Enhancing Engineering Education through Wearable Technology: A Focus on Eye-Tracking and Multisensory Approaches

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Abstract

This doctoral research investigates the efficacy of wearable technology with a multisensory approach, particularly eye-tracking and physiological sensors, in capturing and interpreting cognitive engagement among engineering students in higher education. Responding to the growing interest in data-driven, personalised learning, the study develops and validates a multisensory framework to detect attention and mind-wandering during video-based instruction.

This study systematically analysed different wearable devices and first identified head-mounted eye-trackers as the most promising tools for monitoring visual attention in educational settings. To evaluate their practicality, a comparative study was conducted using a commercial wearable eye-tracker (Pupil Core) and a custom-built desktop-based solution. The wearable eye-tracker provided greater flexibility for natural head movement and enabled real-time detection of visual attention patterns. It also helped identify segments of the learning material that were skipped or overlooked, offering insights into content that learners found confusing or cognitively demanding. The commercial device outperformed the desktop-based system in both usability and richness of data, validating its utility in dynamic learning environments.

To address the limitations of eye-tracking in detecting internal cognitive states, the research implemented a multimodal sensing system by integrating galvanic skin response (GSR) and photoplethysmography (PPG) sensors. Data were collected during learning sessions, and supervised machine-learning models were trained to classify episodes of mind-wandering. The multimodal sensor fusion achieved the highest accuracy of 89% , significantly outperforming unimodal baselines.

The experiments in this thesis concluded that the proposed multisensory device, combining eye-tracking with physiological signals (PPG and GCR), provides a robust method for detecting cognitive disengagement in real-time. The outcomes have implications for developing adaptive educational technologies capable of personalising instruction based on learners' cognitive states.

Publications and Contributions

The findings of this research have been disseminated through the following peer-reviewed journal articles and conference papers:

[1] **Khosravi, S.**, Li, H., Khan, A. R., Zoha, A., and Ghannam, R. (2024). Exploring the Elusive Mind: A Multimodal Wearable Sensor Solution for Measuring Mind Wandering in University Students. Advanced Sensor Research, 3(1), 2300067. https://doi.org/10.1002/adsr.202300067

[2] **Khosravi, S.**, Bailey, S. G., Parvizi, H. and Ghannam, R. Wearable sensors for learning enhancement in higher education. Sensors, 22(19), 7633, 2022. (doi: 10.3390/s22197633) (PMID:36236732) (PMCID:PMC9573685)

[3] **Khosravi, S.**., A. R. Khan, A. Zoha and R. Ghannam, "Employing a Wearable Eye-tracker to Observe Mind-wandering in Dynamic Stimuli," 2022 29th IEEE International Conference on Electronics, Circuits and Systems (ICECS), Glasgow, United Kingdom, 2022, pp. 1-4, doi: 10.1109/ICECS202256217.2022.9970787.

[4] A. R. Khan, S. M.Bokhari, **Khosravi, S.**, S.Hussain, R.Ghannam, M. A.Imran, and A.Zoha, "Feature Selection Mechanism for Attention Classification using Gaze Tracking Data," 2022 29th IEEE International Conference on Electronics, Circuits and Systems (ICECS), Glasgow, United Kingdom, 2022, pp. 1-4, doi: 10.1109/ICECS202256217.2022.9970936.

[5] **Khosravi, S.**, Khan, A. R., Zoha, A. and Ghannam, R. (2021) Self-Directed Learning using Eye Tracking: A Comparison Between Wearable HeadWorn and Webcam-based Technologies.In: IEEE Global Engineering Education Conference (EDUCON 2022), 28-31 Mar 2022, Tunisia.

[6] Khan, A. R., **Khosravi, S.**, Hussain, S. , Ghannam, R. , Zoha, A. and Imran, M. A. (2021) EXECUTE: Exploring Eye Tracking Data to Support E-Learning. In: IEEE Global Engineering Education Conference (EDUCON 2022), 28-31 Mar 2022, Tunisia.

[7] **Khosravi, S.** and Ghannam, R. (2021) Enhancing STEM Education using Wearable Biofeedback. 3rd IEEE Postgraduate STEM Research Symposium, 10 Nov 2021. (Accepted for

Publication)

[8] **Khosravi, S.**, Bailey, S. and Ghannam, R. (2021) Outreach Approach to Electronic Engineering Education via Wearable Technology. ESLTIS21 Enhancing Student Learning Through Innovative Scholarship Conference, 10 Sep. 2021.

