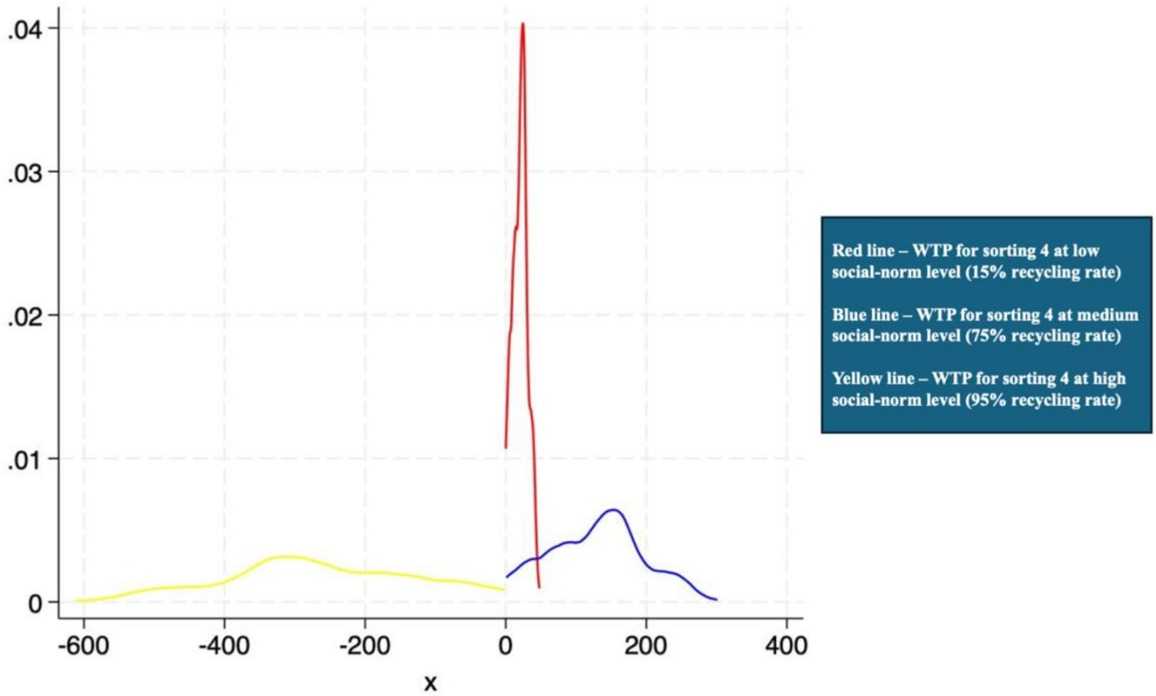
Figure 4. 4: The Kernel Density Functions of Individual WTP for All Waste Sorting Levels across Treatment 1, 2, or 3 vs 4.

Panel a: WTP for 7-category sorting under different social norms. Medium social-norm levels (blue) shift WTP distributions rightward, indicating stronger support for recycling compared to low (red) and high (yellow) norm levels.



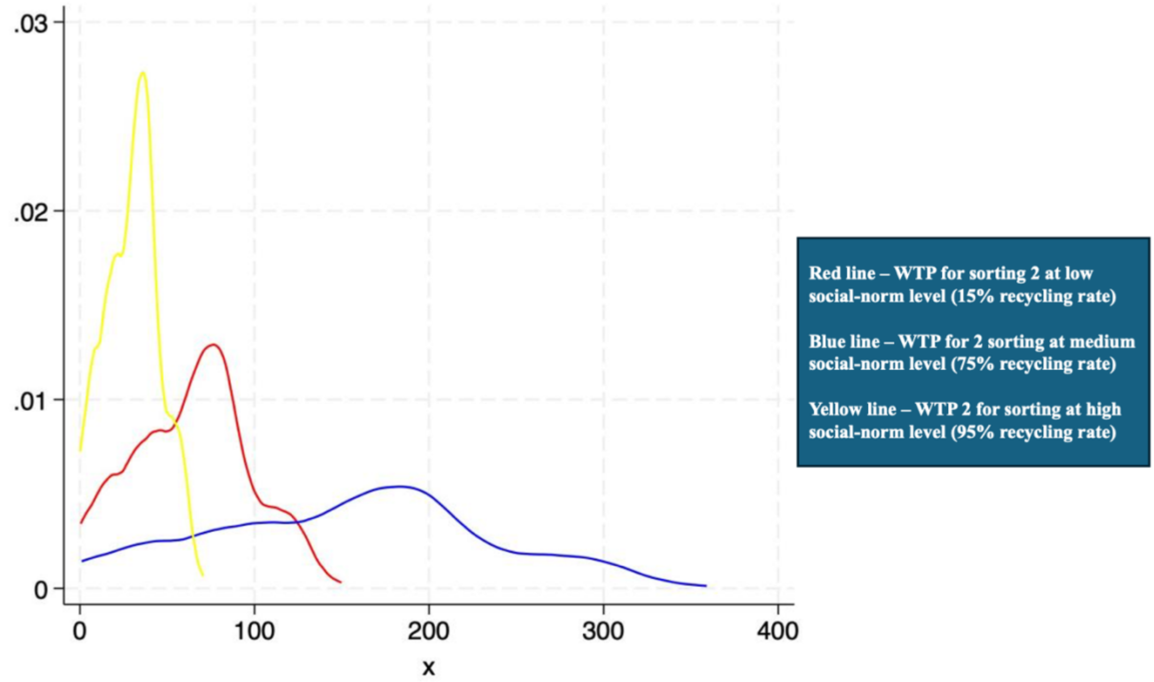
The distributions, differentiated by colour for each treatment group (Red line -T1, blue line- T2, yellow line- T3)

Panel b: WTP for 4-category sorting under different social norms. medium social-norm levels (blue) shift WTP distributions rightward, indicating stronger support for recycling compared to low (red) and high (yellow) norm levels.



The distributions, differentiated by colour for each treatment group (Red line -T1, blue line- T2, yellow line- T3)

Panel c: WTP for 2-category sorting under different social norms. medium social-norm levels (blue) shift WTP distributions rightward, indicating stronger support for recycling compared to low (red) and high (yellow) norm levels.



The distributions, differentiated by colour for each treatment group (Red line -T1, blue line- T2, yellow line- T3)

4.4.4. H3. Geographic proximity

Our hypothesis posited that a higher level of social norms could notably influence willingness to pay (WTP) for better household waste sorting in Shanghai, given its geographical proximity to where social norm data originated. To investigate this, the data was segmented according to Model M1, resulting in three distinct models for the three cities, labelled Model M5 (C1, C2, C3). Using the "backward" method, each city-specific model, incorporating significant variables—age and gender interacting with ASC—analyses how absolute social norm values influence preferences for enhanced household sorting efforts through interactions between information interventions and waste sorting attributes across different city samples.

In preference space, Table 4.7 shows the effect of T1, T2, and T3 versus T4, examining the influence of different social norm levels on household sorting preferences relative to no sorting across each city. In Shanghai, none of the treatment showed a significant effect. In Zhengzhou, T1 and T2 were positively linked to a preference for four-category sorting over T4, while T3 displayed a notable negative association with this preference compared to T4.

In Shijiazhuang, T1 exhibited significant positive relationships with the preference for all levels of waste sorting compared to T4 (Full version in Appendix A3). The log-likelihood ratio test showed significant differences in parameter estimates among the cities, highlighting unique variations in preferences across city pairings test. The derived equation for −2LL is: −2LL=−2(−1828.45+944.55+857.92) = 51.96 Given this, the ascertained −2LLvalue of 43.4572 surpasses the critical chi-square threshold of 42.557 with 29 degrees of freedom at a 5% significance level. This indicates that there is a significant difference in the parameter estimates between the two cities. Furthermore, analogous procedures were conducted for each pair of city combinations. The findings consistently indicated a rejection of the null hypothesis for Shanghai and Shijiazhuang, implying parameter inequality between those two cities combinations in the dataset. (Shanghai vs Zhengzhou: 42; Shanghai vs Shijiazhuang: 160; Zhengzhou vs Shijiazhuang: -12)

For willingness to pay, Figure 4.5 shows Shijiazhuang participants exhibit higher willingness to pay for all sorting levels over no sorting in T1 and T2, compared to T4, with their WTP exceeding those in Shanghai and Zhengzhou. However, the highest norm (T3) reduces WTP for sorting into 4 categories in all cities. Results also indicate a negative WTP for sorting into 4 and 2 categories in Shanghai's respondents in T1 compared to T4, contrasting with positive WTP in Zhengzhou and Shijiazhuang. For detailed information on the WTP values, please refer to the Appendix – A4.

Our research rejected Hypothesis 3, suggesting that the influence of social norms nudging on WTP for recycling is stronger in Shanghai compared to Shijiazhuang and Zhengzhou. Instead, WTP is linked to the local area's existing waste sorting levels and current waste sorting policies. Participants from cities with advocative policies show a stronger WTP response to social norms than those from cities with mandatory policies. Moreover, in areas with high waste sorting levels, social norms may not significantly boost recycling efforts. However, this experiment's comparison might lack rigor due to the higher proportion of waste sorting behaviours among Shanghai residents, which could have influenced the comparative results. Additionally, the rejection of H3 indirectly supports H2, as the increased WTP for extensive waste sorting in Shanghai isn't primarily driven by the impact of social norm nudges on its residents.

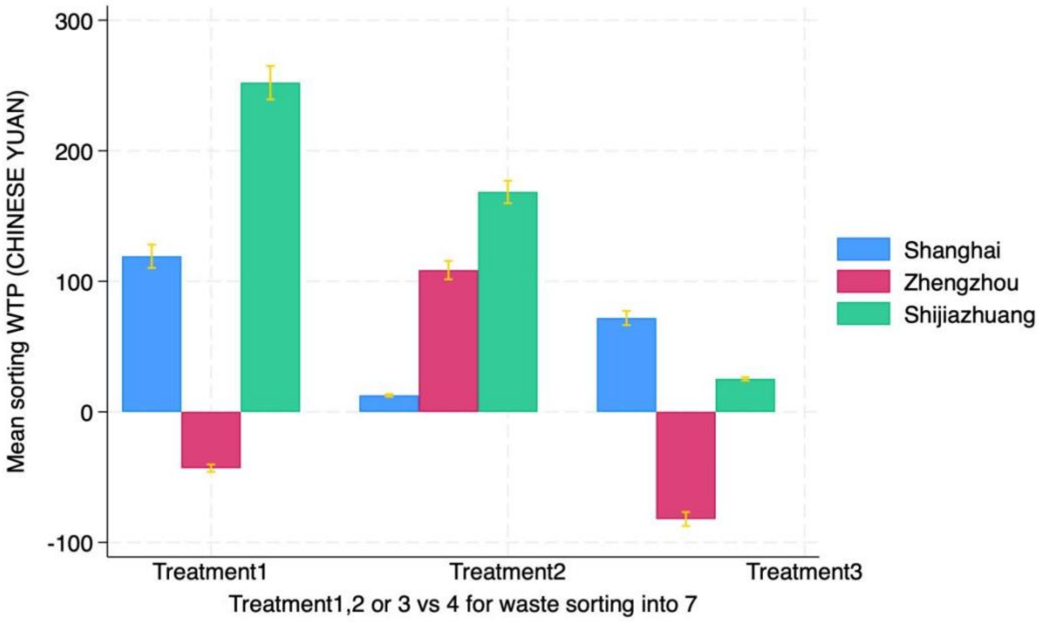
Table 4. 7: Estimation results of The Mixed Logit Model M5 for Three Cities (Interaction terms between Waste Sorting Levels and Treatments; Full version in Appendix A6)

Variables	Model M5C1 (Shanghai)	Model M5C2 (Zhengzhou)	Model M5C2 (Shijiazhuang)
	Coefficient	**Coefficient**	**Coefficient**
Non-random parameters (Interaction)			
sex_asc	.-0.67 (0.60)	.-0.05 (0.67)	.-2.37***(0.928)
age_asc	.-0.84** (0.37)	0.19 (0.36)	.-0.78** (0.39)
Sort7(vs. no in-home sorting)_T1vs.T4	0.48 (0.63)	.-0.14 (0.49)	1.15* (0.64)
Sort4(vs. no in-home sorting)_T1vs.T4	.-0.07 (0.87)	0.35 (0.11)**	1.34** (0.56)
Sort2(vs. no in-home sorting)_T1vs.T4	.-0.19 (0.57)	0.08 (0.46)	1.35** (0.65)
Sort7(vs. no in-home sorting)_T2vs.T4	0.05 (0.59)	0.35 (0.49)	0.77 (0.60)
Sort4(vs. no in-home sorting)_T2vs.T4	0.63 (0.92)	0.27*** (0.07)	0.79 (0.52)
Sort2(vs. no in-home sorting)_T2vs.T4	0.15 (0.58)	.-0.09 (0.45)	0.45 (0.6)
Sort7(vs. no in-home sorting)_T3vs.T4	0.29 (0.59)	.-0.27 (0.48)	0.12 (0.58)
Sort4(vs. no in-home sorting)_T3vs.T4	.-0.50 (0.83)	.-0.84** (0.38)	.-0.36 (0.49)
Sort2(vs. no in-home sorting)_T3vs.T4	0.34 (0.57)	.-0.62 (0.42)	0.01 (0.60)
LL at constant(s) only	.-944.54	.-857.92	.-890.02
AIC	1947.08	1773.85	1838.04
BIC	2128.92	1954.73	2019.06
pseudo R2	0.32	0.38	0.36
n (observations)	3906	3780	3798
r (respondents)	638	638	638

Notes: Standard errors are in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

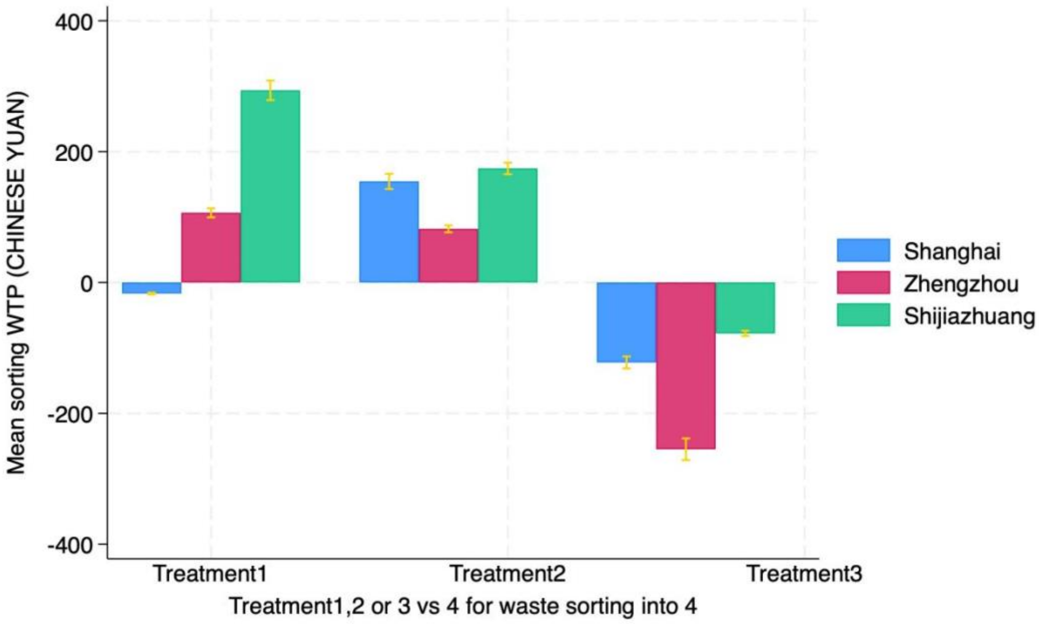
Figure 4. 5: Comparison of the Estimation results of Average Individual WTP with 95% CI for Interaction between Waste Sorting Levels and Treatments for Three cities.

Panel a: WTP for sorting into 7 categories by treatment across three cities. Treatment effects vary by city: only Treatment 2 (medium social norm) shows a consistently positive effect across all three cities.



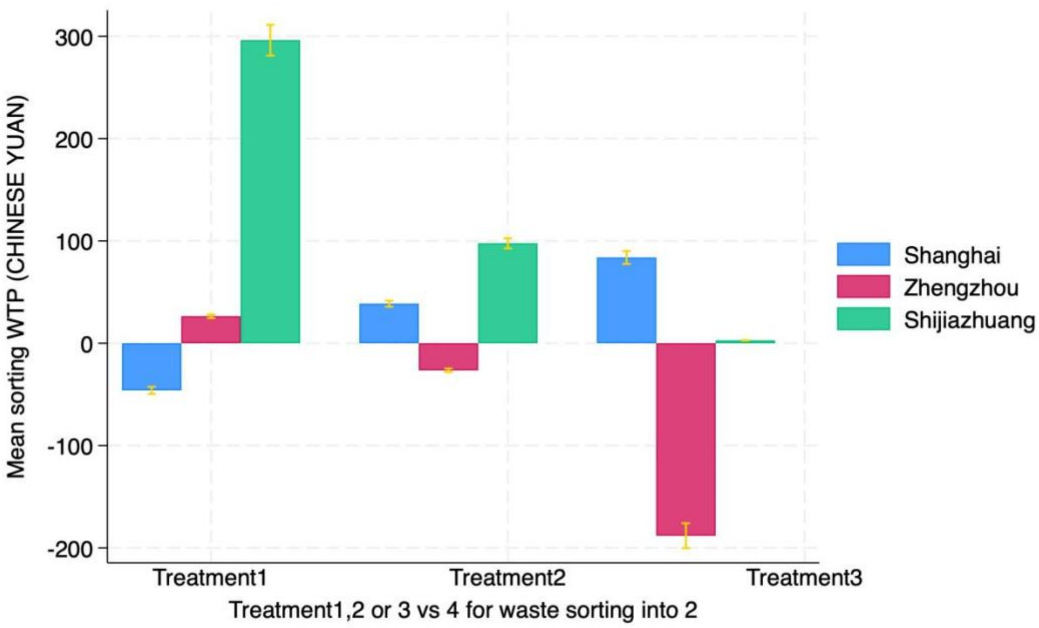
Parameter estimates represent WTP expressed in Chinese Yuan per month per household.

Panel b: WTP by treatment and city for sorting into 4 categories. Only Treatment 2 (medium social norm) increases WTP across cities; Treatment 3 (highest norm) lowers it.



Parameter estimates represent WTP expressed in Chinese Yuan per month per household.

Panel c: WTP by treatment and city for sorting into 2 categories. WTP increases only in Shijiazhuang (T1- low social norm); declines in Zhengzhou (T3 – highest norm).



Parameter estimates represent WTP expressed in Chinese Yuan per month per household.

4.4.5 H4. Waste separation habit

Given China's current policy of four main waste categories, based on Model M1 we divided respondents into two sub-groups for Model M6L and Model M6H: those who sort waste into 1-2 categories (Low self-stated waste sorting behaviour) and those sorting into 4 or more categories (High self-stated waste sorting behaviour) (Appendix A5).The subgroup models integrate interactions between different informational interventions and waste sorting attributes, with essential controls for age and gender interacting with ASC, to assess how an individual's prior recycling habit moderates the effectiveness of these nudges.

In preference space, Table 4.8 compares two sub-groups[31]—low and high self-stated waste sorting behaviour groups—assessing the impact of social norm treatments T1, T2, and T3 against T4 (the control group). The study found that in the high-level sorting group, the negative effect of T3 on choosing to sort waste into 4 categories was significant, aligning with the low-level group's findings. However, the low-level group showed significant positive effects for T2 and T1 on choosing to sort into 4 categories. (Full version in Appendix A6)

For willingness to pay, Figure 4.6 shows that respondents in the low recycling group have a significantly higher WTP for waste sorting improvements when presented with information about a low social norm (T1). (Full version in Appendix A7)

In summary, we have obtained evidence that fails to reject our hypothesis H4. For individuals currently displaying low sorting levels, the relatively modest level of descriptive recycling social norms can be more effective in enhancing their enthusiasm and positive attitude towards improving waste sorting methods.

[31] The equality of parameter estimates between high recycling group and low recycling group was evaluated using the log-likelihood ratio test. The computation of -2LL, which is twice the difference of the log-likelihood of the pooled model (both high and low recycling respondents) and the sum of the log-likelihood of high and low recycling groups, resulted in a value of 134.8. Specifically, it was computed as -2 * (-2741.882 – (-1464.76 -1209.72)) = 134.8.This calculated -2LL value (134.8) exceeded the critical chi-square value (42.557) at 29 degrees of freedom, at the 5% significance level. Hence, the null hypothesis, which assumes parameter equality between high and low recycling groups, was rejected.