[9] **Khosravi, S.** and Ghannam, R., Calling all engineers: we need you! IEEE Potentials, 40(5), pp. 14-17, 2021. (doi: 10.1109/MPOT.2021.3073885)

[10] Ghannam, R. , Curia, G., Brante, G., **Khosravi, S.** and Hua, F. (2020) Implantable and wearable neuroengineering education: a review of postgraduate programmes. IEEE Access, 8, pp. 212396-212408. (doi: 10.1109/ACCESS.2020.3040064)

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Nomenclature

AI Artificial Intelligence

AOI Area of Interest

AR Augmented Reality

ART Attention Restoration Theory

BCI Brain-Computer Interface

BLE Bluetooth Low Energy

CLT Cognitive Load Theory

CNN Convolutional Neural Network

DSP Digital Signal Processing

ECG Electrocardiogram

Edtech Education Technology

EEG Electroencephalography

EMG Electromyography

GDP Gross Domestic Product

GDPR General Data Protection Regulation

GRU Gated Recurrent Unit

GSR Galvanic Skin Response

GUI Graphical User Interface

HMD Head Mounted Display

HRV Heart Rate variability

HRV Heart-Rate Variability

HUD Heads-Up Display

IoT Internet of Things

IQR Interquartile Range

k-NN k-Nearest Neighbour

LED Light Emitting Diodes

LMS Learning Management System

LSTM Long Short Term Memory

ML Machine Learning

MW Mind-Wandering

NFC Near Field Communication

NPD National Purchase Diary

OECD Organisation for Economic Co-operation and Development

PCA Principal Component Analysis

PPG Photoplethysmography

PPG Photoplethysmography

RMSD Root Mean Square of Successive Differences

RNN Recurrent Neural Network

SCL Skin Conductance Level

SDNN Standard Deviation of Normal-to-Normal Intervals

SRL Self Regulated Learning

SVM Support Vector Machine

SVR Support Vector Regression

TOS Tracheostomy Overlay System

TPB Theory of Planned Behaviour

VR Virtual Reality

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Declaration

With the exception of chapters 1 and 2, which contain introductory material the state-of-the-art, all work in this thesis was carried out by the author unless otherwise explicitly stated.

Chapter 1

Introduction

1.1 Background

Wearable technology, defined as small digital devices designed to be worn on the user's body, has become a ubiquitous part of modern life [1, 2]. These devices, equipped with wireless connectivity and real-time data processing capabilities, enable seamless access to and exchange of contextually relevant information, enhancing their utility across various applications [3, 4]. Over the past decade, advancements in technology have propelled wearable devices from niche innovations to mainstream tools, allowing them to interact with computers and the environment in ways that were once considered the realm of science fiction.

1.1.1 The Evolution of Wearable Technology

The concept of wearable technology dates back decades, with early examples like wristwatches and hearing aids being among the first devices designed to be worn on the body. However, it was not until the late 20th and early 21st centuries that the potential of wearable technology began to be fully realised, thanks to advancements in miniaturisation, wireless communication, and sensor technologies [5]. These advancements allowed wearable devices to become more sophisticated, enabling them to perform complex tasks such as monitoring physiological signals, tracking movement, and interacting with other digital devices [6].

Initially, wearable technology was primarily used in specialised fields such as healthcare and military applications. For example, wearable heart rate monitors were developed for athletes and patients with cardiovascular conditions, while the military explored the use of wearable sensors for monitoring soldiers' health and performance in the field [4]. As technology continued to evolve, wearable devices became more accessible and affordable, leading to their adoption in a wide range of consumer applications [2].

Today, wearable technology encompasses a broad spectrum of devices, including smartwatches, fitness trackers, smart glasses, and wearable cameras. These devices have become integral to our daily lives, offering a range of functionalities that extend beyond simple data collection. For instance, modern wearables can track physical activity, monitor sleep patterns, provide navigation assistance, and even serve as communication tools by enabling users to make phone calls and send messages without needing to use a smartphone [1, 3].

The growing popularity of wearable technology has also led to the development of new use cases in various sectors. In healthcare, wearables are being used to monitor chronic conditions, manage medication adherence, and provide remote patient care [6]. In the workplace, wearable devices are being used to enhance worker safety and productivity by monitoring fatigue levels and providing real-time feedback on ergonomics. In sports, wearables are helping athletes optimise their performance by providing detailed metrics on their physical activity and recovery [5].

1.1.2 The Integration of Wearables in Education

The potential of wearable technology to transform education has only recently begun to be explored. Traditionally, education has relied on static, one-size-fits-all approaches to teaching and learning. However, the introduction of wearable devices offers the opportunity to create more dynamic, personalised, and engaging learning experiences. Wearable technology in education can take many forms, from fitness trackers used in physical education classes to augmented reality (AR) glasses that overlay digital content onto the physical world, allowing students to interact with learning materials in new and immersive ways.

One of the key advantages of wearable technology in education is its ability to provide real-time feedback and data. For example, in a classroom setting, wearable devices can monitor students' physiological responses to learning stimuli, such as heart rate, skin conductance, and eye movements. This data can be used to assess student engagement, identify areas where students may be struggling, and provide targeted interventions to support learning. Additionally, wearable devices can facilitate collaborative learning by enabling students to share data and work together on projects in real time, regardless of their physical location.

The use of wearable technology in education is not limited to monitoring and assessment. Wearable devices can also enhance the learning experience by providing new ways for students to interact with educational content. For example, virtual reality (VR) headsets can transport students to different environments, allowing them to explore historical sites, conduct virtual experiments, or practice complex tasks in a safe and controlled setting. Similarly, AR glasses can provide students with additional layers of information as they engage with physical objects, helping them to better understand complex concepts and apply their knowledge in practical situations.

The literature consistently demonstrates that the use of wearable devices in the classroom has led to improved student learning outcomes across a wide range of subjects and age groups, from K–12 to higher education [7, 8]. In the initial phase of this PhD research, an extensive review was conducted on various wearable devices implemented in higher education. These devices

Figure 1.1: *Classification of wearable devices for educational purposes into three major categories based on their placement on the body. These devices can be worn on the head, wrist, or chest to collect and monitor information from students and teachers.*

were categorised into three broad groups based on their placement on the body: head-worn, wrist-worn, and chest-worn, as illustrated in Figure 1.1.

1.1.3 Challenges and Opportunities

Despite the potential benefits of wearable technology in education, its adoption is not without challenges. One of the primary challenges is the cost of wearable devices, which can be prohibitive for many schools and institutions, particularly in underfunded areas. Additionally, the integration of wearable technology into existing curricula requires significant planning and training for educators who may be unfamiliar with the technology or uncertain about how to use it effectively in the classroom.

Another challenge is the issue of privacy and data security. Wearable devices often collect sensitive data, such as biometric information, which raises concerns about how this data is stored, used, and shared. Schools and institutions must ensure that they have robust data protection policies to safeguard students' privacy and comply with legal and ethical standards. Despite these challenges, wearable technology presents significant opportunities for educational transformation. Such devices have the potential to revolutionise teaching and learning by enabling more personalised, engaging, and accessible educational experiences. Through the provision of real-time feedback and data, wearable technology can support educators in identifying student needs and tailoring instruction accordingly. Furthermore, these technologies can facilitate innovative forms of collaboration and interaction, allowing learners to engage with one another in ways that were previously not possible.

1.2 Research Questions and Objectives

This PhD research is guided by the following overarching questions, which reflect the core aims of the thesis in enhancing engineering education through wearable and multisensory technologies:

- What are the key factors influencing the adoption of wearable devices in engineering education?
- How do wearable eye-trackers compare with traditional methods in terms of improving student engagement and learning outcomes?
- How can multisensory approaches be effectively integrated into educational settings to monitor and reduce mind-wandering?

To address these questions, the study pursues the following objectives:

- To evaluate the effectiveness of wearable eye-trackers in monitoring student engagement.
- To explore the potential of multisensory systems in detecting mind-wandering in educational environments.
- To design, integrate, and evaluate a framework for the application of wearable technology within engineering education curricula, focusing on its impact on student engagement and learning outcomes.

These objectives provide a clear focus for the research and outline the expected contributions to the field of educational technology. The research questions also highlight the practical implications of the study, as they address both the technical aspects of wearable technology and its impact on teaching and learning.

1.2.1 Methodological Considerations

To address the research questions, this study employs a mixed-methods approach that combines quantitative and qualitative data collection techniques. Quantitative data will be collected through experiments that use wearable eye-trackers to monitor student engagement during learning activities. This data will be analysed to identify patterns and correlations between eye movements, cognitive load, and learning outcomes.