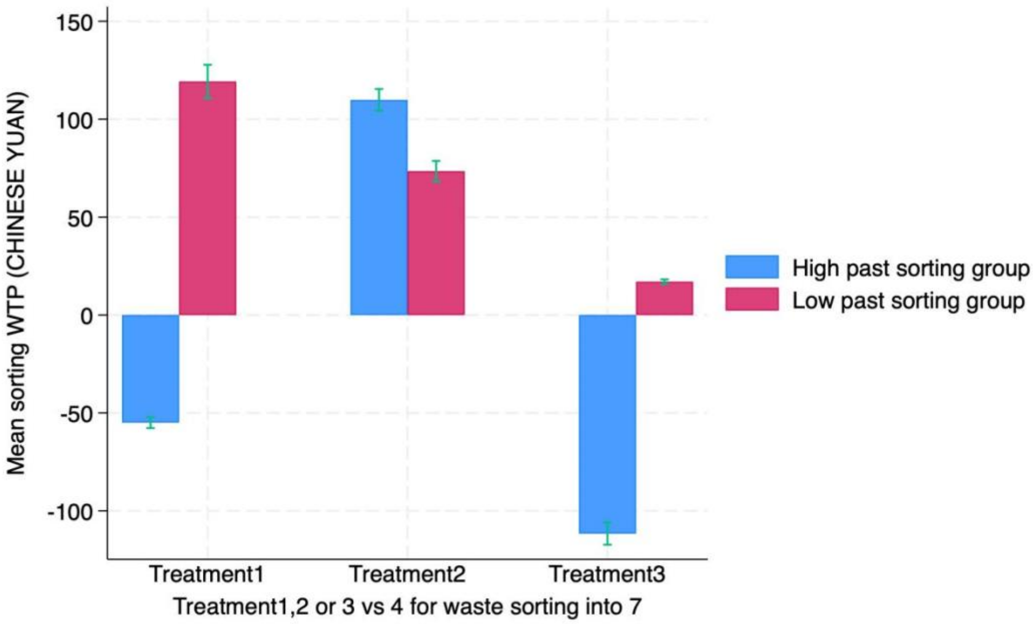
Table 4. 8: Estimation results of the mixed logit (ML) model M6 (Interaction terms between waste sorting levels and treatments) (Full version in Appendix A7)

	Low recycling group M6L		High recycling group M6H	
choice	Coefficient	Std. err.	Coefficient	Std. err.
Non-random parameters (Interaction)				
sex_asc	.-2.00***	0.57	0.83	0.55
age_asc	.-0.46*	0.28	.-0.96***	0.36
Sort7(vs. no in-home sorting)_T1vs.T4	0.38	0.35	-0.17	0.52
Sort4(vs. no in-home sorting)_T1vs.T4	0.70**	0.35	0.06	0.49
Sort2(vs. no in-home sorting)_T1vs.T4	0.47	0.39	0.19	0.45
Sort7(vs. no in-home sorting)_T2vs.T4	0.23	0.34	0.34	0.55
Sort4(vs. no in-home sorting)_T2vs.T4	0.26*	0.18	0.40	0.50
Sort2(vs. no in-home sorting)_T2vs.T4	-0.08	0.39	0.48	0.45
Sort7(vs. no in-home sorting)_T3vs.T4	0.05	0.34	-0.35	0.50
Sort4(vs. no in-home sorting)_T3vs.T4	.-0.69**	0.33	.-0.81*	0.47
Sort2(vs. no in-home sorting)_T3vs.T4	-0.33	0.37	0.09	0.43
LL at constant(s) only	-1464.75		-1209.72	
AIC	2987.51		2477.44	
BIC	3180.61		2670.36	
pseudo R2	0.30		0.42	
n (observations)	5760		5724	
r (respondents)	320		318	

Notes: Significance levels. *** p<0.01 ** p<0.05 * p<0.1.

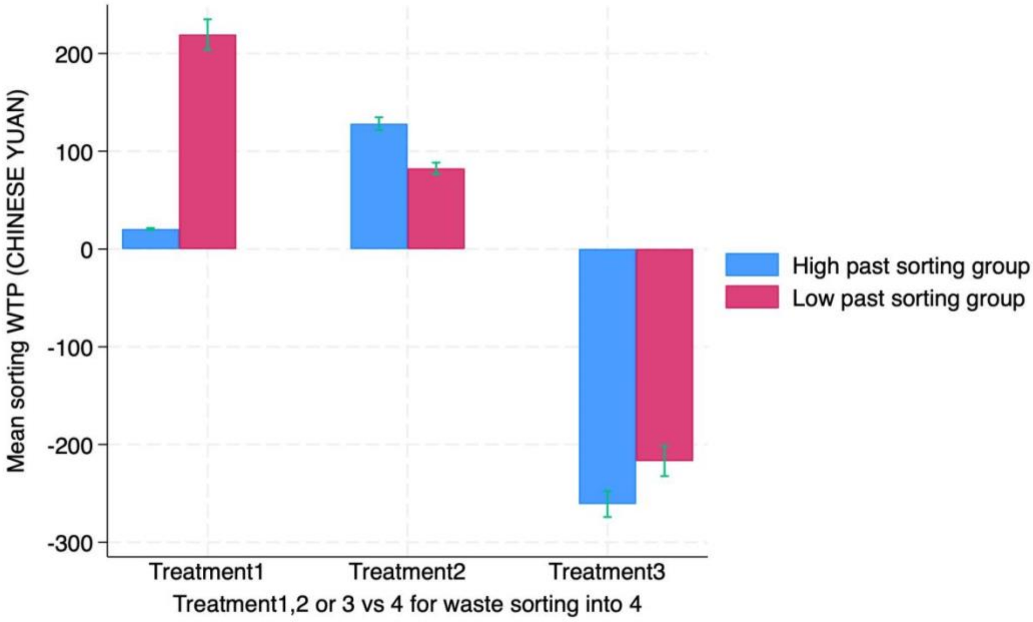
Figure 4. 6: Comparison of the Estimation results of Average Individual WTP with 95% CI between Different Treatments for Two Subgroups (Interaction terms between Waste Sorting Levels and Treatments)

Panel a: Subgroup WTP differences by treatment for 7-category sorting. WTP rises most under Treatment 2 (median social norm); effects vary between subgroups.



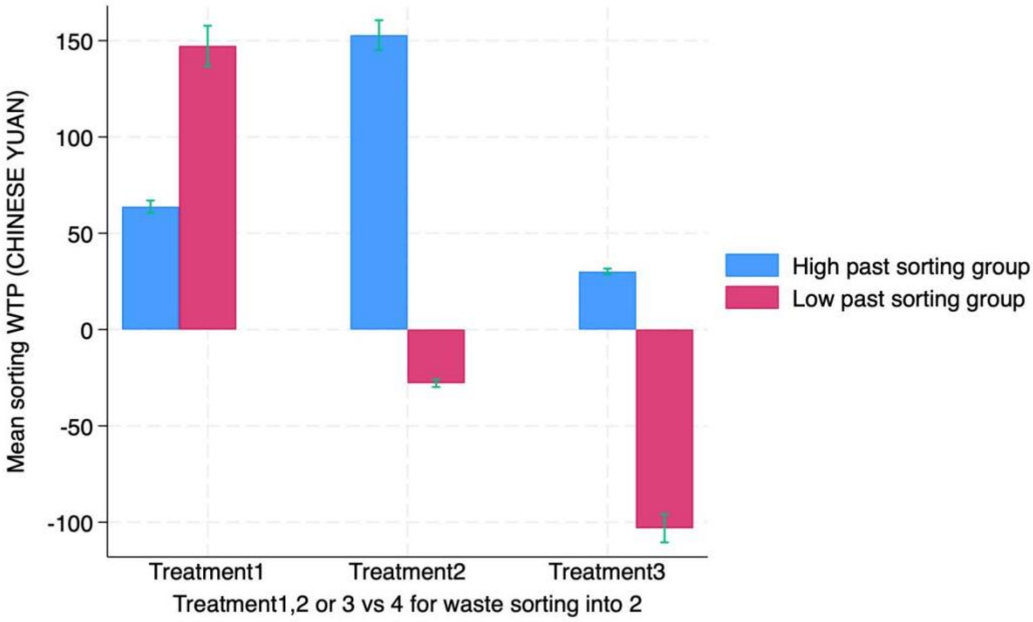
Parameter estimates represent WTP expressed in Chinese Yuan per month per household.

Panel b: Subgroup WTP by treatment for 4-category sorting. Treatment 3 (highest social norm) reduces WTP most, particularly in the high past sorting group.



Parameter estimates represent WTP expressed in Chinese Yuan per month per household.

Panel c: Subgroup WTP by treatment for 2-category sorting. WTP rises only for high sorters; Treatment 2 and 3 (median and highest social norm) reduce WTP in low sorters.



Parameter estimates represent WTP expressed in Chinese Yuan per month per household.

4.5 Latent Class

In our latent class model LC1, we explored preference heterogeneities by categorizing respondents based on their past pro-environmental behaviours (PEB) and sociodemographic variables. Initially, we included variables for those engaged in high numerous PEBs (more than three actions), high-level waste sorting behaviour (sorting more then two categories), sorting for sale (dummy variable), long-term commitment to waste sorting (more than three years), and strict adherence to waste sorting rules (from not adhering at all at 1, to fully adhering at 5, we considered the group that chose above 3), and incorporated all five sociodemographic variables.

After employing the backward method, Model LC1 classified respondents based on high PEB involvement, high-level waste sorting behaviour, sorting for sale, and demographic factors like age, gender, and location. We also factored in treatment group variables (T1-15%, T2-75%, T3-95%) as controls. Detailed definitions of these classification variables are provided in Table 4.9a. For our Latent Class (LC) model, we selected a three-class structure based on AIC, CAIC, and BIC criteria. We normalized the membership coefficients for the final latent class to zero to determine coefficients across classes (Table 4.10)[32].

[32] Table 4.10 presents the estimation results. Due to convergence issues with five latent classes, failing to converge within 72 hours, our attention is directed towards the model incorporating three latent classes. The rationale for this focus is that both the Consistent Akaike Information Criterion (CAIC) and the Bayesian Information Criterion (BIC) are minimized in this scenario as compared to the case with two latent classes and four latent classes. However, if we were to base our decision on the lowest Akaike Information Criterion (AIC), we would have identified four preference classes. Nevertheless, this interpretation resulted in a confusing pattern of estimates, replete with many statistically insignificant parameter estimates when we identified four preference classes.

Table 4. 9: Descriptive statistics of the past pro-environmental behaviour variables.

Variable	Obs	Defination	Mean	Std. dev.
Self past PEBs (5 vars)				
Involvement in green activities (1.Using recycled paper bag 2.Driving electric vehicle or riding bicycle 3.E-waste recycling, old for new services 4.Donating secondhand clothes)	638	Discrete: 1 = None of it, 2 = One of these behaviours, 3 = Two of these behaviours, 4 = Three of these behaviours, 5 = Four of these behaviours, 6 = More than that	3.96	0.95
Current numbers of sorting category.	638	Discrete: 1 = No sorting (mixed disposal), 2 = (2 categories), 3 = (4 categories), 4 = (more than 4 categories)	2.51	0.67
Selling recyclable wastes after classification	638	Dummy: 1 = Yes, 0 No	1.29	0.45
How long have you kept following the waste classification you selected	638	Discrete: 1 = Within or one year, 2 = Two or three years, 3 = Four or five years, 4 = More than five years	2.57	0.99
Adherence level to separation and disposable of recyclable materials	638	Discrete: 1 = Strongly NON-Adherence, 2 = NON-Adherence, 3 = Moderately, 4 = Adherence, 5 = Strongly Adherence	4.16	0.79

Table 4. 10: Evaluation of the tested models (Latent class)

Classes	LLF	N param	AIC	BIC	CAIC
2	-2831.178	28	5718.35	5924.12	6044.68
3	-2689.095	47	5472.19	5817.58	5841.48
4	-2636.827	66	5405.65	5890.67	5900.76
5	Convergence issue				

Main attributes levels (Preference space)

Table 4.11 reveals three latent classes in respondents' waste sorting preferences. Classes 1 and 2 show significant positive preferences for all waste sorting levels, indicating a higher inclination towards waste sorting compared to the baseline of no sorting. Conversely, respondents in class 3 do not show statistically significant preferences for enhanced waste sorting compared to the baseline scenario. All classes prefer improved waste management strategies, particularly recycling plans over incineration. Class 1, making up over half the sample (56.6%), is the only group significantly willing to pay more for additional waste recycling stations. The ASC coefficient is significant only in class 1, highlighting disutility in opting out of waste management activities. Class 2 participants exhibit the highest preference for waste sorting among all classes. Thus, class 2 is labelled as the 'High Willingness to Pay for Waste Sorting' group (56.6%), class 1 as the 'Medium Willingness to Pay' group (34.3%), and class 3 as the 'Low Willingness to Pay' group (9.3%).

Memberships (Preference space)

Table 4.11 reveals that younger individuals, males, those with experience in selling recyclable waste, and residents of Zhengzhou and Shijiazhuang are more likely to belong to classes 1 and 2, indicating a preference for improved recycling management. Moreover, those engaged in substantial pro-environmental actions (over three actions) or demonstrating higher levels of waste sorting (sorting into more than two categories) are predominantly associated with class 2. The introduction of treatments did not show a strong link with

Table 4. 11: Latent class model estimation results with three classes.

	Medium WTP sorting group (Class 1)		High WTP sorting group (Class 2)		Low WTP sorting group (reference class 3)	
	Coefficient	Std. err.	Coefficient	Std. err.	Coefficient	Std. err.
Utility function coefficients						
asc	2.91***	0.25	-1.64	1.19	-0.70**	0.30
Sort in 7 categories (vs. no in-home sorting)	0.66***	0.11	6.42***	1.18	0.29	0.26
Sort in 4 categories (vs. no in-home sorting)	1.05***	0.13	6.51***	1.20	0.29	0.30
Sort in 2 categories (vs. no in-home sorting)	0.98***	0.11	3.87***	1.11	-0.21	0.36
Waste collection point in every block (vs. collection point in every community)	0.19**	0.08	0.21	0.25	-0.15	0.26
Waste collection point in every floor (vs. collection point in every community)	-0.05	0.09	0.49	0.34	-0.34	0.29
Disposal plan-composting (vs. incineration)	0.21***	0.07	0.03	0.20	0.19	0.28
Disposal plan-recycling plants (vs. incineration)	0.62***	0.09	0.59**	0.23	0.79***	0.27
Fix coefficient						
Monthly cost per household	-0.004***	0.0006	-0.004***	0.0006	-0.004***	0.00062
Class membership Coefficients						
Male	0.80**	0.36	1.31***	0.38		
age	-0.58***	0.20	-0.43**	0.21		
Zhengzhou	1.78***	0.47	1.36***	0.50		
Shijiazhuang	1.20***	0.40	0.53	0.44		
Information that 15% of Shanghai's inhabitants recycle	-0.33	0.47	-0.33	0.51		
Information that 75% of Shanghai's inhabitants recycle	-0.78*	0.45	-0.62	0.48		
Information that 95% of Shanghai's inhabitants recycle	0.35	0.53	-0.14	0.58		

Table 4.11 (continued)

Selling recyclable wastes after classification	1.11***	0.34	1.23***	0.38	
High Current numbers of sorting category	0.17	0.37	1.65***	0.42	
High Involvement in green activities	0.41	0.35	1.10***	0.41	
_cons	2.08***	0.81	-0.18	0.97	
Shares	0.566		0.343		0.091

Notes: Significance levels. *** p<0.01 ** p<0.05 * p<0.1.

preferences for advanced waste categorization, suggesting that one-time information about Shanghai's recycling rates had a limited impact.[33] Respondents past pro-environmental behaviours and location significantly influence their preferences for waste recycling plans and aligning with their current waste sorting behaviour.

WTP (Main attributes levels)

Table 4.12 highlights the willingness-to-pay (WTP) outcomes for different attribute levels across the three classes. It is particularly noteworthy that respondents in class 2 displayed the highest WTP for all waste sorting levels, in contrast with those in classes 1 and 3 (7 Categories: 1666/171/77 YUAN; 4 Categories: 1688/273/75 YUAN; 2 Categories: 1004/255/-55 YUAN). Moreover, individuals in all three classes demonstrated a similar WTP for end disposal plan 3 (recycling plan), as compared to the baseline option of incineration (Ending Plan: 161/153/202). This suggests that three classes participants are

[33] Instead of being used as a separate control for class memberships, as suggested by Hess (2024), the variable indicating whether a respondent was exposed to the information intervention is combined with environmental protection. This interaction is designed to specifically measure the influence of "induced awareness" on the preference for environmental protection. Therefore, the modified Model LC1 (termed LC2), which incorporated interactions between waste sorting attributes and three dummy variables, accurately represented the treatment groups. The emergence of significant associations between advanced waste classification preferences and Treatments 1, 2, or 3 corresponds with Shanghai's recycling demographics and aligns with predictions made in the Mixed Logit Model.

more inclined to pay a premium for selecting the most environmentally friendly and sustainable waste disposal alternative level.

Table 4. 12: Marginal WTP of each class of the latent class model for main attribute levels

	Medium WTP sorting group (Class 1)		High WTP sorting group (Class 2)		Low WTP sorting group (reference) (Class 3)	
choice	Coefficient	Std. err.	Coefficient	Std. err.	Coefficient	Std. err.
Sort in 7 categories (vs. no in-home sorting)	170***	41.76	1665***	422.74	77	67.73
Sort in 4 categories (vs. no in-home sorting)	272***	47.77	1688***	425.03	75	77.82
Sort in 2 categories (vs. no in-home sorting)	254***	36.27	1003***	335.29	-54	94.65
Waste collection point in every block (vs. collection point in every community)	50 **	21.51	54	68.48	-39	67.71
Waste collection point in every floor (vs. collection point in every community)	-12	24.08	128	91.79	-88	76.51
Disposal plan-composting (vs. incineration)	55***	19.05	9	54.05	5	71.85
Disposal plan-recycling plants (vs. incineration)	161***	31.87	153 **	66.53	205***	78.21

Notes: Significance levels. *** p<0.01 ** p<0.05 * p<0.1.

In summary, our research highlights the significant impact of respondents' personal characteristics and general pro environmental habits on their preferences for enhanced waste recycling efforts. There's a strong correlation between individuals' existing waste management practices and their expressed preferences, indicating a tendency to adhere to established waste sorting behaviours. Moreover, the study reveals that not only does an individual's current recycling behaviour influence their preference and WTP to improve recycling efforts, but participation in other environmental actions also plays a crucial role in shaping their attitudes and willingness to pay for enhanced recycling initiatives.

4.6 Discussion and Conclusion

Increasing attention is being paid to nudges as a supplement to local environmental policy, which has become of increasing interest in the economics literature. This research uses the choice experiment method to collect individual-level data from residents in three Chinese cities. It compares Zhengzhou and Shijiazhuang, which have advocacy-based waste sorting policies, with Shanghai, where waste sorting is mandatory. The study explores whether local policy differences in these areas affect WTP for improved household recycling and if the way norm information is presented impacts WTP under different local policies.

For H1, the data suggests that Shanghai's mandatory policy significantly increases individuals' WTP for improved recycling, compared to the advocative policies in Zhengzhou and Shijiazhuang. Since participants from Shanghai exhibited a higher intention to pay more for better recycling, the potential crowding out of intrinsic motivation does not result in a net negative effect on household behaviour. This could be due to several reasons: firstly, the threat of financial penalties increases the cost of non-compliance with waste separation mandates; secondly, the official endorsement of injunctive norms for household waste sorting raises the moral cost of non-compliance; thirdly, the formation of better recycling habits reduces the effort required to engage in the behaviour; fourthly, improvements in waste separation tools for households lower the cost of waste separation and make the process more convenient, thereby encouraging waste separation practices. These factors might have a positive impact that outweighs the loss of intrinsic motivation, and the increased economic costs associated with waste classification. Additionally, evidence suggests the mandatory policy produces a positive spillover effect on individuals' WTP towards the waste collection and waste disposal stages of the recycling process. Hence, if a mandatory policy proves to be more effective, households might favor it over individual freedom if it means moving towards a safer and cleaner world where all homes act in an environmentally friendly manner (Vollaard et al., 2024).