Qualitative data will be collected through interviews and surveys with educators and students to gain insights into their perceptions and experiences with wearable technology. This data will be used to explore the factors that influence the adoption of wearable devices in education and to identify potential barriers to their implementation.

The integration of quantitative and qualitative data will provide a comprehensive understanding of the impact of wearable technology on engineering education. By triangulating data from multiple sources, the study aims to produce robust and reliable findings that can inform both theory and practice.

1.2.2 Expected Contributions

This research is expected to make several significant contributions to the field of educational technology:

Empirical Evidence: The study will provide empirical evidence on the effectiveness of wearable eye-trackers in improving student engagement and learning outcomes in engineering education. This evidence will be valuable for educators and policymakers seeking to implement wearable technology in their institutions.

Framework for Implementation: The research will develop a framework for integrating wearable technology into engineering education curricula. This framework will include guidelines and best practices for using wearable devices to enhance teaching and learning, as well as recommendations for addressing the challenges associated with their adoption.

Theoretical Insights: The study will contribute to the theoretical understanding of the role of wearable technology in education. By exploring the relationship between wearable devices, cognitive load, and student engagement, the research will offer new insights into the mechanisms through which technology can influence learning.

1.3 Scope and Limitations

This research primarily focuses on the application of wearable technology in higher education, specifically within the context of engineering disciplines. Engineering education is an ideal setting for this research because it often involves complex and abstract concepts that can benefit from the immersive and interactive capabilities of wearable technology.

This thesis explores various types of wearable technologies, with particular emphasis on head-worn devices such as eye-trackers due to their potential to enhance cognitive and visual engagement in learning environments. While the study also considers wrist-worn and chest-worn devices, these are not the primary focus. The rationale for concentrating on head-worn devices is their capacity to provide detailed, real-time data on visual attention and cognitive load, key indicators for understanding student engagement and learning processes.

However, the study has certain limitations that should be acknowledged. Firstly, the focus on higher education, specifically within engineering disciplines, means that the findings may not be fully generalised to other educational contexts, such as K-12 education or non-STEM fields. The specific demands and learning environments of engineering education may differ significantly from other disciplines, and as such, the results of this research may have limited applicability outside of this context.

Secondly, the study's reliance on advanced wearable technologies, such as eye-trackers, presents practical limitations. These devices are often expensive and require specialised knowledge to operate and interpret the data they produce. This could limit the scalability of the findings, as not all educational institutions may have the resources or expertise to implement such technologies. Additionally, the study will need to account for potential technical challenges, such as device calibration, data accuracy, and the potential for device malfunctions during experiments.

Another limitation involves the subjective nature of interpreting mind-wandering episodes despite the objective data collected through sensors. While wearable devices can provide valuable data on physiological and behavioural indicators of mind-wandering, interpreting this data in the context of learning outcomes requires careful consideration of individual differences among students. Factors such as prior knowledge, motivation, and learning styles may influence how students engage with the material, and these factors may not be fully captured by the wearable devices used in the study.

Finally, ethical considerations related to data privacy and the potential for surveillance in educational settings must be addressed. The use of wearable technology to monitor students' physiological and cognitive states raises important questions about consent, data security, and the potential for misuse of data. The research will need to navigate these ethical challenges carefully to ensure that the rights and privacy of participants are protected.

In addition to the limitations, there are certain boundaries set by the researcher to ensure the study remains focused and manageable. For example, this research will not explore the long-term effects of wearable technology on learning outcomes beyond the scope of the study period. The study will also not address the use of wearable technology in informal learning settings, such as museums or extracurricular activities, focusing instead on formal education within higher education institutions.

Furthermore, while the study explored multisensory approaches, it did not encompass all available sensors and physiological data types. The research focused on well-established, non-invasive sensors such as eye-tracking, photoplethysmography (PPG), and galvanic skin response (GSR), which are particularly relevant for assessing cognitive and emotional engagement in educational contexts. More advanced or less validated technologies such as electroencephalography (EEG), electromyography (EMG), or novel experimental biosensors were excluded from the scope due to their complexity, invasiveness, or limited applicability in real-world classroom settings.

1.4 Significance of the Study

The significance of this thesis lies in its potential to transform engineering education by leveraging wearable technology to create more engaging and personalised learning experiences. This thesis contributes to the growing body of literature on educational technology and human-computer interaction, offering both theoretical and practical insights into how wearable devices can enhance learning outcomes.

1.4.1 Theoretical Contributions

The study aims to contribute to the theoretical understanding of the relationship between technology, cognition, and learning. By investigating how wearable devices can influence cognitive processes such as attention, focus, and mind-wandering, the research will add to the existing knowledge of cognitive load theory and attention restoration theory. These insights will be valuable for educators and researchers seeking to design more effective learning environments that minimise cognitive overload and enhance student engagement.

Moreover, the study will explore the concept of Cognitive Augmentation through wearable technology. Cognitive augmentation refers to the use of technology to enhance cognitive abilities, such as memory, attention, and problem-solving skills. By examining how wearable devices can support cognitive augmentation in educational settings, the research will offer new perspectives on the potential of technology to extend and enhance human cognitive capabilities.

1.4.2 Practical Implications

On a practical level, the findings of this thesis aim to provide actionable recommendations for educators, instructional designers, and policymakers. The research offers guidance on the selection and implementation of wearable devices in engineering education, supporting institutions in making informed decisions regarding technology investments. Furthermore, the development of a framework for integrating wearable technology into curricula is intended to serve as a practical tool for enhancing teaching practices and improving student outcomes.

In addition, the study's focus on multisensory approaches to education has the potential to influence the design of future educational technologies. By demonstrating the value of integrating multiple data streams, such as eye movements, heart rate, and skin conductance, the research could encourage the development of more comprehensive and adaptive learning systems that respond to the needs of individual students in real-time.

1.4.3 Social Impact

Beyond the classroom, this thesis aims to contribute to broader social goals, particularly in promoting diversity, inclusion, and equity within engineering education. Under-represented groups such as women, ethnic minorities, and students from lower socio-economic backgrounds often face systemic barriers, including a lack of role models, feelings of exclusion, and limited access to engaging STEM learning experiences. Wearable technologies offer the potential to mitigate some of these barriers by creating more personalised, interactive, and student-centred learning environments. For example, real-time feedback from wearable sensors can help instructors tailor interventions to individual needs, reducing performance anxiety and improving confidence among students who might otherwise struggle in traditional classroom settings. Devices like AR/VR headsets and biosensors can support multiple learning styles: visual, kinaesthetic, or experiential, thereby creating more inclusive pedagogies. In particular, students who may be marginalised by conventional lecture-based delivery could benefit from immersive, hands-on experiences that make abstract engineering concepts more tangible and relatable.

Additionally, wearable technology supports remote and flexible learning formats, which are particularly important for students who may be balancing education with work, caregiving responsibilities, or other constraints. By enabling access to just-in-time, data-driven feedback outside the classroom, wearable devices can empower learners who might otherwise be at risk of disengaging.

This research also considers the role of wearable technologies in fostering a sense of belonging and participation. By collecting objective data on engagement and affective states, educators can identify students who are struggling silently and provide timely, personalised support potentially reducing attrition rates among under-represented students. Furthermore, the thesis explores the broader implications of wearable technology for lifelong learning. As technological change accelerates, continuous upskilling is critical. Wearable devices can facilitate on-the-go learning, making educational content and feedback accessible in real-time, regardless of location or traditional institutional barriers. This has important implications for widening participation in STEM fields beyond the traditional academic pipeline.

1.5 Ethical Considerations

Given that wearable technology often involves the collection of sensitive data, such as eye movements and physiological responses, this thesis adheres to strict ethical guidelines. Informed consent was obtained from all participants, ensuring that they were fully aware of the nature and purpose of the study. Participants were provided with detailed information about the types of data being collected, how it would be used, and their rights to withdraw from the study at any time without penalty.

1.5.1 Data Privacy and Security

One of the primary ethical concerns associated with wearable technology is the issue of data privacy and security. Wearable devices often collect sensitive biometric data, which could be misused if not properly protected. To address this concern, the research will implement robust data security measures, including encryption of all data collected from wearable devices and secure storage of data on institutional servers. Access to the data will be restricted to authorised personnel, and all data will be anonymous to protect participants' identities.

Additionally, the research will comply with relevant data protection regulations, such as the General Data Protection Regulation (GDPR) in Europe, ensuring that personal information is used solely for research purposes and is not shared with third parties without explicit consent. Participants will also be informed of their rights under these regulations, including the right to access their data, request corrections, or have their data deleted.