For H2, our research has revealed unexpected outcomes. Contrary to initial assumptions, higher levels of social norms actually increase WTP for recycling. Our finding, highlighting the positive impact of low to medium social norm levels, challenges the traditional *homo economicus* model, and in line with what Czajkowski et al. (2019) observed in their study. It suggests that social norm influences play a significant role in waste sorting behaviours. Specifically, there appears to be a positive but non-linear correlation between WTP and social norm. However, when the information about social norms for waste recycling provided to participants is excessively high, it can dampen their enthusiasm. This phenomenon can be explained by three potential reasons: a significant gap might exist between an individual's initial contribution to recycling and a descriptive social norm. This disparity could be so substantial that the costs and efforts required to reach this norm outweigh the benefits of social approval. Alternatively, an individual's contribution to recycling might already exceed this norm, leading to a conformity effect where the individual feels they are already doing more than what is expected in their social circle. In addition, individual might perceive that a sufficient number of people are already participating in waste sorting and recycling, and that their participation is not essential to achieve the objective of environmental improvement, potentially due to the free-riding effect. However, the density distribution highlights the high degree of heterogeneity in how people respond to each level of social norms. This underscores the significant variation in the impact of social norms on pro-environmental behaviours across different demographic groups.

Our research has rejected H3, indicating that the impact of social norms on WTP for recycling is not necessarily stronger in Shanghai compared to Shijiazhuang and Zhengzhou. Instead, WTP is more closely linked to the existing waste sorting practices in the local area. In cities where advocative waste sorting policies are in place, residents showed a higher WTP response to social norm influences compared to those in cities with mandatory policies. However, the comparison's validity might be restricted due to the higher engagement levels in waste sorting among Shanghai residents compared to the other two cities. Additionally, the rejection of H3 indirectly supports H2, as the increased WTP for extensive waste sorting in Shanghai isn't primarily driven by the impact of social norm nudges on its residents.

For H4, for individuals with currently low waste sorting levels compared to those with high levels, a relatively low to medium level of social norms is more effective in boosting their enthusiasm and willingness to enhance their waste sorting practices. This indicates that the reaction of respondents to communicated social norm information is contingent on their present engagement level with household recycling. Additionally, we discover that the highest levels of social norms negatively impact recycling behaviour. This evidence supports the conclusion drawn in H2.

However, one noteworthy limitation of our research: in our stated preference experiments, particularly the geographic proximity test, we found no statistical evidence to suggest that social norms communicated in relation to a local reference group have more nuanced effects than anticipated. This may stem from the limited validity of our experimental design, influenced by the higher baseline of waste sorting behaviour in Shanghai compared to Zhengzhou and Shijiazhuang. Moreover, we chose to use only actual social norm information from Shanghai practices to avoid unethical practices like providing false information to participants, a concern known as "deceptive nudges" highlighted by Croson and Treich (2014). However, in tests T1-T3, the data provided varied, showing the percentage of waste sorted in Shanghai across different years, the varying years could have unexpectedly influenced on individuals' stated preferences. Another limitation is that this paper concentrates on the short-term effects of social norm nudges. To assess enduring changes in recycling behaviour, further analysis would need to be conducted at subsequent time intervals. Consequently, it is recommended that future research explore the long-term impacts of these interventions. In addition, despite the potential for self-selection bias in our sample, which may limit its representativeness of the broader population, it still offers valuable insights into the motivations behind household recycling behaviours.

In summary, the research clearly addresses RO1, showing that Shanghai's mandatory recycling policy significantly increases residents' willingness-to-pay (WTP) compared to the voluntary approaches in Zhengzhou and Shijiazhuang. The mandatory policy raises the cost of non-compliance, strengthens moral responsibility through official endorsement, encourages habit formation, and provides improved recycling infrastructure. These benefits outweigh potential reductions in intrinsic motivation, leading households to favour mandatory policies for achieving more sustainable recycling practices. Regarding RO2, our results indicate that social norm nudges positively influence WTP, but their effectiveness varies. Moderate social norm messages effectively boost recycling intentions (H2), while excessively strong messages can decrease enthusiasm. Contrary to expectations, geographical proximity or policy type does not significantly amplify the effect of these norms (H3). Instead, existing local recycling practices appear more influential. Finally, the impact of social norms depends on prior recycling behaviour (H4): individuals with initially low recycling engagement respond positively to moderate norm cues but negatively to overly strong social pressure. Thus, careful consideration of social norm intensity and audience characteristics is critical when designing nudges to encourage recycling.

4.7 Appendix A

Table 4. 13: (A1) Estimation results of the mixed logit (ML) model M4 (Interaction terms between waste sorting levels and treatments).

choice	Coefficient	Std. err.
Non-random parameters		
Interaction		
Sort7(vs. no in-home sorting)_T1vs.T4	0.30	0.31
Sort4(vs. no in-home sorting)_T1vs.T4	0.56**	0.28
Sort2(vs. no in-home sorting)_T1vs.T4	0.34	0.29
Sort7(vs. no in-home sorting)_T2vs.T4	0.34	0.31
Sort4(vs. no in-home sorting)_T2vs.T4	0.51*	0.27
Sort2(vs. no in-home sorting)_T2vs.T4	0.17	0.29
Sort7(vs. no in-home sorting)_T3vs.T4	0.03	0.29
Sort4(vs. no in-home sorting)_T3vs.T4	.-0.51**	0.26
Sort2(vs. no in-home sorting)_T3vs.T4	-0.16	0.28
Random parameters		
asc	3.26***	0.39
Sort in 7 categories (vs. no in-home sorting)	2.00***	0.23
Sort in 4 categories (vs. no in-home sorting)	2.29***	0.22
Sort in 2 categories (vs. no in-home sorting)	1.45***	0.21
Waste collection point in every block (vs. collection point in every community)	0.24***	0.09
Waste collection point in every floor (vs. collection point in every community)	0.10	0.10
Disposal plan-composting (vs. incineration)	0.31***	0.08
Disposal plan-recycling plants (vs. incineration)	1.02***	0.11
Transferred ln (Monthly cost per household)	.-0.01***	0.001
SD		
asc	.-2.83***	0.33
Sort in 7 categories (vs. no in-home sorting)	1.47***	0.14
Sort in 4 categories (vs. no in-home sorting)	-0.29	0.37
Sort in 2 categories (vs. no in-home sorting)	0.79***	0.18
Waste collection point in every block (vs. collection point in every community)	0.07	0.60
Waste collection point in every floor (vs. collection point in every community)	1.04***	0.14
Disposal plan-composting (vs. incineration)	0.63***	0.16
Disposal plan-recycling plants (vs. incineration)	0.88***	0.15
Transferred ln (Monthly cost per household)	0.05***	0.02
LL at constant(s) only	.-2747.02	

AIC	5548.03
BIC	5746.45

Table 4.13 (continued)

pseudo R2	.346
n (observations)	11484
r (respondents)	638

Notes: *** p<0.01 ** p<0.05 * p<0.1.

Table 4. 14: (A2) Estimation results of average individual WTP (Interaction terms between waste sorting levels and treatments).

Interaction WTP	Individual	Average individual WTP	Std. dev.	[95% conf.	interval]
Sort7(vs. no in-home sorting)_T1vs.T4	638	97	55.01	93.00	101.54
Sort4(vs. no in-home sorting)_T1vs.T4	638	180	102.11	172.63	188.48
Sort2(vs. no in-home sorting)_T1vs.T4	638	109	62.12	105.02	114.66
Sort7(vs. no in-home sorting)_T2vs.T4	638	107	60.99	103.11	112.57
Sort4(vs. no in-home sorting)_T2vs.T4	638	164	92.99	157.21	171.64
Sort2(vs. no in-home sorting)_T2vs.T4	638	54	30.91	52.25	57.05
Sort7(vs. no in-home sorting)_T3vs.T4	638	9	5.46	9.24	10.08
Sort4(vs. no in-home sorting)_T3vs.T4	638	-162	91.78	-169.41	-155.17
Sort2(vs. no in-home sorting)_T3vs.T4	638	-51	28.97	-53.47	-48.97

Table 4. 15: (A3) Estimation results of the mixed logit (ML) model M5 for three cities (Interaction terms between waste sorting levels and treatments).

Variables	Model M5C1 (Shanghai)	Model M5C2 (Zhengzhou)	Model M5C2 (Shijiazhuang)
	Coefficient	Coefficient	Coefficient
Non-random parameters (Interaction)			
sex_asc	.-0.67	.-0.05	.-2.37***
	(0.60)	(0.67)	(0.92)
age_asc	.-0.84**	0.19	.-0.78**
	(0.37)	(0.36)	(0.39)
Sort7(vs. no in-home sorting)_T1vs.T4	0.48	.-0.14	1.15*
	(0.63)	(0.49)	(0.64)
Sort4(vs. no in-home sorting)_T1vs.T4	.-0.06	0.35	1.34**
	(0.87)	(0.12)**	(0.56)
Sort2(vs. no in-home sorting)_T1vs.T4	.-0.18	0.09	1.35**
	(0.57)	(0.46)	(0.65)
Sort7(vs. no in-home sorting)_T2vs.T4	0.05	0.36	0.77
	(0.59)	(0.49)	(0.60)
Sort4(vs. no in-home sorting)_T2vs.T4	0.63	0.27***	0.79
	(0.92)	(0.07)	(0.52)
Sort2(vs. no in-home sorting)_T2vs.T4	0.16	.-0.08	0.45
	(0.58)	(0.45)	(0.62)
Sort7(vs. no in-home sorting)_T3vs.T4	0.29	.-0.27	0.12
	(0.59)	(0.48)	(0.58)
Sort4(vs. no in-home sorting)_T3vs.T4	.-0.49	.-0.84**	.-0.36
	(0.83)	(0.38)	(0.49)
Sort2(vs. no in-home sorting)_T3vs.T4	0.34	.-0.62	0.01
	(0.57)	(0.42)	(0.60)
Random parameters			
Sort in 7 categories (vs. no in-home sorting)	2.53***	1.64***	1.61***
	(0.49)	(0.40)	(0.45)
Sort in 4 categories (vs. no in-home sorting)	3.10***	2.29***	2.10***
	(0.74)	(0.31)	(0.41)
Sort in 2 categories (vs. no in-home sorting)	1.23***	1.89***	1.05**
	(0.45)	(0.35)	(0.46)
Waste collection point in every block (vs. collection point in every	0.41**	0.25	.-0.18
community)	(0.18)	(0.28)	(0.23)
Waste collection point in every floor (vs. collection point in every	0.48*	0.14	.-0.23
community)	(0.28)	(0.37)	(0.16)
Disposal plan-composting (vs. incineration)	0.58***	.-0.002	0.44
	(0.22)	(0.15)	(0.1723422)
Disposal plan-recycling plants (vs. incineration)	1.41***	0.73***	1.13***
	(0.27)	(0.22)	(0.19)

asc	6.20***	3.35*	10.49***
	(1.91)	(1.90)	(2.81)

Table 4.13 (continued)

Transfered ln (Monthly cost per household)	.-0.01***	.-0.005***	.-0.006***
	(0.003)	(0.001)	(0.002)
SD			
Sort in 7 categories (vs. no in-home sorting)	2.09***	1.31***	0.97***
	(0.33)	(0.24)	(0.30)
Sort in 4 categories (vs. no in-home sorting)	.-2.37***	.-0.02	0.01
	(0.67)	(0.52)	(0.34)
Sort in 2 categories (vs. no in-home sorting)	.-0.01	.-0.07	1.59***
	(0.83)	(0.57)	(0.29)
Waste collection point in every block (vs. collection point in every	0.58	0.12	0.98***
community)	(0.36)	(0.46)	(0.31)
Waste collection point in every floor (vs. collection point in every	1.85***	0.82***	0.87***
community)	(0.38)	(0.24)	(0.24)
Disposal plan-composting (vs. incineration)	.-1.05***	.-0.44	0.93***
	(0.31)	(0.28)	(0.25)
Disposal plan-recycling plants (vs. incineration)	1.23***	.-0.29	1.06***
	(0.38)	(0.54)	(0.24)
asc	2.02***	2.71***	3.26***
	(0.45)	(0.89)	(0.76)
Transferred ln (Monthly cost per household)	0.07*	0.01**	0.01***
	(0.04)	(0.005)	(0.004)
LL at constant(s) only	.-944.54	.-857.92	.-890.02
AIC	1947.08	1773.84	1838.04
BIC	2128.92	1954.73	2019.07
pseudo R2	0.32	0.38	0.36
n (observations)	3906	3780	3798
r (respondents)	638	638	638

Notes: Standard errors are in parentheses. *** p<0.01 ** p<0.05 * p<0.1.

Table 4. 16: (A4) Estimation results of average individual WTP for three cities (Interaction terms between waste sorting levels and treatments in each city).

Interaction WTP	Individual	Average individual WTP	Std. dev.	[95% conf.	interval]
ModelM5C1 (SHANGHAI)					
Sort7(vs. no in-home sorting)_T1vs.T4	217	119	67.07	110.28	128.13
Sort4(vs. no in-home sorting)_T1vs.T4	217	-16	9.42	-17.99	-15.49
Sort2(vs. no in-home sorting)_T1vs.T4	217	-46	25.92	-49.52	-42.63
Sort7(vs. no in-home sorting)_T2vs.T4	217	12	7.10	11.67	13.56
Sort4(vs. no in-home sorting)_T2vs.T4	217	154	86.95	142.94	166.08
Sort2(vs. no in-home sorting)_T2vs.T4	217	38	21.72	35.71	41.49
Sort7(vs. no in-home sorting)_T3vs.T4	217	71	40.46	66.51	77.28
Sort4(vs. no in-home sorting)_T3vs.T4	217	-122	68.76	-131.34	-113.04
Sort2(vs. no in-home sorting)_T3vs.T4	217	83	47.13	77.47	90.02
ModelM5C2 (ZHENGZHOU)					
Sort7(vs. no in-home sorting)_T1vs.T4	210	-43	20.58	-45.89	-40.33
Sort4(vs. no in-home sorting)_T1vs.T4	210	106	50.87	99.67	113.44
Sort2(vs. no in-home sorting)_T1vs.T4	210	26	12.59	24.68	28.08
Sort7(vs. no in-home sorting)_T2vs.T4	210	108	51.84	101.57	115.59
Sort4(vs. no in-home sorting)_T2vs.T4	210	82	39.15	76.72	87.32
Sort2(vs. no in-home sorting)_T2vs.T4	210	-26	12.64	-28.18	-24.76
Sort7(vs. no in-home sorting)_T3vs.T4	210	-82	39.21	-87.43	-76.83
Sort4(vs. no in-home sorting)_T3vs.T4	210	-255	121.69	-271.34	-238.43
Sort2(vs. no in-home sorting)_T3vs.T4	210	-188	89.78	-200.23	-175.94
ModelM5C3 (SHIJIAZHUANG)					
Sort7(vs. no in-home sorting)_T1vs.T4	211	252.14	94.45	239.39	264.88
Sort4(vs. no in-home sorting)_T1vs.T4	211	293.64	109.99	278.80	308.48
Sort2(vs. no in-home sorting)_T1vs.T4	211	296.11	110.92	281.14	311.08
Sort7(vs. no in-home sorting)_T2vs.T4	211	168.41	63.08	159.90	176.93
Sort4(vs. no in-home sorting)_T2vs.T4	211	174.28	65.28	165.47	183.09
Sort2(vs. no in-home sorting)_T2vs.T4	211	97.63	36.57	92.69	102.56
Sort7(vs. no in-home sorting)_T3vs.T4	211	25.27	9.46	23.99	26.55
Sort4(vs. no in-home sorting)_T3vs.T4	211	-77.82	29.15	-81.76	-73.89
Sort2(vs. no in-home sorting)_T3vs.T4	211	2.76	1.035	2.62	2.90

Table 4. 17: (A5) Descriptive statistics of the past pro-environmental behaviour variables.

Variable	Obs	Definition	Mean	Std. dev.
Current numbers of sorting category.	638	Discrete: 1 = No sorting (mixed disposal), 2 = (2 categories), 3 = (4 categories), 4 = (more than 4 categories)	2.51	0.67

Table 4. 18: (A6) Estimation results of the mixed logit (ML) model M6 (Interaction terms between waste sorting levels and treatments).

	Low recycling group M6L		High recycling group M6H	
choice	Coefficient	Std. err.	Coefficient	Std. err.
Non-random parameters (Interaction)				
sex_asc	.-2.00***	0.57	0.83	0.55
age_asc	.-0.46*	0.28	.-0.95***	0.36
Sort7(vs. no in-home sorting)_T1vs.T4	0.38	0.361	-0.17	0.52
Sort4(vs. no in-home sorting)_T1vs.T4	0.69**	0.35	0.06	0.49
Sort2(vs. no in-home sorting)_T1vs.T4	0.47	0.39	0.19	0.45
Sort7(vs. no in-home sorting)_T2vs.T4	0.23	0.35	0.34	0.55
Sort4(vs. no in-home sorting)_T2vs.T4	0.26	0.34	0.39	0.49
Sort2(vs. no in-home sorting)_T2vs.T4	-0.08	0.38	0.47	0.45
Sort7(vs. no in-home sorting)_T3vs.T4	0.05	0.34	-0.34	0.50
Sort4(vs. no in-home sorting)_T3vs.T4	.-0.69**	0.33	.-0.81*	0.46
Sort2(vs. no in-home sorting)_T3vs.T4	-0.32	0.37	0.09	0.43
Random parameters				
asc	8.47***	1.74	4.73***	1.74
Sort in 7 categories (vs. no in-home sorting)	1.11***	0.25	3.46***	0.45
Sort in 4 categories (vs. no in-home sorting)	1.71***	0.25	3.56***	0.46

Table 4.13 (continued)

Sort in 2 categories (vs. no in-home sorting)	1.53***	0.27	1.39***	0.35
Waste collection point in every block (vs. collection point in every community)	0.25**	0.12	0.19	0.15
Waste collection point in every floor (vs. collection point in every community)	0.03	0.13	0.18	0.16
Disposal plan-composting (vs. incineration)	0.21**	0.11	0.37***	0.14
Disposal plan-recycling plants (vs. incineration)	0.73***	0.14	1.41***	0.19
Transfered ln (Monthly cost per household)	.-0.01***	0.003	.-0.006***	0.001
SD				
asc	2.59***	0.52	.-2.35***	0.46
Sort in 7 categories (vs. no in-home sorting)	0.97***	0.18	1.83***	0.26
Sort in 4 categories (vs. no in-home sorting)	-0.03	0.34	0.77**	0.33
Sort in 2 categories (vs. no in-home sorting)	0.88***	0.24	-0.27	0.76
Waste collection point in every block (vs. collection point in every community)	0.07	0.29	0.63**	0.31
Waste collection point in every floor (vs. collection point in every community)	0.92***	0.17	1.18***	0.23
Disposal plan-composting (vs. incineration)	0.45*	0.25	0.86***	0.25
Disposal plan-recycling plants (vs. incineration)	0.82***	0.18	1.16***	0.24
Transfered ln (Monthly cost per household)	0.11	0.07	0.02**	0.008
LL at constant(s) only	-1464.75		-1209.72	
AIC	2987.51		2477.44	
BIC	3180.61		2670.36	
pseudo R2	0.31		0.42	
n (observations)	5760		5724	
r (respondents)	320		318	

Notes: Significance levels. *** p<0.01 ** p<0.05 * p<0.1.

Table 4. 19: (A7) Estimation results of individual level MWTP for Interaction terms between waste sorting levels and treatments (preference space model M6 (H,L)).