1.5.2 Informed Consent and Transparency

Informed consent is a fundamental ethical principle in research involving human participants. To ensure that participants fully understand the nature of the study and the implications of their participation, the research will use clear and accessible language in consent forms and provide opportunities for participants to ask questions before agreeing to participate.

Transparency is also critical in maintaining trust between researchers and participants. The study will ensure that participants are kept informed about the progress of the research and how their data is being used. Regular updates will be provided to participants, and they will be given the option to receive a summary of the research findings once the study is complete.

1.5.3 Minimising Potential Risks

While the use of wearable technology in education offers many benefits, there are also potential risks that must be considered. For example, the use of wearable devices to monitor students' physiological and cognitive states could lead to concerns about surveillance and the potential for misuse of data. To mitigate these risks, the research will ensure that data collection is non-intrusive and that the use of wearable devices is always voluntary. Participants will be made aware of the specific data being collected and how it will be used, and they will have the option to opt out of certain types of data collection if they are uncomfortable.

The research will also take steps to minimise any physical or psychological discomfort that participants may experience while using wearable devices. This includes ensuring that devices are comfortable to wear, do not interfere with participants' normal activities, and are used for the minimum duration necessary to achieve the research objectives. If any participant experiences discomfort or distress, they will be encouraged to discontinue their participation without penalty.

1.6 Technological Developments and Trends

The field of wearable technology is rapidly evolving, with emerging innovations such as augmented reality glasses, smart clothing, and brain-computer interfaces. These developments have the potential to further revolutionise engineering education by offering even more immersive and personalised learning experiences.

1.6.1 Augmented Reality (AR) and Virtual Reality (VR)

Augmented Reality (AR) and Virtual Reality (VR) are among the most promising developments in wearable technology. AR glasses, such as Microsoft's HoloLens and Google's ARCore, allow users to overlay digital information onto the physical world, creating a blended reality that enhances learning experiences. For example, AR can provide real-time annotations and visualisations of complex systems in engineering education, improving conceptual understanding [9].

Virtual Reality (VR) headsets, such as the Oculus Rift and HTC Vive, create fully immersive environments. In education, VR can simulate real-world engineering scenarios (e.g., lab experiments or fieldwork), enhancing experiential learning and engagement [10].

1.6.2 Smart Clothing and Wearable Sensors

Smart clothing incorporates sensors into fabrics to monitor physiological signals such as heart rate, skin temperature, and muscle activity. These technologies can support well-being and attention monitoring during learning activities [11,12]. In education, such sensors enable tracking of stress, fatigue, and cognitive load, which are closely linked to academic performance [13].

Wearable sensors like fitness trackers and smartwatches are becoming increasingly sophisticated and are widely used in educational technology research to monitor engagement, physical activity, and sleep patterns, all of which impact cognitive performance [14].

1.6.3 Brain-Computer Interfaces (BCIs)

BCIs represent a cutting-edge advancement in wearable tech, enabling communication between the brain and external devices. These systems can detect neural signals via EEG and have applications in adaptive learning systems and neurofeedback training [15]. Though still experimental in mainstream education, BCIs offer great promise for enhancing cognitive training, particularly for students with disabilities or learning challenges [16].

1.6.4 The Future of Wearable Technology in Education

The future integration of wearable tech with artificial intelligence (AI) and machine learning (ML) will drive personalised, context-aware learning experiences. AI-powered wearables may detect when a learner is struggling and adapt content in real-time [17]. Technologies such as smart contact lenses or biometric tattoos are also under development, suggesting the possibility of truly seamless, ubiquitous educational experiences [18].

1.7 Comparative Analysis with Other Fields

Wearable technology is not only transforming education but also making significant impacts in fields such as medicine, sports, and military training. By comparing the use of wearables in engineering education with their applications in these other sectors, this thesis highlights the versatility and potential of wearable devices.

1.7.1 Medicine

In the medical field, wearable technology has revolutionised patient care by enabling continuous monitoring of vital signs and chronic conditions. Devices such as wearable Electrocardiogram(ECG) monitors, glucose monitors, and smart inhalers provide real-time data to healthcare providers, allowing for early detection of issues and more personalised treatment plans [19, 20]. These technologies parallel the use of wearables in education, where real-time data on student engagement and cognitive load can inform instructional interventions and support individualised learning.