Interaction terms	Respondents	WTP	Std. dev.	[95% conf.	interval]
ModelM12H (High sorting group)					
Sort7(vs. no in-home sorting)_T1vs.T4	318	-54	25.34	-57	-52
Sort4(vs. no in-home sorting)_T1vs.T4	318	20	9.41	19	21
Sort2(vs. no in-home sorting)_T1vs.T4	318	64	29.39	61	66
Sort7(vs. no in-home sorting)_T2vs.T4	318	110	50.62	105	114
Sort4(vs. no in-home sorting)_T2vs.T4	318	128	59.08	122	133
Sort2(vs. no in-home sorting)_T2vs.T4	318	153	70.44	146	158
Sort7(vs. no in-home sorting)_T3vs.T4	318	-112	51.45	-116	-107
Sort4(vs. no in-home sorting)_T3vs.T4	318	-261	120.22	-271	-250
Sort2(vs. no in-home sorting)_T3vs.T4	318	30	13.88	28	31
ModelM12L (Low sorting group)					
Sort7(vs. no in-home sorting)_T1vs.T4	320	119	77.33	110	127
Sort4(vs. no in-home sorting)_T1vs.T4	320	219	142.22	203	234.
Sort2(vs. no in-home sorting)_T1vs.T4	320	147	95.45	136	157
Sort7(vs. no in-home sorting)_T2vs.T4	320	73	47.60	68	78
Sort4(vs. no in-home sorting)_T2vs.T4	320	82	53.45	76	88
Sort2(vs. no in-home sorting)_T2vs.T4	320	-27	18.04	-29	-26
Sort7(vs. no in-home sorting)_T3vs.T4	320	17	11.01	15	18
Sort4(vs. no in-home sorting)_T3vs.T4	320	-217	140.61	-232	-201
Sort2(vs. no in-home sorting)_T3vs.T4	320	-103	66.87	-110	-96

Chapter 5

Exploring the influence of Long term life goals on preferences and willingness to pay for household recycling in China, using the theory of planned behaviour.

5.1 Abstract

This chapter builds on survey data from the previous chapter to explore whether integrating goal theories can improve the Theory of Planned Behaviour (TPB) in explaining recycling preferences. Using a choice experiment conducted with households in Shanghai, Zhengzhou, and Shijiazhuang, China, the study investigates two key research objectives (RO3 and RO4). RO3 examines whether TPB factors—attitudes, subjective norms, and perceived behavioural control—positively influence individuals' willingness-to-pay (WTP) for recycling (H1). RO4 explores whether broader life goals, such as altruistic aims to benefit future generations, influence recycling preferences either directly or indirectly through TPB variables (H2). A Hybrid Mixed Logit (HMXL) model is applied to analyse these relationships. The findings confirm that TPB variables significantly shape recycling intentions. Moreover, normative life goals driven by altruistic or moral considerations positively affect recycling choices, both directly and indirectly through TPB factors, while hedonic or gain-oriented goals show little positive impact. Integrating personal normative goals thus offers a more comprehensive explanation of household recycling decisions.

The chapter is structured as follows: Section 5.2 introduces the research questions, Section 5.3 details the survey and methodology, Section 5.4 presents the estimation results, and Section 5.6 discusses the findings and conclusions.

5.2 Introduction

Motivation

The idea for this chapter draws inspiration from Allport and Postman (1947) work, which emphasised the importance of psychologists recognising ‘intention’ as a key concept. His aim was to gain a deeper understanding of the motives and processes that drive individual behaviour. He highlighted the distinction between intentions and innate drives or instincts, suggesting that psychologists explore the "private worlds of desire, aspiration, and conscience." He further argued that comprehending current behavioural intentions as means for achieving long-term aspirations enhances the interpretation and direction of everyday actions; essentially, our current goals often serve our broader, long-term intentions.

In our study, we argue that Allport’s views on the link between long-term goals and the intention to engage in current actions—such as waste sorting—are not fully acknowledged in mainstream cognitive-behavioural theories. Specifically, the Theory of Planned Behaviour (Ajzen, 1985; Ajzen, 1991), which is widely applied to pro-environmental behaviours, does not sufficiently account for this connection. The Theory of Planned Behaviour argues that behaviours are influenced by individuals' attitudes (i.e. whether the behaviour is considered positively or negatively), subjective norms (i.e. the social pressure perceived by the individual to engage in a certain behaviour), perceived behavioural control (i.e. the ease or difficulty of performing the behaviour), and behavioural intention (Bandura, 1977; Bandura, 1982; Bandura and Wessels, 1997; Ajzen, 1998).

In addition, The consensus among many theorists is that goals are structured in a hierarchical manner, where broad, high-level goals are broken down into more concrete, lower-level objectives that eventually guide physical actions (Pribram et al., 1960; Hyland, 1988; Powers and Powers, 1973). Several theories provide frameworks for explaining goal-directed behaviour. These include Perceptual Control Theory (Carver and Scheier, 2012), which emphasises how individuals regulate their actions; Action Control Theory (Kuhl, 1985), which investigates how people initiate and sustain actions; Goal Systems Theory (Kruglanski et al., 2002), which examines the structure and interaction of goals; and Goal-

Framing Theory (Steg & Lindenberg, 2007), which highlights how different goals influence decision-making.

Control Theory views behaviour as a process where individuals act to minimise the discrepancy between their current state and a desired standard or goal. Additionally, individual goals have been more specifically categorized into four types: 1) Current Concerns (e.g., eating lunch), 2) Personal Projects (e.g., learning how to ski), 3) Life Tasks (e.g., getting good grades), and 4) Personal Strivings (e.g., doing as many nice things for people as I can) (Klinger, 1975; Little, 1983; Zirkel and Cantor, 1990; Emmons, 1986). In our study, life goals are defined as Personal Strivings, which are characterised by recurring, long-term goal-pursuing behaviours (Emmons, 1986). In our case, according to Carver and Scheier (2001), Control Theory, self-related goals, or life goals (e.g., "become a responsible citizen"), are positioned at the top of the hierarchy; abstract action goals (principles; e.g., "actively participate in waste sorting") are in the middle, and specific action plans (programmes; e.g., "place recyclable items and organic waste in separate bins") are at the bottom.

Additionally, Goal-Framing Theory highlights the hierarchical nature of goals while taking into account the modular aspects of human perception, thinking, and decision-making. Heath and Gifford (2002) indicate that various factors influence human decision-making, with three primary higher-order goals playing a key role: hedonic, normative, and gain-oriented goals (Lindenberg, 2001; Lindenberg, 2006). Hedonic goals concentrate on immediate satisfaction, such as minimising effort or seeking pleasure. Gain-oriented goals involve securing and protecting resources, including wealth and social status. Normative goals compel individuals to act in accordance with societal expectations, such as demonstrating kindness or supporting environmental initiatives. This raises the question: If waste sorting behaviour is considered altruistic, but someone's life pursuit is to become wealthy, would their long-term life goal affect the effort they put into waste sorting?

Objectives

Therefore, the aim of this paper is to investigate whether TPB theories should be enhanced with insights from goal theories by considering pro-environmental behaviour. Specifically, it examines whether different life goals directly influence stated preferences for recycling or indirectly affect them through current attitudes, perceived behavioural control, and social norms. The empirical context involves choices regarding household waste contracts and recycling actions in China. To explore the relationships between individuals' Theory of Planned Behaviour variables, life goals (various types of long-term intentions, such as happiness (hedonic goals), success (gain-oriented goals), and benefiting future generations (normative goals)), demographic factors, and decision-making preferences for recycling, we employ the Hybrid Mixed Logit (HMXL) model. This approach allows us to integrate both measurable characteristics of the decision-maker and other elements that cannot be directly measured, such as attitudes towards recycling and differing tendencies in life goals. Figure 5.1 provides a clear visual framework for this chapter, showing the proposed relationships between long-term life goals, variables from the Theory of Planned Behaviour (TPB)—attitudes, subjective norms, and perceived behavioural control—and recycling intentions, measured using stated preferences from discrete choice experiments (DCE) explained later. This chapter addresses two key research questions. First, it examines whether attitudes, subjective norms, and perceived behavioural control positively affect recycling preferences individually or together. Second, recognising that goals are hierarchical—with broad, long-term goals guiding specific short-term actions—it explores whether self-reported life goals (such as benefiting future generations) influence recycling preferences directly or indirectly through these TPB variables. As mentioned in Chapter1, this chapter explores the relationship between recycling preferences, the Theory of Planned Behaviour (TPB), and personal goal theories, focusing on two research objectives: RO3 and RO4. Specifically, RO3 tests whether TPB variables—attitudes, subjective norms, and perceived behavioural control—positively shape individuals' recycling choices (H1). RO4 examines whether broader life goals, such as benefiting future generations, affect recycling preferences either directly or indirectly through these TPB factors (H2).

According to Hanley et al. (2009), evaluating environmental values in economic terms is challenges due to their non-market nature. Consequently, stated preference surveys are frequently employed to assess individual preferences. These surveys determine the willingness to pay (WTP) for goods not traded in the market, which then measures the value that individuals place on these goods. Choice Experiments (CE) are particularly flexible among stated preference approaches because they assess the individual attributes of a good or service, allowing for a wide range of scenarios (Hanley et al., 2001). Therefore, we use preference parameters in the choice model as indicators of people's behavioural intentions regarding recycling.

In this paper, we contribute to the behavioural literature on choices by studying the effect of the theory of planned behaviour (TPB) on environmental choices. A novel aspect of our approach is that we model planned behaviour and life goals as dependent on latent and unobservable characteristics of human behaviour, which can only be approximated through stated measures like Likert scales. The HMXL is a simultaneous equation model in which latent variables serve as predictors for TPB and life goal indicators, as well as for the choice model. This way, TPB, life goals, and CE are interconnected through these latent variables. Firstly, we investigated whether self-reported different types of life goals can influence stated preferences for recycling. Additionally, this study examined whether incorporating life goals into our analysis can enhance our understanding of how individuals' attitudes, perceived behavioural control, and social norms regarding their current behaviours are formed, thus illuminating the intrinsic mechanisms that drive their behaviours. Finally, we explored whether environmental knowledge, living environment, and sociodemographic characteristics can indirectly influence preferences for recycling through the TPB latent variables.

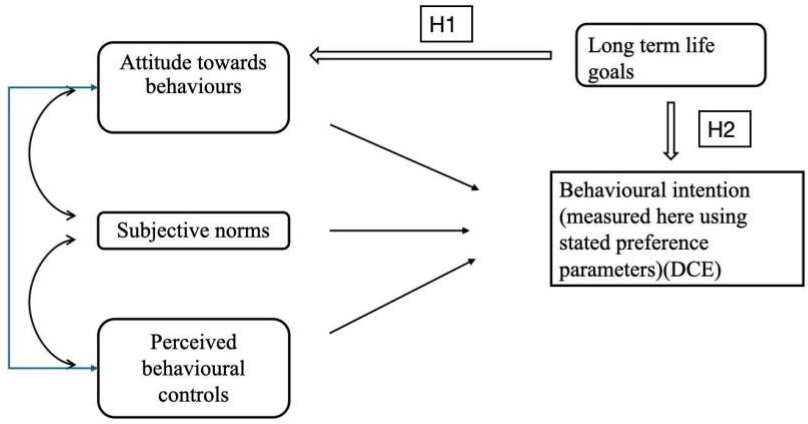
Conceptual Model Framework

As illustrated by the literature summarised above, this study assumes two fundamental propositions of goal theories: that goals are hierarchically organised and may sometimes conflict with one another. Specifically, we propose that an individual’s life goals, situated at the apex of the goal hierarchy, can influence their engagement in specific behaviours, such as waste sorting. To investigate this, we adopted the framework of Goal-Framing Theory (GFT), which posits that multiple goals concurrently shape behaviour. According to GFT, life goals are classified into three categories: hedonic goals (prioritising personal comfort or pleasure), gain goals (focused on resources or social status), and normative goals (motivated by moral or social responsibilities).

We explored how these overarching life goals interact with the key factors outlined in the Theory of Planned Behaviour (TPB), including attitudes, subjective norms, and perceived behavioural control. By examining these interactions, we aim to understand their influence on recycling intentions, which involve a willingness to pay for enhanced recycling plans and the adoption of more effective waste sorting practices. In simpler terms, we consider how life goals, shaped by the pursuit of enjoyment, success, or moral responsibility, influence individuals' attitudes and intentions towards recycling and their choices to engage in improved waste sorting behaviours.

According to the Theory of Planned Behaviour (TPB), Control Theory, and Goal-Framing Theory (GFT), along with the study's objectives, the conceptual model for the current research is illustrated in Figure5. 1. This model examines whether the causal influences proposed by TPB affect stated preferences. Additionally, it assesses both the direct effects of life goals on stated recycling preferences and their indirect effects through TPB components (attitudes towards behaviour, subjective norms, and perceived behavioural control) acting as mediators.

Figure 5. 1: Conceptual Model Framework of Current Study



Hypothesis

The Theory of Planned Behaviour (TPB) has received significant empirical support, with meta-analytical evidence indicating that attitudes, subjective norms, and perceived behavioural control account for a considerable portion of the variance in intentions, ranging from 30 to 50 per cent (Armitage and Conner, 2001; Sheeran and Taylor, 1999). Studies often link willingness to pay (WTP) or stated preferences to these behavioural intentions (Bernath and Roschewitz, 2008), with several TPB components demonstrating correlations with stated WTP for goods and services in non-market settings (Ajzen and Driver, 1992; Börger and Hattam, 2017). Based on this, we propose the following initial hypothesis.

H1: The latent variables of theory of planed behaviour are positively related to preference parameters for recycling.

In addition, as mentioned above, goals are structured in a hierarchical manner, where broad, high-level goals are broken down into more concrete, lower-level objectives that eventually guide physical actions. This implies that individuals' short-term behaviour serves their long-term life intentions. Therefore, based on this, we propose the following hypothesis.

H2: The latent variables representing different types of self-reported quests for well-being (e.g., seeking to benefit future generations) are either directly related to the preference parameters for recycling or indirectly related to these parameters through the latent variables of the Theory of Planned Behaviour (TPB).

5.3 Survey Design and Methodology

5.3.1Survey Design

In this study, I use the same survey data as in the previous chapter to examine whether the Theory of Planned Behaviour (TPB) should be enhanced with insights from goal theories within the context of recycling. The choice experiment was conducted among Chinese households in Shanghai, Zhengzhou, and Shijiazhuang. The survey comprised five main sections: (1) an introduction, (2) questions regarding current environmental knowledge and living conditions, (3) items concerning long-term life goals and TPB factors, (4) an explanation of the attributes in the choice scenarios and the choice sets employed to assess preferences for different waste recycling systems, and (5) socio-demographic questions.

The data collected from sections 3, 4, and 5 were used to analyse the relationship between TPB factors and recycling preferences, as well as to explore whether self-reported well-being goals, such as a desire to benefit future generations, directly influence recycling preferences or if this effect is mediated through TPB variables. Given this focus, I provide a detailed explanation of the data from section 2, which covers environmental knowledge and living conditions, and section 3, which addresses long-term life goals and TPB factors. A comprehensive discussion of section 1 (the introduction), section 4 (the attributes of the choice scenarios and choice sets used to estimate recycling preferences), section 5 (socio-demographic questions), and details on case study selection, description, and questionnaire development, is provided in Chapters 3 and 4.

Table 5. 1: Questions about Environmental Knowledge and Living Conditions

	Questions (section 2)	option	Symbol
Environmental knowledge	How much of what you just read ABOVE did you know beforehand (Part 1 ENVIRONMENT ISSUES IN CHINA; Part 2 WHAT PROBLEMS CAN MUNICIPAL SOLID WASTES CAUSE?; Part 3 TREATMENT)	1 I never heard before. 2 I knew a general idea of environmental issues or problems or treatments in China. 3 I knew most of issues, problems and treatments, also I knew some numbers and details. 4 I knew everything 5 I knew much more	Environmental knowledge 1
	Have you heard of **global warming, plastic pollution, PM 2.5, soil contamination previously?**	1 None of it 2 One of these issues 3 Two of these issues 4 Three of these issues 5 Four of these issues 6 More than that	Environmental knowledge 2
Living condition	Which of a following photo best describes the collection point sanitation of your current living area?	The questionnaire provided five images depicting the sanitation environment of a neighborhood, ranging from poor to good.	Living condition 1
	Currently, how many collection points in your living area or community	1 Every floor of the building you live 2 Every block of the building you live 3 Every community	Living condition 2

As illustrated in Table 5.1, section 2 of our survey investigated the relationship between respondents' environmental knowledge, living conditions, and waste-sorting behaviours. The aim was to evaluate whether these observed variables affect recycling preferences within the framework of a structural equation model.

Environmental Knowledge:

To evaluate prior awareness, respondents were asked about their familiarity with environmental issues in China, including municipal solid waste problems and treatment methods. This question measured their level of knowledge, from no prior awareness to a comprehensive understanding. Additionally, participants reported their awareness of specific global environmental issues such as climate change, plastic pollution, PM 2.5, and soil contamination, providing insight into their exposure to environmental challenges.

Living Conditions:

To assess sanitation perception, respondents selected an image that best represented the cleanliness of waste collection points in their area, offering insight into their view of local environmental conditions. Furthermore, collection point availability was examined by asking participants about the number of waste collection points in their residential area, ranging from individual building floors to community-level facilities, providing an indication of the accessibility of recycling infrastructure.

It is essential to understand how environmental knowledge and living conditions affect recycling behaviour. Studies have shown that higher environmental awareness is strongly linked to increased pro-environmental actions. For example, Kollmuss and Agyeman (2002) found that individuals with a greater understanding of environmental issues are more likely to engage in sustainable practices, such as recycling. Likewise, Fischer (2008) demonstrated that improved living conditions—characterised by accessible waste collection facilities and enhanced sanitation standards—can notably boost residents' participation in recycling initiatives. These findings underscore the critical role that both environmental knowledge and quality living conditions play in promoting sustainable waste management practices. By incorporating these observed variables into our structural equation model, we aim to elucidate their direct and indirect effects on recycling preferences, thereby informing strategies to promote sustainable waste management behaviours.

Table 5. 2: Questions about TPB and Life Goals

Display TPB AND LIFE GOAL QUESTIONS		
Theory of Planed behaviours	Display question (section 4)	Symbol
Attitudes	Do you agree that people should care about is life and survival issues, not environmental issues such as improving solid waste disposal?	att1
	Do you agree that people need to participate in waste classification in order to save resources and protect environment for human being and future generations?	att2
	Do you agree that recycling is waste of your time. If You are working full time and do not have the time to recycle?	att3
Percieved Social Norm	Do you agree that your family and friends expect you to engage in recycling behaviours?	norm1
	Do you agree that most people would approve of your recycling behaviours?	norm2
	Do you agree that the local government have responsibility to waste classification and recycling and have nothing to do with residents?	norm3
Perceived Behavioural Control	Do you agree that it is very inconvenient when you classify your house wastes?	behcontrol1
	Do you agree that it is a piece of cake to remember how to sort waste?	behcontrol2
	Do you agree that there are plenty of opportunities to recycle in your normal life? (deleted)	behcontrol3
Life Goals		
	Seeking pleasure	lifegoal 1
	Seeking to do what you believe in	lifegoal 2
	Seeking to pursue excellence or a personal ideal? (deleted)	lifegoal 3
	Seeking to contribute to others in your local area or the surrounding world	lifegoal 4
	Seeking to have lots of money and nice possessions	lifegoal 5
	Seeking to benefit future generations	Lifegoal 6
	Seeking enjoyment	lifegoal 7
	Seeking to prevent harm to the local environment and wildlife	Lifegoal 8

As illustrated in Table 5.2, Section 3 of this survey aimed to gather respondents' views on recycling behaviour through statements based on the Theory of Planned Behaviour (TPB) and life goals. Participants were asked to indicate their level of agreement on a scale from "strongly disagree" to "strongly agree" concerning various aspects of waste sorting. The

TPB-related questions assessed whether individuals regarded environmental issues as important as basic survival needs or viewed them as secondary. Furthermore, they were asked about their beliefs regarding the necessity of waste sorting for conserving resources and benefiting both current and future generations. Other questions examined the influence of family, friends, and local government expectations on recycling habits, as well as whether respondents found waste classification inconvenient or easy to manage.

In addition to TPB-related items, the survey included questions about life goals to explore deeper motivational factors. These questions aimed to evaluate long-term personal objectives, such as pursuing happiness, adhering to personal beliefs, contributing to the community, accumulating wealth, ensuring benefits for future generations, enjoying life, and preventing harm to the environment and wildlife. By incorporating TPB constructs and life goal indicators into the measurement equation, this study aims to comprehend how these unobserved variables collectively influence recycling preferences. This integrated approach offers a more comprehensive insight into the behavioural drivers behind sustainable waste management practices (Ajzen, 1991; Steg and Lindenberg, 2007).

5.3.2 Econometric Approach

To empirically test the relationships clearly presented in Figure 5.1, we employ the Hybrid Mixed Logit (HMXL) model. This method is particularly suitable because it integrates both observable characteristics (e.g., demographic factors) and latent psychological factors (e.g., attitudes, life goal tendencies). The choice experiment measures stated preferences for recycling schemes, allowing us to estimate willingness to pay (WTP) as behavioural intention indicators. Each latent construct—life goals and TPB variables—is explicitly operationalised and measured through relevant survey scales, enabling clear testing of Figure 5.1's conceptual paths.

Hybrid choice models comprise up to three components: structural equations, measurement equations, and a discrete choice model. Our approach concurrently identifies the connections between psychological factors (TPB factors and life goals) and examines the relationships relevant to explaining choices within the choice model. Furthermore, we incorporate a socio-demographic, environmental knowledge, and living environment component that utilises respondents' observed characteristics to elucidate variations in these latent psychological traits. This integrated approach enhances our understanding of the variability in recycling preferences among households, taking into account the influences of perceived social norms, behavioural control, attitude, long-term life goals, socio-economic characteristics, environmental knowledge, and living environment.

In exploring stated preference for recycling using the Hybrid Choice Model (HCM), this study introduces three latent variables: TPB attitudes towards recycling, subjective norm, perceived behavioural control, and life goals, each represented by observable indicators. Initially, a structural equation model is constructed to calculate the associations among latent variables and the impact of corresponding observable factors. Subsequently, variables representing sociodemographic characteristics and latent variables depicted through observable indicators are incorporated into a mixed Logit model, as illustrated in Figure 1, to assess how each factor influences stated preference for recycling. Table 1 details the observable indicators related to the latent variables described above. These indicators are measured using a Likert scale method, with options ranging from "strongly support" and "strongly agree" to "strongly disagree" and "strongly oppose," with a corresponding numerical range of one to five. A detailed derivation of the estimation formulas for the Hybrid Choice Model is provided in Chapter 3.8.

5.4 Data analysis and main results

To analyse the connections between respondents' life goals, their TPB components, socio-demographic characteristics, and discrete choices, we employ the Hybrid Mixed Logit (HMXL) model. This model integrates the widely used framework for analysing DCE data, the mixed Logit (Revelt and Train, 1998), with the Multiple Indicators and Multiple Causes (MIMIC) model (Jöreskog and Goldberger, 1975). These models are utilised to investigate the relative effects of life goals, TPB components, and social factors, as well as environmental knowledge and living conditions, on preference heterogeneity, and consequently on WTP for recycling.

5.4.1 Pre-Test, EFA, and CFA

Before the HCM model, it is important to note that the life goals questions (eight items) and the TPB questions (nine items) pertain to two distinct dimensions (Table 5.2)—one related to life choices and the other to attitudes towards specific behaviours. Therefore, I initially performed an exploratory factor analysis (EFA) on the life goal questions and TPB questions separately, using half of the data (even-numbered IDs). Based on the EFA results and the indicator loadings, I proposed a hypothesised model. Subsequently, I utilised confirmatory factor analysis (CFA) with the remaining half of the data (odd-numbered IDs) to validate and test the fit of this hypothesised model. Combining EFA and CFA provides a robust approach for understanding the latent structure of observed variables.

EFA results

Before carrying out the EFA, we conducted a statistical analysis on all Likert scale items (including 9 TPB questions and eight life goal questions). The distributions of these items were approximately normal, with moderately acceptable levels of kurtosis and skewness (below 2 and 7, respectively; as detailed in Appendix B1). Furthermore, since some TPB questions are reverse-scored (att1, att3, norm3, behcontrol1), these questions were reverse-coded to prevent potential interference in grouping due to negative correlations with other TPB questions. Principal component analysis was utilised for the exploratory factor analysis to evaluate the variable loadings.

Furthermore, we conducted the KMO test and Bartlett's test of sphericity separately on the data from the 9 TPB questions and the eight life goal questions. The results in Table 5.3 were as follows: for the 9 TPB questions, the overall KMO test result was 0.807, which lies within the acceptable range of 0.5 to 1. Bartlett's test of sphericity yielded a p-value of less than 0.05, thereby rejecting the null hypothesis of an identity matrix. For the eight life goal questions, the KMO test result was 0.71, also within the acceptable range, and Bartlett's test of sphericity again had a p-value of less than 0.05. Consequently, these factors demonstrated sufficient discriminant validity in both data sets.

Table 5. 3: KMO and Bartlett's test

TPB questions data results

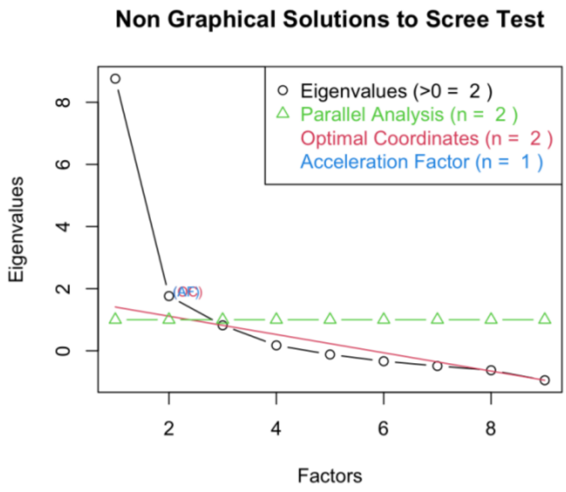
Test	Value
KMO Overall MSA	0.81
Bartlett's Test Chi-Square	680.45
Bartlett's Test df	36
Bartlett's Test p-value	5.67E-120

Life goal questions data results

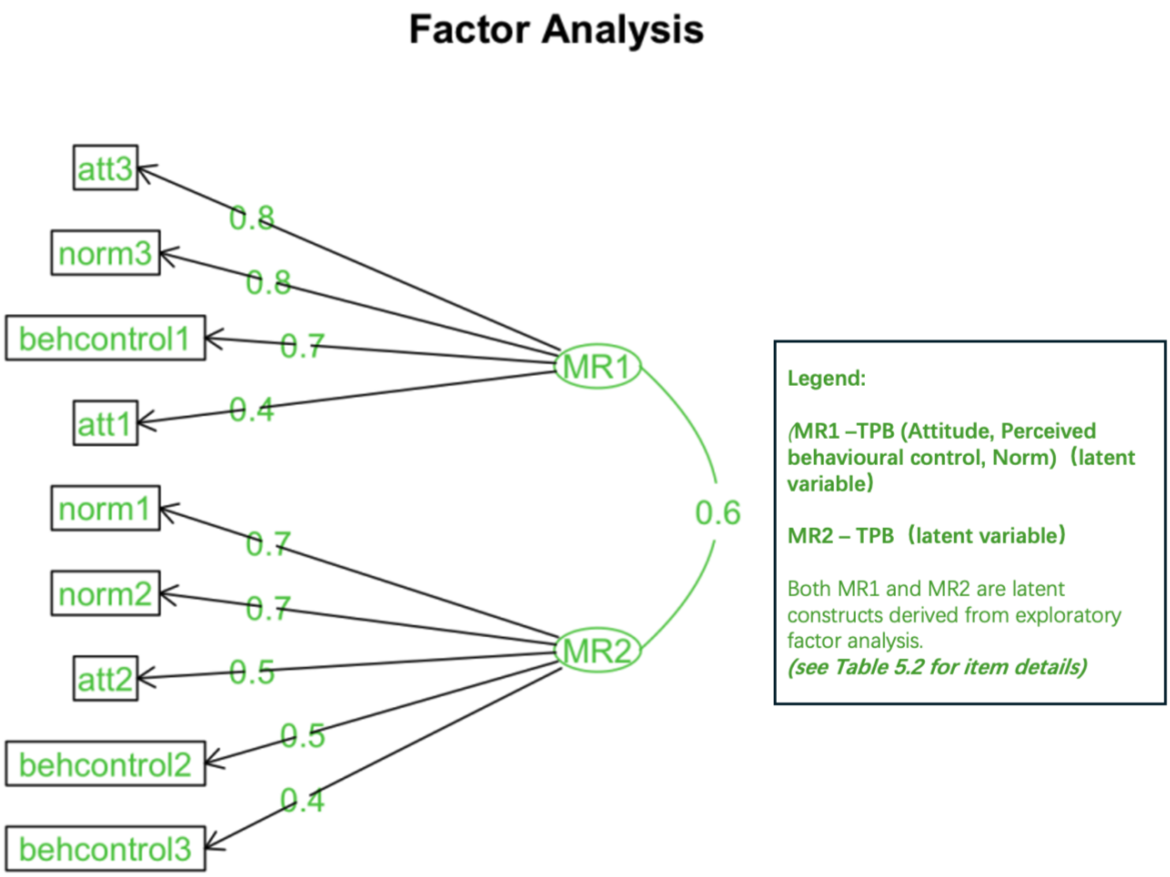
Test	Value
KMO Overall MSA	0.71
Bartlett's Test Chi-Square	302.31
Bartlett's Test df	28
Bartlett's Test p-value	8.54E-48

Firstly, Figure 5.2 illustrates that the 9 TPB observed variables converged onto two factors with Eigenvalues exceeding 1, and all factor loadings of the observed variables were above 0.3. For the 9 TPB questions, we utilised two latent variables. The findings revealed that the 9 TPB questions clustered into two latent variables rather than the three theoretically anticipated (attitudes, perceived behavioural control, social norms). We discovered that the attitudes questions were highly correlated with the perceived behavioural control and social norm questions. Respondents frequently assigned median and high scores to the TPB indicators. The two latent classes suggested by the EFA were organised according to the questionnaire, separating the five positive questions from the four negative questions into two latent classes. Consequently, I allocated all positive TPB questions to one latent variable and all negative TPB questions to another latent variable. This outcome corroborates previous studies, such as those by López-Mosquera et al. (2014) and Grilli and Notaro (2019), which indicate a high correlation between the components of the Theory of Planned Behaviour (TPB). Both papers proposed the three components of TPB as a singular latent variable.

Figure 5. 2 a: Scree test results for TPB data. All criteria suggest 2 factors, except acceleration factor which indicates 1.



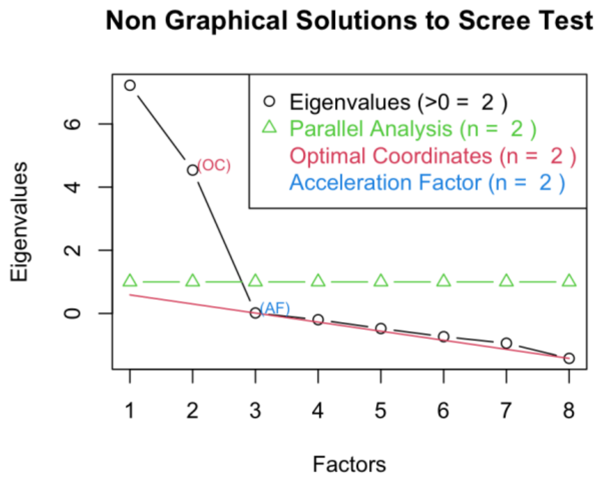
b: Factor structure of TPB items from exploratory analysis. Two latent constructs (MR1 and MR2) emerged, reflecting patterns based on positively and negatively worded items



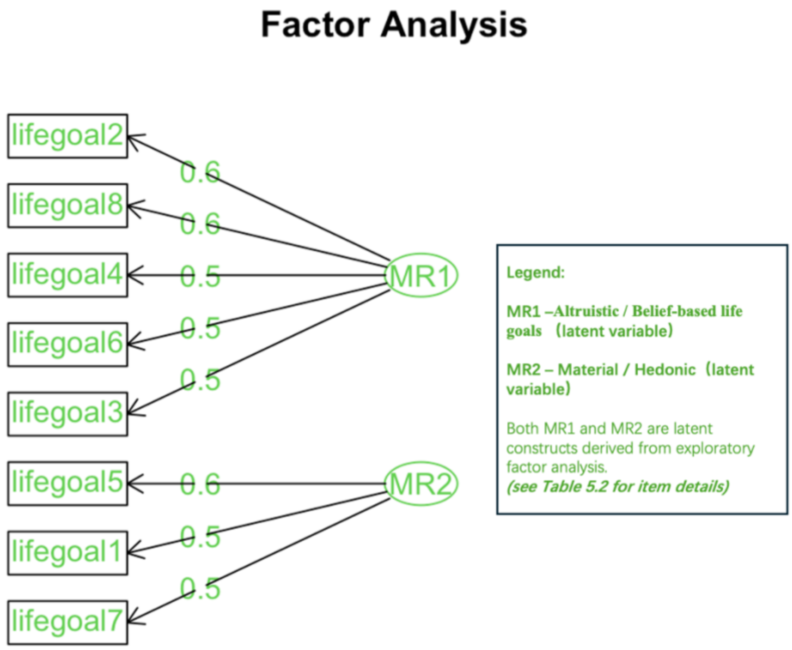
Secondly, Figure 5.3 illustrates that the eight-life goal observed variables converged upon two factors with Eigenvalues greater than 1, and all factor loadings of the observed variables exceeded 0.5. Based on the EFA results, it is recommended to employ two latent variables for the eight life goal questions. The results are as follows:

For the life goal questions, the EFA results indicate that the pursuit of pleasure and wealth merged into one latent variable, while the pursuit of beliefs, altruism, and environmentalism combined into another latent variable.

Figure 5. 3 a: Scree test results for life goal data. All criteria suggest retaining two factors.



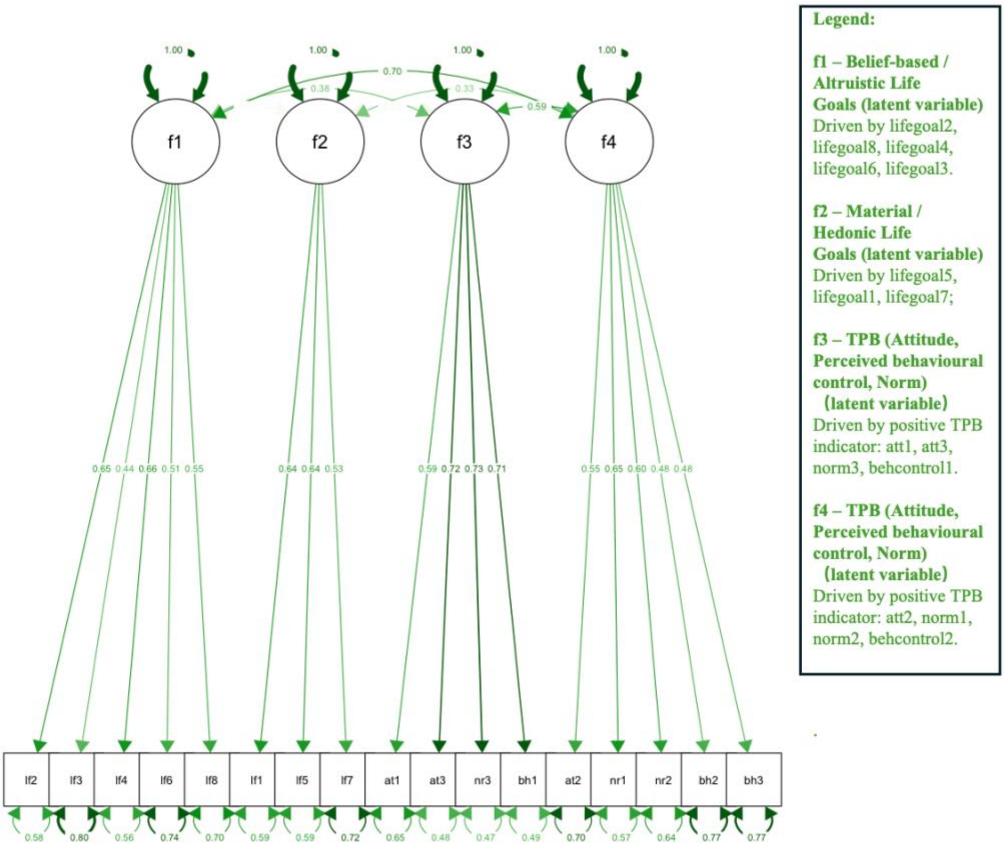
b: Factor structure of life goal items from exploratory analysis. Two latent constructs emerged: MR1 reflects believe based and altruistic goals; MR2 reflects material and hedonic goals.



CFA results

Below are the results from a CFA conducted on the other half of the data, based on the EFA structure. We tested all 17 TPB and life goal Likert scale questions following the EFA results. The RMSEA values below 0.05, alongside CFI and TLI values between 0.90 and 0.95, indicate an adequate model fit. The chi-square (χ^2) value and its corresponding significance level were also reported. The CFA results for two TPB factors (f3 and f4) and two life goal factors (f1 and f2) are shown in Figure 5.4. Consistent with the literature, this analysis confirmed that a four-factor solution provided an acceptable fit to the data (RMSEA = 0.041, CFI = 0.95, TLI = 0.94; further details are provided in Appendix B2).

Figure 5. 4: CFA results for life goal and TPB constructs (odd ID sample). Four latent factors were confirmed: two for life goals (f1-altruistic and f2-material) and two for TPB (positive vs negative framing). All items show acceptable loadings.



Note:
All f-factors (f1,f2,f3, f4) are latent variables derived from exploratory factor.
Indicators serve as abbreviated references to the longer question titles listed in Table 5.2

Table 5.4 showed that two items were excluded from the measurement model due to inconsistent loading and insignificant factor loadings in the CFA. The items that were removed include: "Do you agree that there are plenty of opportunities to recycle in your daily life? (behcontrol3)" and "Are you seeking to pursue excellence or a personal ideal? (lifegoal3)" (Table 5.2). The removal of these items enhanced the model fit (RMSEA = 0.041, CFI = 0.96, TLI = 0.95; refer to Appendix 3 for further details).

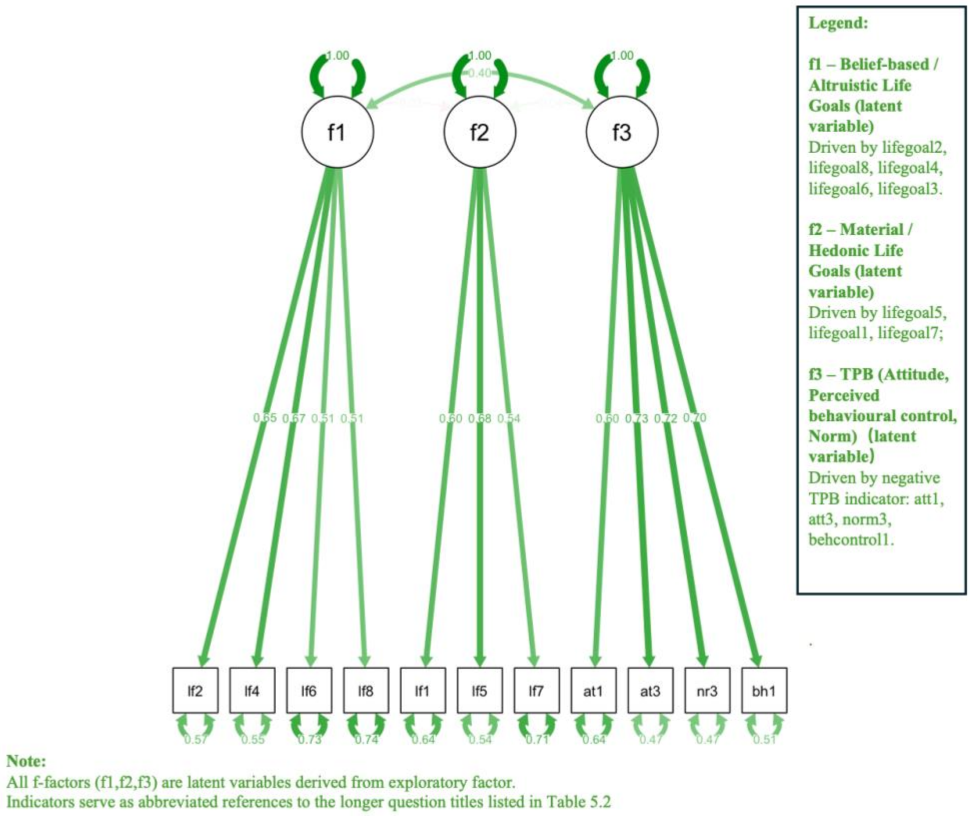
In addition, since both factor f3 and factor f4 reflect the same TPB construct—where factor f4 comprises positively worded TPB items and factor f3 comprises negatively worded items—we simplified the model by including only one TPB latent variable (f3) in the HCM measurement model below to eliminate the influence of question phrasing on data collection. Moreover, we also ran the model using the other TPB latent variable (f4) instead of f3 as a comparative model to explore whether different question phrasings affect the accuracy of the questionnaire results.