Moreover, medical applications of wearables have advanced telehealth and remote monitoring, which has direct parallels to remote and hybrid learning environments supported by wearable learning analytics [21].

1.7.2 Sports

In the sports domain, wearables such as GPS trackers, heart rate monitors, and motion sensors are used to optimise athletic performance and reduce injury risk [22, 23]. These tools provide real-time feedback to athletes and coaches, allowing for adaptive training and performance enhancement.

Similarly, in education, wearable technologies can help students adjust their learning strategies based on biofeedback, for example, recognising when they are cognitively fatigued or disengaged. This data-driven feedback loop mirrors coaching methods in sports performance science [24].

1.7.3 Defence Training

Military and defence sectors have long adopted wearable technologies for simulation, situational awareness, and health monitoring in high-stress environments [25, 26]. For example, AR headsets are used to overlay battlefield data, and biometric wearables monitor fatigue and stress.

These innovations align closely with the use of AR/VR in education for simulated lab work or engineering system training, creating safe, immersive spaces for learning without real-world consequences.

1.7.4 Lessons for Education

Cross-sector analysis shows how data-driven decision-making and personalised feedback are foundational to wearables' success in medicine, sports, and defence. In education, similar principles can enhance instructional design, learner support, and performance tracking [27].

Another key lesson is the emphasis on experiential learning, mirroring sports drills or military simulations, which can be translated into engineering education through immersive, hands-on, wearable-supported activities.

1.8 Interdisciplinary Approach

This research bridges multiple disciplines, including education, engineering, technology, and psychology. The interdisciplinary nature of the study allows for a more holistic understanding of how wearable technology can influence learning and cognition.

1.8.1 Educational Technology

Within the field of educational technology, this thesis contributes to the development of new tools and methodologies aimed at enhancing learning outcomes. By integrating wearable devices into classroom settings, it demonstrates how educators can create more interactive and engaging learning environments that address the diverse needs of students. The study also explores broader questions regarding the role of technology in supporting student-centred learning, offering insights into the design of adaptive and personalised educational systems.

1.8.2 Engineering

In the context of engineering, this thesis explores how wearable technology can be used to support hands-on learning and experiential education. Engineering education often involves complex and abstract concepts that can be difficult for students to grasp through traditional methods alone. Wearable devices, such as VR headsets and AR glasses, offer new ways for students to interact with and visualise these concepts, making them more tangible and easier to understand.

The research also considers the role of wearable technology in developing practical skills. Engineering students need to acquire not only theoretical knowledge but also the ability to apply that knowledge in real-world situations. Wearable devices can provide students with real-time feedback as they work on projects and experiments, helping them to refine their skills and improve their performance.

1.8.3 Psychology

From a psychological perspective, this thesis examines the cognitive processes underlying learning and attention. By analysing eye-tracking data and other physiological indicators, the study provides insights into how students engage with educational content and how wearable technology can be used to support their cognitive development.

The research also explores the emotional and motivational aspects of learning. Wearable devices that monitor stress levels, heart rate, and other physiological signals can provide valuable data on students' emotional states and how these states affect their learning. Understanding the relationship between emotion, cognition, and learning can help educators design interventions that support students' well-being and academic success.

The interdisciplinary approach of this research enables a more comprehensive understanding of the role of wearable technology in education, highlighting its potential to enhance learning outcomes across multiple domains.

1.9 Eye-Tracking and Mind-Wandering

The connection between eye movements and cognitive processing is well-established, underscoring the importance of a comprehensive approach to understanding attention and mind-wandering in educational settings. Eye-tracking technology provides a powerful tool for estimating cognitive load, attention, focus, and instances of mind-wandering by capturing and analysing gaze behaviour [28].

This thesis primarily focused on the use of dynamic stimuli, particularly video lectures, rather than static materials, to gain a more nuanced understanding of mind-wandering. Following the methodology described by [29], the research aimed to capture instances of mind-wandering during video-based instruction. A wearable eye-tracker was employed to enhance the precision of the experimental procedure, enabling more accurate measurement of students' visual attention and providing deeper insights into the patterns and dynamics of mind-wandering

Two key hypotheses guided this aspect of the research:

- Duration of Visual Attention or Fixation: It is hypothesised that the duration of visual attention would be longer when a person is experiencing mind-wandering.
- Instructor Presence: The presence of an instructor in the video might contribute to an increase in student mind-wandering.