Table 5. 4: Display variables that characterize latent variables.

Table 2: Display variables that characterize latent variables.		
Theory of planed behaviours	Display variable	Symbol
Negitive TPB factor **(f3)**	Do you agree that people should care about is life and survival issues, not environmental issues such as improving solid waste disposal?	att1
	Do you agree that recycling is waste of your time. If You are working full time and do not have the time to recycle?	att3
	Do you agree that the local government have responsibility to waste classification and recycling and have nothing to do with residents?	norm3
	Do you agree that it is very inconvenient when you classify your house wastes?	behcontrol1
Positive TPB factor **(f4)**	Do you agree that people need to participate in waste classification in order to save resources and protect environment for human being and future generations?	att2
	Do you agree that your family and friends expect you to engage in recycling behaviours?	norm1
	Do you agree that most people would approve of your recycling behaviours?	norm2
	Do you agree that it is a piece of cake to remember how to sort waste?	behcontrol2
	Do you agree that there are plenty of opportunities to recycle in your normal life? (deleted)	behcontrol3
life goals		
Pursuit of beliefs and altruism **(f1)**	Seeking to do what you believe in	lifegoal2
	Seeking to pursue excellence or a personal ideal? (deleted)	lifegoal3
	Seeking to contribute to others in your local area or the surrounding world	lifegoal4
	Seeking to benefit future generations	Lifegoal6
	Seeking to prevent harm to the local environment and wildlife	Lifegoal8
Pursuit of pleasure and money **(f2)**	Seeking pleasure	lifegoal1
	Seeking to have lots of money and nice possessions	lifegoal5
	Seeking enjoyment	lifegoal7

Thus, we simplified the model by including only one TPB latent variable (f3) in the measurement model of HCM below to eliminate the influence of question phrasing on data collection. Moreover, we also used the other TPB latent variable (f4) instead of TPB latent variable (f3) to run the model, The results using the TPB latent variable (f4), which yielded similar conclusions as f3. Thus, we simplified the model by including only one TPB latent variable (f3) in the measurement model of HCM below to eliminate the influence of question phrasing on data collection (Figure 5.5), meaning that our model 1 includes only three latent variables: f1, f2, and f3. Additionally, we ran the HCM model using the other TPB latent variable (f4) instead of f3 (model 2: f1, f2, f4). The results using the TPB latent variable (f4) yielded similar conclusions to those with f3.

Figure 5. 5: CFA results for life goals and TPB attitude construct (Model 1, odd ID). Three latent factors were identified: altruistic goals (f1), material goals (f2), and TPB attitude (f3), with all items showing acceptable loadings.

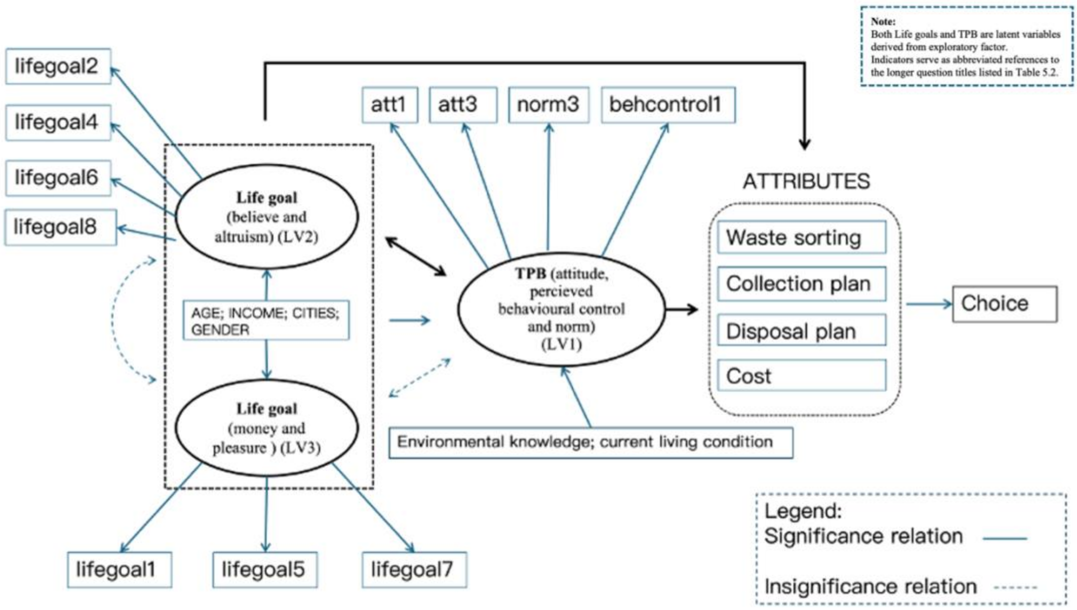


In conclusion, we found that the attitude questions were highly correlated with the perceived behavioural control and social norm questions. Respondents frequently gave median and high scores to the TPB indicators. The EFA and CFA results suggested two latent classes based on the questionnaire, separating the five positive questions and the four negative questions into two latent classes. Therefore, I assigned all positive TPB questions to one latent variable (LV1*) and all negative TPB questions to another latent variable (LV1). For the life goal questions, the EFA and CFA results showed that the pursuit of pleasure was highly correlated with the pursuit of money, so these were combined into one latent variable (LV3). The pursuit of beliefs, altruism, and environmentalism were highly correlated and combined into another latent variable (LV2). therefore, in the measurement model of HCM, we only include three latent variables, one TPB latent variable (f3-LV1) and two life goal latent variables (f1-LV2; f2-LV3). this analysis confirmed that a four-factor solution provided an acceptable fit to the data (RMSEA = 0.04, CFI = 0.96, TLI = 0.94; more details are provided in Appendix 4 and 5).

5.4.2 Main results

Based on the EFA and CFA results, our HCM model (Figure 5.6) comprises three latent variables for the measurement model: LV1 - TPB (f3), LV2 - Pursuit of Beliefs and Altruism (f1), and LV3 - Pursuit of Pleasure and Money (f2). In terms of the measurement equations, LV1 includes four indicators (att1, att3, norm3, behcontrol1), LV2 consists of four indicators (life goal 2, 4, 6, 8), and LV3 features three indicators (life goal 1, 5, 7). For the structural model, we employed a "backward" approach, integrating significant variables such as gender, income, location, and age, along with the three latent variables and their correlations. Furthermore, LV1 is associated with observed environmental knowledge and current living conditions. In the discrete choice component, the choices of respondents among recycling contract alternatives are explained using the attribute levels that characterise these alternatives, alongside individual-specific latent variables. This approach provides insight into how the preferences of respondents with certain traits (latent variables) differ from those of others. These latent variables are defined as interactions with the attribute levels. The three components of the HMXL model were jointly estimated but are presented in separate tables for clarity.

Figure 5. 6: HCM Structure Model linking life goals (LV2, LV3), TPB constructs (LV1), and recycling choices. Altruistic and belief-based life goals influence TPB factors and directly affect recycling preferences.



Therefore, our analysis explicitly tests two primary hypotheses outlined in Figure 5.1:

H1: Latent variables from the Theory of Planned Behaviour (LV1) positively influence recycling preference parameters (attributes).

H2: Latent variables representing different personal life goals (LV2 and LV3) influence recycling preferences either directly or indirectly through TPB variables (LV1).

In addition to these hypotheses, we also tested whether there is a relationship between each of the three latent variables and socio-demographic characteristics. Additionally, we tested if there is a relationship between LV1 and environmental knowledge or/and current living conditions.

HCM model 1

Hybrid choice models consist of up to three components: structural equations, measurement equations, and a discrete choice model. Our approach concurrently identifies the connections between psychological factors (TPB factors and life goals) and considers the relationships pertinent to explaining choices within the choice model. Additionally, we incorporate a socio-demographic component that uses respondents' observed characteristics to explain variations in these latent psychological traits. This combined approach enhances our understanding of the variability in recycling preferences among households, considering the impacts of perceived social norms, behavioural control, attitude, long-term life goals, environmental knowledge and current living environment and socio-economic characteristics.

Measurement equations

Table 5.5 includes the estimation results of the model's measurement component. The Likert-scale responses to four TPB attitudinal statements (att1, att3, norm3, and behcontrol1 - LV1) corresponding to different motives for recycling, and eight life goals statements (LV2 - the pursuit of beliefs, altruism, and environmentalism: life goal2, 4, 6, 8; the pursuit of pleasure and money; LV3 - the pursuit of beliefs, altruism, and environmentalism: life goal 1, 5, 7) were modelled using an ordered probit framework. The first columns present the estimated parameters for the latent variables—underlying unobserved psychological factors that explain respondents' attitudes and choices. We found that the model with three factors outperformed those with fewer factors, providing consistent and reasonable results in all three components. This measurement component provides insights into the three main factors (latent variables) underlying respondents' attitudes, perceived social norms, behavioural control, and various long-term life goals, thereby explaining their responses to the questions illustrated in Figure. 5.5.Table 5.5 presents the results for the measurement equations, where the responses to indicator variables are explained by the latent variables (LVs). The threshold parameters Tau1, Tau2, and Tau3 are all significant, indicating that an ordered analysis is suitable for modelling the data (Hensher and Greene, 2010). Additionally, the coefficient preference representing the effect of the LV, is significant for all coefficients, confirming that the LVs are appropriate for modelling the indicators.

LV1 reflects attitudes, perceived social norms, and perceived behavioural control. LV1 is linked to a greater likelihood of stating that individuals should care about environmental issues, such as enhancing solid waste disposal, that recycling is not a waste of time, that local residents bear a responsibility for waste classification and recycling, and that classifying household waste is very convenient.

Table 5. 5: Measurement equation results

LV	Indicator	Mean (SE) & P-value	Threshold1	Threshold2	Threshold3	Threshold4
LV1	att1	1.22 *** (0.16)	-3.68 *** (0.36)	-2.10 *** (0.26)	-1.07 *** (0.25)	1.79 *** (0.28)
LV1	att3	2.70 *** (0.51)	-6.35 *** (0.89)	-4.32 *** (0.65)	-3.13 *** (0.59)	0.84 (0.51)
LV1	norm3	2.65 *** (0.62)	-6.47 *** (0.98)	-4.35 *** (0.71)	-3.46*** (0.62)	0.36 (0.49)
LV1	behcontrol1	2.11】 *** (0.28))	-5.17 *** (0.63)	-3.14*** (0.47)	-2.09 *** (0.43)	1.93 *** (0.46)
LV2	lifegoal2	1.30】 *** (0.19)	-5.96 *** (1.06)	-3.24 *** (0.40)	-0.05 (0.36)	2.35 *** (0.45)
LV2	lifegoal4	1.16 *** (0.16)	-4.06*** (0.49)	-1.45 *** (0.30)	1.002*** (0.34)	3.56 *** (0.44)
LV2	Lifegoal6	0.79 *** (0.11)	-5.17 *** (0.74)	-2.79 *** (0.28)	-0.79 *** (0.21)	1.15 *** (0.22)
LV2	Lifegoal8	1.04*** (0.14)	-5.88*** (1.03)	-3.07*** (0.34)	-1.01 *** (0.26)	1.51 *** (0.27)
LV3	lifegoal1	-1.34*** (0.25)	-6.40 *** (0.68)	-5.23 *** (0.51)	-2.32 *** (0.33)	1.23 *** (0.29)
LV3	lifegoal5	-1.99 *** (0.46)	-7.40*** (1.03)	-4.76 *** (0.72)	-2.13*** (0.47)	1.49 *** (0.46)
LV3	lifegoal7	-1.17 *** (0.18)	-5.12 *** (0.49)	-3.76 *** (0.34)	-1.94*** (0.26)	0.41 (0.25)

LV2 reflects the pursuit of beliefs, altruism, and environmentalism. LV2 is linked to a higher likelihood of individuals reporting that their life goals include doing what they believe in, contributing to others within their local community or the broader world, benefiting future generations, and preventing harm to the local environment and wildlife.

LV3 reflects the pursuit of pleasure and wealth. It is associated with a greater likelihood of individuals reporting that their life goals include seeking enjoyment, accumulating substantial wealth, and acquiring nice possessions.

Table 5. 6 Structure equation results

	LV1	LV2	LV3
Male	0.01 (0.18)	0.25 (0.17)	0.09 (0.12)
Income	0.22 *** (0.05)	0.325 *** (0.05)	-0.07 (0.05)
Shanghai	-0.36* (0.19)	-0.39 (0.22)	0.24* (0.12)
Age	-0.02 (0.06)	0.16 * (0.07)	0.04 (0.07)
Knowledge1	.-0.11 [0.14]		
Knowledge2	0.80*** [0.14]		
	0.44 [0.24]		
	0.137 [0.21]		
	Mean	SE	P value
lv1_lv2	0.506	0.082	***
lv1_lv3	0.001	0.093	
lv2_lv3	0.024	0.076	

Structure equation results

The next section of Table 5.6 presents the structural components of the model, where the three latent variables are connected to the respondents' observed socio-demographic characteristics, and the interaction between the three latent variables. In addition, LV1 is related to observed variations in environmental knowledge and current living condition characteristics. This enables us to identify the latent traits that influence responses to the attitudinal Theory of Planned Behaviour (TPB) and life goals questions, while also providing insights into how these traits differ among respondents with varying levels of environmental knowledge, living conditions, and socio-demographic characteristics.

This indicates that individuals with attitudes, perceived social norms, and behaviour control represented by LV1 (TPB latent variable) are influenced solely by income and location. Higher income groups exhibit stronger TPB indicators, suggesting more favourable attitudes towards recycling, enhanced perceived social norms, and greater behavioural control. Moreover, LV2 is significantly associated with income, implying that those with higher incomes are more inclined to pursue their beliefs and altruistic goals. LV3 is significantly connected to the dummy variable for Shanghai. In comparison to Zhengzhou and Shijiazhuang, Shanghai, with its higher GDP and more advanced urban development, demonstrates a greater pursuit of wealth and happiness. Furthermore, LV2 shows a significant relationship with age, suggesting that older individuals are more likely to pursue their beliefs and altruistic goals.

LV1 is significantly positively correlated with Knowledge2, suggesting that individuals who are more aware of global warming, plastic pollution, PM 2.5, and soil contamination tend to have a more favourable attitude towards recycling (LV1).

Finally, we discovered that LV1 and LV2 are positively correlated and highly significant. This suggests that individuals who pursue their beliefs and altruism (LV2) tend to have a more positive attitude towards recycling (LV1).

Discrete choice equation results

Next, we present results from the mixed logit (MXL) model in Table 5.7, which incorporates a representation of respondents' unobserved preference heterogeneity. This model offers a superior fit compared to the equivalent MNL version, as indicated by the lower score of the normalised Akaike Information Criterion, and is formally supported by the results of the LR test. Table 5.7 presents the discrete choice component of the model. In this section, respondents' choices among recycling contract alternatives are elucidated using the attributes of these alternatives and individual-specific latent variables. This clarifies how the preferences of respondents with certain characteristics (latent variables) differ from those of others. These latent variables are modelled as interactions with the attribute level parameters. Since the LVs are normalised to have a mean of 0 and a standard deviation of 1, the first column (showing main effects) closely resembles the results of a standalone simple MNL model.

This approach provides insight into how respondents' preferences are influenced by their traits, highlighting differences between those with specific latent variables and the broader respondent group.

Turning to the interactions reveals a clear pattern concerning the three latent variables: a positive preference for waste sorting (sort2, sort4, and sort7) is significantly linked to LV1, while a positive preference towards sorting (sort7) is significantly with LV2. Moreover, a positive preference towards recycling disposal plans is also significantly associated with LV2.

In other words: Individuals with a more positive attitude, perceived behaviour control and social norm (LV1) towards waste sorting are more likely to choose to sort their waste. In addition, This indicates that individuals who pursue their beliefs and altruism (LV2) are more inclined to engage in complex waste sorting and are more concerned about the final disposal of waste. In addition, the structure equation result indicates that individuals who pursue their beliefs and altruism (LV2) have a more positive attitude, perceived social norm and behaviour control towards recycling (LV1).

Table 5. 7: Discrete choice model with three LVs interactions results.

	Main effects		Interactions		
	Mean	SD	LV1	LV2	LV3
Sort in 2 categories (vs. no in-home sorting)	1.52*** (0.32)	-0.43 (0.37)	0.79** (0.31)	-0.54 (0.29)	-0.123231 (0.280125)
Sort in 4 categories (vs. no in-home sorting)	1.54*** (0.34)	-0.77 (0.52)	0.85** (0.49)	0.21 (0.49)	0.04 (0.38)
Sort in 7 categories (vs. no in-home sorting)	0.93*** (0.29)	-1.45*** (0.20)	0.65* (0.26)	0.66** (0.30)	0.21 (0.31)
Waste collection point in every block (vs. collection point in every community)	.-0.16 (0.19)	0.03 (3.21)	-0.18 (0.18)	0.32* (0.16)	0.02 (0.24)
Waste collection point in every floor (vs. collection point in every community)	.-0.21 (0.25)	0.97*** (0.17)	-0.08 (0.22)	0.23 (0.27)	-0.06 (0.19)
Disposal plan-composting (vs. incineration)	0.05 (0.14)	-0.63* (0.31)	0.07 (0.13)	0.01 (0.12)	-0.08 (0.19)
Disposal plan-recycling plants (vs. incineration)	0.12)*** (0.25)	-0.92*** (0.19)	0.07 (0.29)	0.59 (0.23)	-0.35 (0.22)
(Monthly cost per household)	-0.006** (0.002)	-0.01*** (0.001)	-0.003** (0.001)	0.005*** (0.001)	0.002 (0.001)

Lastly, there is no significant relationship between LV3 and the preference for sorting, indicating that those who prioritise money and pleasure do not have a marked preference for waste sorting.

5.5 Discussion

In this chapter, we explored whether the Theory of Planned Behaviour (TPB) ought to be expanded by integrating insights from goal theories in the context of pro-environmental behaviour. Specifically, we examined whether diverse life goals have a direct impact on individuals' stated recycling preferences or whether their influence is mediated through attitudes, perceived behavioural control, and social norms. Using a Hybrid Mixed Logit (HMXL) model, we analysed household recycling choices in Shanghai, Zhengzhou, and Shijiazhuang, clearly addressing two hypotheses outlined in Figure 5.1:

H1: TPB variables (attitudes, perceived behavioural control, and social norms) positively affect recycling preferences.

H2: Personal life goals influence recycling preferences directly or indirectly via TPB variables.

Firstly, there is a strong link between a positive preference for waste sorting (sort2, sort4, and sort7) and the latent variable LV1. This suggests that individuals who hold more positive attitudes towards waste sorting, feel more in control of their ability to recycle, and perceive greater social support for such actions (LV1) are more inclined to engage in waste sorting practices. These factors indicate that both individual motivation and social influences play a crucial role in shaping recycling behaviour. This result is consistent with the Theory of Planned Behaviour (TPB), which suggests that attitudes, social expectations (subjective norms), and perceived control over a behaviour together influence an individual's intention, ultimately impacting their actual actions (Ajzen, 1991). Previous research has corroborated this notion. For example, Armitage and Conner (2001) conducted a meta-analysis demonstrating that these TPB factors play a key role in predicting various behaviours, including recycling. Similarly, Knussen et al. (2004) found that individuals with positive attitudes and a strong sense of control over their recycling capabilities were more likely to intend to recycle and to follow through with the behaviour.

Secondly, a positive preference for waste sorting (sort7) and recycling disposal plans is significantly related to latent variable LV2. This implies that individuals motivated by normative goals—such as adhering to their beliefs or altruistic values—are more likely to engage in detailed waste sorting and to pay greater attention to the final disposal of waste. This finding is consistent with goal theories that describe goals as hierarchical, with higher-level goals guiding more specific behaviours (Kruglanski et al., 2002; Abraham and Sheeran, 2003). It also aligns well with Goal-Framing Theory, which posits that when a normative goal frame prevails, individuals are more inclined to perform pro-environmental behaviours because they view them as morally correct or socially responsible (Lindenberg and Steg, 2007; Moussaoui and Desrichard, 2016; Yang et al., 2021; Liu and Yang, 2022).

The results of the structural equation indicate that individuals who hold altruistic beliefs (LV2) tend to develop more positive attitudes, stronger perceived behavioural control, and supportive social norms towards recycling (LV1). This implies that normative goals indirectly influence recycling preferences by shaping key determinants identified in the Theory of Planned Behaviour (TPB), such as attitudes, perceived behavioural control, and subjective norms (Fan et al., 2019; Shen et al., 2020)

These findings align with existing literature. Shen et al. (2020), for instance, demonstrated that moral norms significantly influence recycling intentions indirectly by shaping attitudes and perceived control within the TPB framework. Similarly, Unanue et al. (2016) discovered that individuals with intrinsic life goals, such as community contribution and altruism, displayed stronger pro-environmental attitudes and intentions, which manifested in environmentally responsible behaviours. Lindenberg and Steg (2007) further support this viewpoint by arguing that normative goals frame environmental actions as morally appropriate, thereby promoting pro-environmental behaviours through enhanced attitudes and social expectations.

LV1 is significantly positively related to Knowledge2, indicating that people with greater awareness of global warming, plastic pollution, PM 2.5, and soil contamination have a more positive attitude towards recycling (LV1). This implies that environmental knowledge and awareness indirectly influence respondents' preference for recycling through their attitudes, perceived behavioural control, and perceived social norms.

These findings are consistent with previous research. For instance, Wu et al. (2022) demonstrated that increased environmental knowledge positively influenced attitudes and perceived behavioural control, leading to a rise in pro-environmental behaviours, including recycling. Similarly, Ali et al. (2022) found that enhanced environmental knowledge significantly contributed to stronger recycling intentions through improved TPB constructs. However, some studies provide a more complex perspective. De Leeuw et al. (2015) pointed out that knowledge alone may not always lead to environmentally friendly actions, as additional motivational factors are often required to translate awareness into behaviour. Likewise, Arli et al. (2018) found that attitudes had a weaker influence on recycling intentions in certain contexts, suggesting that the impact of TPB factors on recycling behaviour can depend on specific situational or individual differences. The policy's relevance, limitations, and directions for future research are fully explained in Chapter 6.

Our analysis supports the two main hypotheses proposed in Figure 5.1. For H1, we find that latent variables from the Theory of Planned Behaviour (TPB)—including attitudes, perceived behavioural control, and subjective norms—significantly and positively influence individuals' recycling preferences. Individuals with positive recycling attitudes, higher perceived control, and stronger social support are more likely to engage in waste sorting behaviours.

For H2, our findings demonstrate that personal life goals, particularly normative or altruistic goals, influence recycling choices directly and indirectly through TPB factors. Specifically, normative goals (e.g., helping future generations or acting morally) enhance positive recycling attitudes, perceived control, and social norms, thereby increasing the likelihood of recycling behaviours.

Additionally, our analysis indicates a significant positive relationship between TPB variables (LV1) and environmental knowledge, suggesting that greater awareness of environmental issues strengthens attitudes towards recycling. However, the link between socio-demographic characteristics or current living conditions and the latent variables remains less clear, highlighting the complexity of recycling behaviours and their motivations.

In summary, our analysis clearly addresses RO3 and RO4 by demonstrating that TPB variables (attitudes, perceived behavioural control, and social norms) significantly influence recycling intentions. Additionally, self-reported life goals, particularly normative goals driven by altruism and morality, strongly shape recycling behaviours both directly and indirectly through TPB factors. In contrast, hedonic or gain-oriented goals have little positive effect. Thus, combining TPB variables with personal normative motivations provides a fuller explanation of recycling preferences.

5.6 Appendix B

Table 5. 8: (B1) A Statistical result on all Likert scale items (Skewness and Kurtosis)

VARIABLE	SKEWNESS	KURTOSIS
ATT1	-1.22	1.46
ATT2	-1.98	4.35
ATT3	-2.12	5.47
NORM1	-0.58	-0.41
NORM2	-1.156	0.77
NORM3	-2.36	6.52
BEHCONTROL1	-1.52	3.02
BEHCONTROL2	-0.54	-0.42
BEHCONTROL3	-1.49	2.32
LIFEGOAL1	-0.61	1.11
LIFEGOAL2	-0.56	-0.45
LIFEGOAL3	-0.94	0.53
LIFEGOAL4	-0.34	-0.24
LIFEGOAL5	-0.72	0.59
LIFEGOAL6	-0.99	0.48
LIFEGOAL7	-1.18	1.59
LIFEGOAL8	-1.01	0.76

Table 5. 9: (B2) CFA Result for Odd ID and All 17 Questions

B2-1: MODEL FIT INDICES

FIT INDEX	**Value**	**Threshold**	**Interpretation**
X² (CHI-SQUARE)	173.11	-	*p* < .001
DEGREES OF FREEDOM (DF)	113	-	-
CFI (COMPARATIVE FIT INDEX)	0.947	≥0.90	Excellent
TLI (TUCKER-LEWIS INDEX)	0.936	≥0.90	Good
RMSEA	0.041	≤0.06	90% CI [0.028–0.053]
SRMR	0.052	≤0.08	Acceptable
AIC (AKAIKE CRITERION)	11723	-	-
BIC (BAYESIAN CRITERION)	11873	-	-
SABIC	11747	-	-
LOGLIKELIHOOD (H0)	-5821	-	-
LOGLIKELIHOOD (H1)	-5735	-	-

Notes:

- Estimation method: Maximum Likelihood (ML) with NLMINB optimisation.
- Model converged normally after 26 iterations.
- Baseline model $\chi^2 = 1266.683$ ($p < .001$), supporting improved fit of the hypothesised model.

B2-2: Standardised Factor Loadings

Latent Factor	**Observed Variable**	**Estimate (λ)**	**SE**	**z-value**	***p*-value**	**Std. All (λ)**
f1	lifegoal2	0.507	0.046	11.097	<0.001***	0.647
f1	lifegoal3	0.34	0.047	7.206	<0.001***	0.442
f1	lifegoal4	0.578	0.051	11.38	<0.001***	0.661
f1	lifegoal6	0.404	0.048	8.382	<0.001***	0.506
f1	lifegoal8	0.421	0.046	9.19	<0.001***	0.549
f2	lifegoal1	0.432	0.047	9.111	<0.001***	0.64
f2	lifegoal5	0.495	0.054	9.105	<0.001***	0.64
f2	lifegoal7	0.441	0.056	7.847	<0.001***	0.529
f3	att1	0.547	0.052	10.492	<0.001***	0.594
f3	att3	0.509	0.038	13.329	<0.001***	0.722
f3	norm3	0.513	0.038	13.486	<0.001***	0.729
f3	behcontrol1	0.595	0.045	13.145	<0.001***	0.714
f4	att2	0.411	0.044	9.315	<0.001***	0.546
f4	norm1	0.515	0.045	11.497	<0.001***	0.653
f4	norm2	0.427	0.041	10.438	<0.001***	0.602
f4	behcontrol2	0.464	0.057	8.122	<0.001***	0.484
f4	behcontrol3	0.349	0.043	8.097	<0.001***	0.482

Notes:

- All loadings significant at $p < .001$.
- Standardised loadings (Std. All) >0.4 indicate adequate item reliability (Kline, 2016).

B2-3: Factor Covariances					
Factor Pair	**Covariance**	**SE**	**z-value**	***p*-value**	**Std. All (r)**
f1 ~~ f2	0.02	0.083	0.238	0.812	0.02
f1 ~~ f3	0.383	0.067	5.753	<0.001***	0.383
f1 ~~ f4	0.702	0.055	12.816	<0.001***	0.702
f2 ~~ f3	0.034	0.079	0.435	0.664	0.034
f2 ~~ f4	0.333	0.078	4.257	<0.001***	0.333
f3 ~~ f4	0.594	0.057	10.42	<0.001***	0.594

Key findings:

- Strong correlations: f1-f4 ($r = 0.70$), f3-f4 ($r = 0.59$).
- Non-significant: f1-f2 ($p = 0.812$), f2-f3 ($p = 0.664$).

Table 5. 10: (B3) CFA Result for Odd ID and All 17 Questions (Improvement version)

B3-1: Model Fit Indices			
Fit Index	**Value**	**Threshold**	**Interpretation**
χ^2 (Chi-square)	129.12	-	$p = .001$
Degrees of freedom (df)	84	-	-
CFI (Comparative Fit Index)	0.955	≥0.90	Excellent
TLI (Tucker-Lewis Index)	0.944	≥0.90	Good
RMSEA	0.041	≤0.06	90% CI [0.026–0.055]
SRMR	0.051	≤0.08	Acceptable
AIC (Akaike Criterion)	10389	-	-
BIC (Bayesian Criterion)	10524	-	-
SABIC	10410	-	-
Loglikelihood (H0)	-5158	-	-
Loglikelihood (H1)	-5094	-	-

Notes:

- Estimation method: Maximum Likelihood (ML) with NLMINB optimisation.
- Model converged normally after 27 iterations.
- Baseline model $\chi^2 = 1111.604$ ($p < .001$).

B3-2: Standardised Factor Loadings						
Latent Factor	**Observed Variable**	**Estimate (λ)**	**SE**	**z-value**	***p*-value**	**Std. All (λ)**
f1	lifegoal2	0.51	0.046	11.006	<0.001***	0.65
f1	lifegoal4	0.594	0.051	11.556	<0.001***	0.68
f1	lifegoal6	0.403	0.049	8.287	<0.001***	0.505
f1	lifegoal8	0.398	0.047	8.528	<0.001***	0.518
f2	lifegoal1	0.429	0.047	9.061	<0.001***	0.637
f2	lifegoal5	0.5	0.055	9.15	<0.001***	0.645
f2	lifegoal7	0.44	0.056	7.825	<0.001***	0.528
f3	att1	0.551	0.052	10.562	<0.001***	0.598
f3	att3	0.509	0.038	13.293	<0.001***	0.722
f3	norm3	0.509	0.038	13.333	<0.001***	0.724
f3	behcontrol1	0.597	0.045	13.162	<0.001***	0.716
f4	att2	0.396	0.045	8.81	<0.001***	0.526
f4	norm1	0.532	0.045	11.714	<0.001***	0.675
f4	norm2	0.412	0.042	9.855	<0.001***	0.58
f4	behcontrol2	0.475	0.058	8.222	<0.001***	0.495

Notes:

- All loadings significant at $p < .001$.
- Standardised loadings (Std. All) >0.4 indicate adequate reliability.

B3-3: Factor Covariances					
Factor Pair	**Covariance**	**SE**	**z-value**	***p*-value**	**Std. All (r)**
f1 ~~ f2	-0.022	0.084	-0.259	0.796	-0.022
f1 ~~ f3	0.4	0.067	5.969	<0.001***	0.4
f1 ~~ f4	0.727	0.057	12.797	<0.001***	0.727
f2 ~~ f3	0.034	0.079	0.437	0.662	0.034
f2 ~~ f4	0.321	0.08	3.995	<0.001***	0.321
f3 ~~ f4	0.57	0.06	9.443	<0.001***	0.57

Key findings:

- Strong correlations: f1-f4 (r = 0.727), f3-f4 (r = 0.570).

- Non-significant: f1-f2 (p = 0.796), f2-f3 (p = 0.662).

Table 5. 11: (B4) CFA Results for Odd ID (only f1, f2 and f3 included)

B4-1: Model Fit Indices			
Fit Index	**Value**	**Threshold**	**Interpretation**
χ^2 (Chi-square)	70.527	-	p = .003
Degrees of freedom (df)	41	-	-
CFI (Comparative Fit Index)	0.957	≥0.90	Excellent
TLI (Tucker-Lewis Index)	0.943	≥0.90	Good
RMSEA	0.048	≤0.06	90% CI [0.028–0.066]
SRMR	0.053	≤0.08	Acceptable
AIC (Akaike Criterion)	7632.6	-	-
BIC (Bayesian Criterion)	7726.8	-	-
SABIC	7647.5	-	-
Loglikelihood (H0)	-3791	-	-
Loglikelihood (H1)	-3756	-	-

Notes:

- Estimation method: Maximum Likelihood (ML) with NLMINB optimisation.
- Model converged normally after 21 iterations.
- Baseline model χ^2 = 743.995 (p < .001).

B4-2: Standardised Factor Loadings						
Latent Factor	**Observed Variable**	**Estimate (λ)**	**SE**	**z-value**	***p*-value**	**Std. All (λ)**
f1	lifegoal2	0.512	0.049	10.448	<0.001***	0.653
f1	lifegoal4	0.589	0.055	10.759	<0.001***	0.673
f1	lifegoal6	0.411	0.05	8.168	<0.001***	0.515
f1	lifegoal8	0.393	0.048	8.124	<0.001***	0.512
f2	lifegoal1	0.402	0.049	8.262	<0.001***	0.597
f2	lifegoal5	0.525	0.059	8.888	<0.001***	0.678
f2	lifegoal7	0.447	0.058	7.728	<0.001***	0.537
f3	att1	0.554	0.052	10.572	<0.001***	0.602
f3	att3	0.515	0.039	13.361	<0.001***	0.731
f3	norm3	0.51	0.039	13.233	<0.001***	0.725
f3	behcontrol1	0.586	0.046	12.759	<0.001***	0.703

Notes:

- All loadings significant at $p < .001$.
- Standardised loadings (Std. All) >0.5 indicate strong item reliability.

B4-3: Factor Covariances					
Factor Pair	**Covariance**	**SE**	**z-value**	***p*-value**	**Std. All (r)**
f1 ~~ f2	-0.034	0.084	-0.401	0.688	-0.034
f1 ~~ f3	0.403	0.067	6.007	<0.001***	0.403
f2 ~~ f3	0.041	0.078	0.523	0.601	0.041

Key findings:

- Significant correlation: f1-f3 ($r = 0.403$, $p < .001$).
- Non-significant: f1-f2 ($p = 0.688$), f2-f3 ($p = 0.601$).

Table 5. 12: (B5) CFA Results for Odd ID (only f1, f2 and f4 included)

B5-1: Model Fit Indices			
Fit Index	**Value**	**Threshold**	**Interpretation**
χ^2 (Chi-square)	59.883	-	$p = .029$
Degrees of freedom (df)	41	-	-
CFI (Comparative Fit Index)	0.967	≥0.90	Excellent
TLI (Tucker-Lewis Index)	0.956	≥0.90	Good
RMSEA	0.038	≤0.06	90% CI [0.013–0.058]
SRMR	0.047	≤0.08	Acceptable
AIC (Akaike Criterion)	7768.7	-	-
BIC (Bayesian Criterion)	7862.9	-	-
SABIC	7783.6	-	-
Loglikelihood (H0)	-3859	-	-
Loglikelihood (H1)	-3829	-	-

Notes:

- Estimation method: Maximum Likelihood (ML) with NLMINB optimisation.
- Model converged normally after 26 iterations.
- Baseline model $\chi^2 = 635.259$ ($p < .001$).

B5-2: Standardised Factor Loadings						
Latent Factor	**Observed Variable**	**Estimate (λ)**	**SE**	**z-value**	***p*-value**	**Std. All (λ)**
f1	lifegoal2	0.513	0.046	11.074	<0.001***	0.655
f1	lifegoal4	0.598	0.051	11.623	<0.001***	0.684
f1	lifegoal6	0.395	0.049	8.104	<0.001***	0.496
f1	lifegoal8	0.396	0.047	8.477	<0.001***	0.516
f2	lifegoal1	0.424	0.047	8.956	<0.001***	0.629
f2	lifegoal5	0.509	0.055	9.233	<0.001***	0.657
f2	lifegoal7	0.435	0.056	7.751	<0.001***	0.523
f4	att2	0.382	0.046	8.286	<0.001***	0.508
f4	norm1	0.539	0.047	11.528	<0.001***	0.684
f4	norm2	0.415	0.043	9.696	<0.001***	0.584
f4	behcontrol2	0.479	0.059	8.139	<0.001***	0.499

Notes:

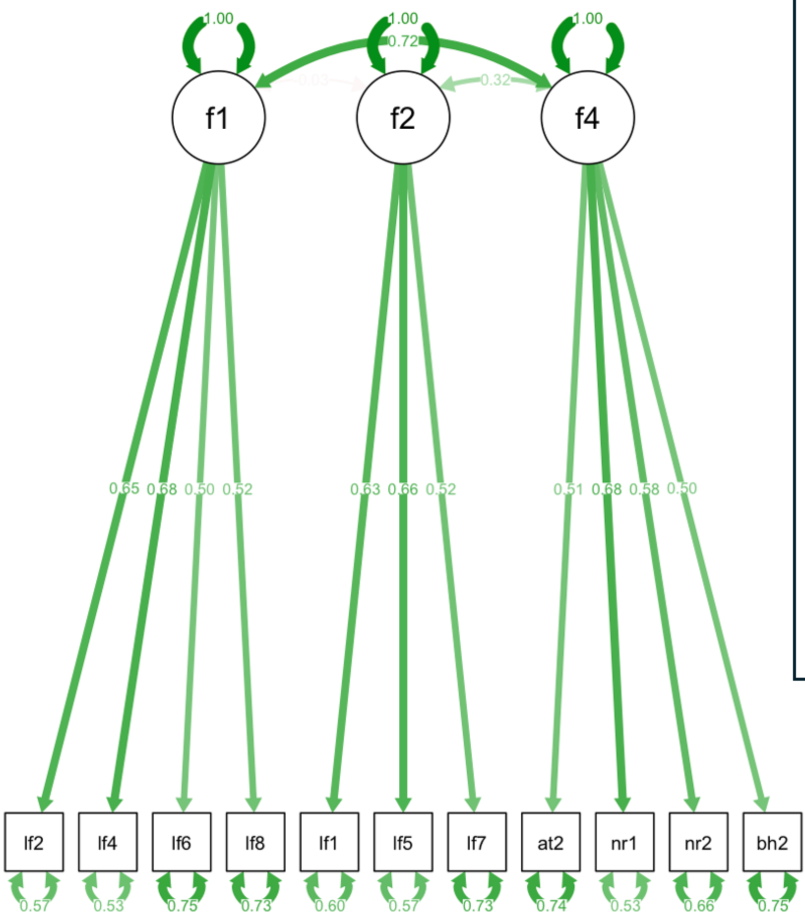
- All loadings significant at $p < .001$.
- Standardised loadings (Std. All) >0.5 indicate strong reliability.

B5-3: Factor Covariances					
Factor Pair	**Covariance**	**SE**	**z-value**	***p*-value**	**Std. All (r)**
f1 ~~ f2	-0.026	0.084	-0.316	0.752	-0.026
f1 ~~ f4	0.725	0.057	12.768	<0.001***	0.725
f2 ~~ f4	0.316	0.08	3.937	<0.001***	0.316

Key findings:

- Strong correlation: f1-f4 ($r = 0.725$, $p < .001$).
- Non-significant: f1-f2 ($p = 0.752$).

Figure 5. 7: (B6) CFA model for f1, f2, and f4 (odd ID). Three factors confirmed: altruistic goals, hedonic goals, and TPB attitude.



Legend:

f1 – Belief-based / Altruistic Life Goals (latent variable)
Driven by lifegoal2, lifegoal8, lifegoal4, lifegoal6, lifegoal3.

f2 – Material / Hedonic Life Goals (latent variable)
Driven by lifegoal5, lifegoal1, lifegoal7;

f4 – TPB (Attitude, Perceived behavioural control, Norm) (latent variable)
Driven by positive TPB indicator: att2, norm1, norm2, behcontrol2.

Note:
All f-factors (f1,f2,f4) are latent variables derived from exploratory factor.
Indicators serve as abbreviated references to the longer question titles listed in Table 5.2

Table 5. 13: (B7) Basic results for the main HCM model

B7-1 Basic results for the main HCM model (PART 1)

Number of individuals	638
Number of rows in database	3828
Number of cores used	10
Number of inter-individual draws	2000(mlhs)
LL(start)	-13283.57
LL (whole model) at equal shares, LL(0)	-15500.52
LL (whole model) at observed shares, LL(C)	-10813.64
LL(final, whole model)	-9593.43
Rho-squared vs equal shares	0.3811
Adj.Rho-squared vs equal shares	0.3741
Rho-squared vs observed shares	0.1128
Adj.Rho-squared vs observed shares	0.107
AIC	19404.85
BIC	20086.11

B7-2 Basic results for the main HCM model (PART 2)

Component	1 (%)	2 (%)	3 (%)	4 (%)	5 (%)
Do you agree that people should care about is life and survival issues, not environmental issues such as improving solid waste disposal?	2.19	6.27	8.93	48.28	34.33
Do you agree that recycling is waste of your time. If You are working full time and do not have the time to recycle?	0.78	2.35	2.82	28.84	65.2
Do you agree that the local government have responsibility to waste classification and recycling and have nothing to do with residents?	0.63	2.51	2.04	24.61	70.22
Do you agree that it is very inconvenient when you classify your house wastes?	1.1	3.76	4.39	44.98	45.77
Seeking pleasure	0.31	0.63	10.97	56.11	31.97
Seeking to do what you believe in	0.16	1.88	19.91	38.56	39.5
Seeking to contribute to others in your local area or the surrounding world?	0.94	8.15	30.56	42.32	18.03
Seeking to have lots of money and nice possessions?	0.31	2.51	14.26	49.84	33.07
Seeking enjoyment	0.94	2.35	11.44	39.18	46.08
benefit future generations	0.31	2.82	13.64	34.8	48.43
prevent harm to the local environment	0.16	2.19	10.34	39.18	48.12

Chapter 6

Discussion

6.1 Introduction

This chapter explores my thesis's key findings and their implications. It begins with a brief review of each data chapter, summarising the primary results in relation to the research questions (Section 6.2). Section 6.3 then evaluates the policy relevance of these findings. Lastly, Section 8.4 addresses the thesis's main limitations and contemplates potential alternative approaches.

6.1.1 Research Aims

This thesis explores the relationship between pro-environmental behaviour—specifically household waste recycling—and intervention policies and long-term personal goals. It investigates whether factors outside the standard neoclassical choice model, including external influences such as social norms and internal factors such as personal values, affect individuals' willingness to participate in community recycling programmes and their willingness to pay for recycling.

Chapter 4 of this thesis explores the connections between past recycling behaviour, social norm nudges, local waste sorting policies (whether mandatory or advocative), and the willingness to financially support recycling initiatives in China. Employing a randomised experimental design, we varied the social norm information presented to participants by modifying details regarding others' recycling efforts. The willingness to pay (WTP) of households for enhanced recycling standards under a waste collection agreement was then utilised as an indicator of their recycling intentions. For the econometric analysis, we employed a Mixed Logit (ML) model (McFadden and Train, 2000). This approach included interaction terms to examine how different waste sorting policies interact with social-norm nudges. We also analysed participants' reported past recycling habits to assess if previous recycling experience affects responses to social-norm nudges.

Chapter 5 explores whether the Theory of Planned Behaviour (TPB) should be enhanced with insights from goal theories in the context of pro-environmental behaviour. It investigates whether life goals directly shape stated recycling preferences or influence them indirectly through attitude, perceived behavioural control, and social norms. The study focuses on household waste contracts and recycling decisions in China. To analyse the relationships between TPB variables, life goals—such as aspirations for happiness, success, and altruism—demographic factors, and recycling preferences, we employ the Hybrid Mixed Logit (HMXL) model. In this chapter, I focus on two main research questions. First, I examine whether the three factors of the Theory of Planned Behaviour (TPB)—attitudes, perceived behavioural control, and subjective norms—each separately or together positively influence recycling preferences. Second, considering that personal goals are organised hierarchically, where broad long-term aims guide specific short-term actions, I investigate if various life goals (e.g., benefiting future generations) affect recycling choices directly, or indirectly through TPB factors.

Before presenting the findings, I will first reiterate the research objectives.

Chapter 4 focuses on household recycling preferences and the effects of social norm nudges. It addresses two main research objectives. RO1 examines whether mandatory recycling policies in Shanghai lead to greater willingness-to-pay (WTP) for recycling compared to advocative policies in Zhengzhou and Shijiazhuang, as tested by Hypothesis 1 (H1). RO2 investigates the role of social norm nudges in shaping households' WTP for improved recycling services. Specifically, it assesses whether stronger social norms increase recycling-related WTP (H2), if these nudges have a greater impact under Shanghai's mandatory system compared to advocative cities (H3), and whether previous recycling experience influences the effectiveness of social norm nudges (H4).

Chapter 5 examines the relationships between recycling preferences, the Theory of Planned Behaviour (TPB), and personal goal theories. It addresses two research objectives: RO3 and RO4. RO3 investigates whether TPB variables (attitudes, subjective norms, perceived behavioural control) positively influence individuals' recycling preferences (H1). RO4 explores whether personal life goals (such as benefiting future generations) influence recycling preferences directly or indirectly via TPB variables (H2).

6.2 Summary of key results

6.2.1 The effect of mandatory versus advocacy-based waste sorting policies on recycling preferences.

The findings from Chapter 4 indicate that Shanghai's mandatory waste sorting policy significantly increases individuals' willingness to pay (WTP) for improved recycling compared to the advocacy policies in Zhengzhou and Shijiazhuang. Participants from Shanghai demonstrated a stronger willingness to contribute financially, suggesting that concerns about crowding out intrinsic motivation do not result in a net negative effect on household behaviour. Several factors may account for this: the threat of financial penalties raises the cost of non-compliance, official endorsement of waste sorting norms enhances moral responsibility, habit formation reduces the effort required for recycling, and better waste separation tools facilitate the process. These benefits seem to outweigh any loss of intrinsic motivation or additional economic costs. Furthermore, the mandatory policy has a positive spillover effect, increasing WTP for later stages of the recycling process, such as waste collection and disposal. If such policies prove more effective, households may prefer them over voluntary approaches, recognising their role in fostering a cleaner and more sustainable environment (Vollaard and van Soest, 2024). The findings presented in Chapter 4 directly address RO1 by demonstrating that Shanghai’s mandatory waste sorting policy significantly enhances residents' willingness-to-pay (WTP) for recycling compared to the voluntary policies in Zhengzhou and Shijiazhuang. The mandatory approach effectively increases household recycling intentions by raising the cost of non-compliance, strengthening moral responsibility through official endorsement, promoting habit formation, and providing better recycling facilities. Overall, these results suggest households favour mandatory policies for their superior capacity to encourage pro-environmental behaviour and sustainability.

6.2.2 The influence of social norm nudges on recycling preferences.

Our research demonstrates that social norm nudges can effectively increase WTP for recycling, though their impact is non-linear and varies among demographic groups. I will first analyse hypotheses H2, H3, and H4 from Chapter 4, as they are all pertinent to this issue.

H2 is supported, as higher levels of social norm cues generally increase willingness to pay (WTP), particularly at low to medium levels, which aligns with previous research by Czajkowski et al. (2019). However, when social norm information becomes excessively high, enthusiasm for recycling declines. This may be due to a significant gap between an individual's initial recycling efforts and the suggested norm, making it challenging to bridge the difference. Alternatively, individuals who already exceed the norm might feel less compelled to change their behaviour, or they may perceive that enough people are already recycling, thereby reducing their sense of responsibility due to the free-riding effect. The findings highlight a considerable degree of variation in responses to social norms across different demographic groups.

Rejecting H3 suggests that social norms do not exert a stronger influence on willingness to pay (WTP) for recycling in Shanghai compared to Shijiazhuang and Zhengzhou. Instead, WTP is more closely associated with existing local waste sorting practices. In cities with supportive policies, residents responded more strongly to social norm cues than those in cities with mandatory policies. However, this comparison may be constrained by the generally higher engagement in waste sorting among residents of Shanghai. Furthermore, rejecting H3 indirectly lends support to H2, as the increased WTP for waste sorting in Shanghai seems to be driven by factors other than social norm nudges.

H4 is confirmed, indicating that for individuals with low initial engagement in waste sorting, low to moderate levels of social norm cues are more effective at encouraging participation. However, the highest levels of social norm information adversely affect recycling behaviour, reinforcing the findings from H2 that excessive social pressure can diminish motivation.

These results suggest that the effectiveness of social norm nudges relies on an individual's current level of recycling engagement.

The analysis presented clearly addresses RO2 by demonstrating the role social norm nudges play in influencing households' willingness-to-pay (WTP) for enhanced recycling. It shows that moderate social norm cues effectively boost WTP, while excessive cues have diminishing returns (H2). Additionally, the influence of social norm nudges does not intensify with geographical proximity or policy type (H3), indicating other local factors are more important. Finally, the effectiveness of these nudges varies depending on individuals' prior recycling habits: people with lower initial engagement respond positively to moderate norms but negatively to overly strong social pressures (H4).

Contributions

Overall, this thesis provides original theoretical and empirical insights into household recycling behaviour in China. It is the first to apply discrete choice experiments (DCE) with descriptive social norm nudges in this context. Theoretically, it shows that mandatory recycling policies significantly increase households' willingness-to-pay (WTP), potentially driven by penalties, stronger moral responsibility, habit formation, and improved recycling facilities. Empirically, it demonstrates for the first time in China that moderate social norm nudges effectively raise WTP, particularly among individuals with lower initial recycling engagement, though excessive norm pressure reduces their effectiveness.

6.2.3 The effect of TPB variables on recycling preferences.

In Chapter 5, our analysis revealed a strong correlation between attitudes, perceived behavioural control, and subjective social norms related to recycling. To encapsulate these interrelations, we consolidated all positive TPB-related questions into a single latent variable (LV1). The findings indicate a significant association between a favourable disposition towards waste sorting (as reflected in sort2, sort4, and sort7) and LV1. This suggests that individuals who possess positive attitudes towards recycling, feel confident in their ability to sort waste, and perceive strong social norm are more inclined to engage in waste sorting activities. These insights are consistent with the Theory of Planned Behaviour, which asserts that attitudes, subjective norms, and perceived behavioural control collectively influence behavioural intentions, thereby affecting actual behaviour (Ajzen, 2011; Ajzen and Driver, 1991).

These factors may be highly correlated because behavioural intention is shaped by both individual motivation and external influences. When individuals possess a positive attitude towards recycling, they are more likely to perceive it as a valuable action. Simultaneously, perceived behavioural control—the belief in one's ability to perform waste sorting—reinforces this intention by reducing barriers to action. Social norms further strengthen this connection by providing external validation and pressure to conform to environmentally responsible behaviour. Collectively, these elements create a reinforcing cycle in which positive attitudes, self-efficacy, and social expectations drive pro-environmental behaviour (Fishbein, 1975; Fishbein and Ajzen, 1977; Ajzen, 1985).

This analysis clearly addresses RO3 by showing that key variables from the Theory of Planned Behaviour (TPB)—attitudes, perceived behavioural control, and social norms—are significantly and positively associated with recycling preferences. Individuals who view recycling favourably, believe they can effectively sort waste, and perceive social norm for recycling demonstrate stronger intentions to participate. These findings reinforce TPB’s claim that attitudes, perceived control, and social expectations jointly encourage pro-environmental actions, such as household recycling.

6.2.4 The influence of life goals, either directly or indirectly through TPB variables, on recycling preferences.

In Chapter 5, we observed that a positive preference for waste sorting (sort7) and recycling disposal plans is significantly associated with the latent variable LV2. This suggests that individuals motivated by normative goals—such as adhering to personal beliefs or altruistic values—are more likely to engage in meticulous waste sorting and remain attentive to the final disposal of waste. This finding aligns with goal theories that propose a hierarchical structure, in which higher-level goals guide specific behaviours. It also corresponds with Goal-Framing Theory, which posits that when a normative goal frame prevails, individuals are more inclined to perform pro-environmental behaviours because they view them as morally correct or socially responsible (Lindenberg and Steg, 2007). Furthermore, our structural equation modelling indicates that individuals with strong normative goals (LV2) tend to develop more positive attitudes, greater perceived behavioural control, and subjective social norms towards recycling (LV1), suggesting that normative goals indirectly influence recycling preferences by shaping key determinants identified in the Theory of Planned Behaviour (TPB) (Lindenberg and Steg, 2013; Yin et al., 2024). Furthermore, our results demonstrate that hedonic and gain-oriented life goals are insignificantly negatively correlated with recycling behaviours, both directly and indirectly. This suggests that when higher-level life goals influence current goals, the brain may prioritise normative objectives, which could lead individuals inclined towards altruism to engage more readily in pro-environmental actions. This observation aligns with Goal-Framing Theory, which distinguishes among normative, gain, and hedonic goal frames, noting that normative goals often promote pro-environmental behaviour, whereas gain and hedonic goals may not (Lindenberg & Steg, 2007). Additionally, research indicates that activating normative goals can result in increased pro-environmental behaviour, while the activation of hedonic or gain goals may not yield the same effect (Steg et al., 2014).

Therefore, this analysis directly addresses RO4 by showing that self-reported life goals influence recycling preferences primarily through normative goals. Individuals driven by altruistic or moral values are more likely to prefer recycling options and demonstrate careful waste sorting behaviour. These normative goals indirectly shape recycling preferences by enhancing positive attitudes, perceived behavioural control, and subjective social norms, consistent with TPB. Conversely, hedonic and gain-oriented goals have minimal or slightly negative impacts on recycling behaviours, suggesting normative motivations play a crucial role in encouraging pro-environmental choices.

Contributions

This thesis makes novel theoretical and methodological contributions to understanding recycling behaviour by integrating personal life goals into the Theory of Planned Behaviour (TPB). Theoretically, it is the first study to demonstrate that normative life goals, such as altruism and moral responsibility, directly or indirectly shape recycling intentions through attitudes, subjective norms, and perceived behavioural control. Empirically, it provides the first evidence from China confirming that individuals driven by normative goals are more likely to participate positively in recycling. Methodologically, it pioneers the use of the Hybrid Mixed Logit (HMXL) model in this context, offering deeper insights into how psychological motivations influence household recycling decisions beyond standard TPB factors.

6.3 Policy relevance

From a policy perspective, the findings presented in Chapter 4 and 5 suggest several key recommendations for improving recycling behaviour through targeted policies.

In Chapter 4, mandatory recycling policies can enhance residents' willingness to pay (WTP) for subsequent waste management stages, such as collection and disposal, as they are perceived to contribute to a cleaner and more sustainable environment (Vollaard et al., 2024). However, these policies must be implemented with care to prevent negative spillover effects, such as diminished intrinsic motivation or resistance if individuals feel compelled to comply (Yang et al., 2021; Halvorsen, 2012). To mitigate this risk, policymakers should pair mandatory measures with clear communication regarding their environmental benefits and provide public recognition for participation, thereby sustaining motivation and public support.

Secondly, when social norm information is too strong, enthusiasm for recycling tends to decline. This may occur if the gap between an individual's current efforts and the suggested norm appears too large to bridge. Alternatively, those who are already exceeding the norm may feel less inclined to modify their behaviour or assume that a sufficient number of people are recycling, diminishing their sense of personal responsibility due to the free-riding effect. While social norms can effectively encourage recycling, policymakers should avoid overwhelming residents with normative messages, as this might result in fatigue or counterproductive reactions. Excessive or negatively framed messages, such as emphasising low compliance rates, can dissuade individuals who perceive the recycling goal as unrealistic or believe they are already doing more than required. Instead, normative messages should be framed positively, reinforcing widespread participation in recycling without fostering complacency among regular recyclers (Richter et al., 2018).

Furthermore, the effectiveness of social norm nudges largely depends on local policies and existing recycling practices. In cities with mandatory recycling policies, residents already regard recycling as a norm. Therefore, instead of merely promoting participation, interventions should concentrate on enhancing recycling quality or fostering additional sustainable behaviours (Kip Viscusi et al., 2014). In areas lacking robust recycling systems, normative messages can aid in establishing new habits, but they must align with local realities to be effective. For instance, Shanghai’s mandatory recycling policy successfully reinforced internalised recycling norms, illustrating that compulsory measures, when paired with appropriate messaging, can strengthen pro-environmental behaviour (Li et al., 2020).

The effectiveness of social norm-based interventions also depends on individuals' existing level of recycling engagement. Highly engaged recyclers may react negatively if messages suggest they are already exceeding expectations, potentially leading to reduced effort due to moral licensing. To maintain their motivation, policies should provide recognition and introduce new recycling challenges. Meanwhile, those with lower engagement often face practical barriers, such as inconvenient facilities or a lack of knowledge about recycling (Strydom, 2018b). To address this, policymakers should combine normative nudges with practical measures, such as improving infrastructure and providing clear, accessible information to support and encourage less active recyclers.

In Chapter 5, my results indicate the crucial role of environmental knowledge and awareness in fostering positive recycling attitudes and behaviours. Greater environmental awareness significantly shapes individuals' attitudes, perceived behavioural control, and social norms, indirectly increasing their recycling commitment. To enhance recycling participation, policymakers should prioritise educational initiatives, including school programmes, community outreach, and public campaigns. These efforts should provide clear recycling instructions, address misconceptions, and emphasise environmental benefits (Tran, 2018). Research shows that when people understand both the process and impact of recycling, their commitment to recycling and other pro-environmental behaviours strengthens (Noh, 2024).

In addition, my findings indicate that individuals motivated by normative goals, such as personal beliefs or altruistic values, are more likely to engage in thorough waste sorting and remain conscious of waste disposal. Governments should actively encourage the activation of normative goals, as it significantly improves recycling behaviour (Lindenberg & Steg, 2007). Policies should frame recycling as a moral obligation, emphasising community benefits and environmental protection to reinforce individuals' sense of duty (Steg et al., 2014). This approach aids in internalising recycling as a social and ethical norm, fostering consistent participation (Richter et al., 2018). Furthermore, policies must tackle the negative impacts of hedonic (comfort-seeking) and gain-oriented (self-interested) goals. Since convenience plays a crucial role in recycling participation, governments should enhance access to recycling infrastructure, ensuring that collection points are user-friendly and readily accessible to reduce perceived effort (Yang et al., 2021).

Policy Recommendations for City Planners to Improve Recycling in China

Based on the policy implications discussed above, given that Shanghai's mandatory waste-sorting crackdown is scheduled to conclude at the end of 2025, the Chinese government should carefully manage this transition. If recycling habits among residents remain weak, authorities might consider temporarily extending mandatory enforcement measures, or implementing periodic enforcement checks (for example, annual intensive inspections) to reinforce compliance. Concurrently, introducing positively framed social-norm nudges that highlight broad community participation could effectively maintain public motivation. Policymakers should avoid excessively strong or negative normative messages, which risk discouraging highly committed recyclers. Additionally, investments in improved recycling infrastructure and clear public communication would support sustainable behavioural change in the long term.

6.4 Limitations and future research

In this section, I will discuss the limitations of the research and what I might have done differently if there had been no time or monetary constraints, as well as provide recommendations for future research.

The online survey conducted during the COVID-19 pandemic may have introduced sampling bias, as respondents were predominantly younger and better educated, making the sample less representative of the wider Chinese population. To enhance representativeness in future studies, a mixed-method approach that combines online and offline surveys should be employed to include a more diverse range of participants in terms of age, education, and socioeconomic background (Creswell and Hirose, 2019).

The geographic proximity test in Chapter 4 revealed that the effects of social norms were weaker than anticipated, likely due to regional differences in baseline recycling practices. Previous research indicates that the effectiveness of social norm interventions relies on existing local norms. Furthermore, our choice to utilise authentic local data rather than "deceptive nudges" resulted in variations across experimental treatments (T1–T3), which may have affected respondents' stated preferences in unexpected ways. Future studies should evaluate local recycling behaviours in advance and devise norm interventions that align with the specific context and baseline conditions of each community.

A key limitation of this study is that data was collected at a single point in time, which makes it difficult to assess the long-term impact of recycling interventions. Research suggests that behavioural changes driven by nudges may fade without reinforcement. To address this, future studies should employ a longitudinal approach to evaluate whether changes in recycling behaviour are sustained over time or diminish once interventions conclude.

Fourthly, the relatively limited geographic scope and sample size of the survey in Chapter 5 may constrain the external validity of the findings. Our study covered only three cities, which limits generalisability. Increasing the number of surveyed locations—specifically, cities with varying levels of recycling infrastructure and policies—and conducting separate surveys in each city could enhance the insight gained from the research.

In Chapter 5, time and funding constraints limited the study to a single questionnaire conducted with 697 participants across three cities. Future research should broaden the geographic scope to encompass more diverse locations. Additionally, separate studies could be undertaken to investigate the effects of social norms on recycling (as discussed in Chapter 4) and the relationships between life goals, TPB constructs, and recycling preferences (as outlined in Chapter 5). Although social norms were initially incorporated into the structural equation model, their impact on recycling preferences was statistically insignificant, resulting in their removal for the sake of simplicity. Exploring these two research areas individually in future studies could yield clearer insights and more robust findings.

A limitation of this study was the measurement of latent psychological variables (TPB constructs). Due to constraints on the length of the questionnaire, each TPB construct was assessed with only a few items, which may have increased measurement error and reduced reliability. Future research should employ more comprehensive measurement scales that include multiple validated items for each construct to enhance model robustness and minimise measurement errors.

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