This study employs the probe-caught method, a widely recognised approach in mind-wandering research, and incorporates a multisensory approach that combines biological, physiological, and gaze-tracking sensors to collect data for the experiments.

1.10 Sensor Fusion

While visual attention is a crucial aspect of engagement, it is not the only indicator. A student may appear to be focused on a task, with their gaze directed toward the intended subject, but they might still be thinking about something entirely different. Since visual attention alone does not fully indicate task engagement, additional indicators are needed to validate the results obtained from wearable eye-trackers.

A multisensory approach offers a more reliable solution by incorporating multiple data sources that can be validated through experiments. Mind-wandering has been identified through various physiological biomarkers, including heart rate, skin conductance [30], and respiration. Other technologies, such as pressure sensors [31], electroencephalograms (EEG), galvanic skin response (GSR), and photoplethysmography (PPG) are also considered precise for such measurements [32]. Table 1.1 presents a comparison of the pros and cons of various sensors for measuring mind-wandering.

Table 1.1: *Advantages and disadvantages of wearable technologies used for mind-wandering measurement*

Technology	**Advantages**	**Disadvantages**
Respiration/pressure sensors	Unique to its specific purpose	immobile, discomfort
Heart rate sensors	Ease of access	Need for validation
Galvanic Skin Response sensor	Measuring the emotional state	Sensitive to movement
EEG	Provides data on cognitive state	Sensitive to environment
Eye-tracker	Can be used with moving target	Only collects visual data

In practical scenarios, measuring all these signals concurrently is not always feasible. Therefore, this study focuses on GSR, PPG, and eye-tracking sensors. These sensors are ideally suited for incorporation into a basic wearable device that can unobtrusively collect data from students without causing discomfort or raising privacy concerns.

1.10.1 Multisensory Data Integration

The integration of data from multiple sensors such as GSR, PPG, and Eye-trackers enables a more comprehensive understanding of student engagement. By combining data from these different sources, researchers can develop a richer and more accurate picture of how students interact with educational content.

For example, eye-tracking data might indicate that a student is visually engaged with a learning task, but data from GSR and PPG sensors might reveal that the student is experiencing high levels of stress or cognitive overload. By integrating these data streams, educators can gain deeper insights into the student's overall cognitive and emotional state, allowing them to intervene more effectively.

The fusion of multisensory data also enables the development of more sophisticated algorithms for detecting and responding to mind-wandering. For instance, machine learning models can be trained on multisensory data to predict when a student is likely to experience mind-wandering, enabling real-time interventions to re-engage the student.

1.11 Anticipated Challenges and Solutions

Integrating wearable technology into educational settings presents several challenges, including technological limitations, participant recruitment, and data analysis complexities. This thesis anticipates these challenges and proposes solutions, such as selecting user-friendly devices, employing a mixed-methods approach for data collection, and using advanced analytical techniques to ensure accurate and reliable results.

1.11.1 Technological Challenges

One of the key challenges in using wearable technology for educational research is the reliability and accuracy of the devices. Wearable sensors can be prone to technical issues, such as calibration errors, signal interference, and data loss. To address these challenges, the research will implement rigorous testing and calibration procedures to ensure that the devices are functioning correctly before data collection begins. Redundant data collection methods, such as backup devices or alternative measurement techniques, will also be employed to minimise the impact of technical failures.

Another technological challenge involves the integration of multiple sensors into a single wearable device. Combining data from different sensors, each with its own limitations and sensitivities requires careful calibration and synchronisation. The research will explore different approaches to sensor integration, including hardware and software solutions, to ensure that data from all sensors is accurately captured and aligned.

1.11.2 Participant Recruitment and Engagement

Recruiting participants for wearable technology studies can be challenging, particularly when the devices being used are unfamiliar or perceived as intrusive. To overcome this challenge, the research will employ strategies to ensure that participants are comfortable with the technology and understand its purpose. This includes providing thorough explanations of the study, conducting demonstrations of the devices, and addressing any concerns that participants may have.

Participant engagement is also crucial for the success of the study. Wearable devices must be worn consistently and correctly throughout the study period to ensure that valid data is collected. To promote engagement, the research will provide participants with clear instructions on how to use the devices and offer incentives for their participation. Regular check-ins with participants will help to address any issues that arise and ensure that the study proceeds smoothly.

1.11.3 Data Analysis Complexities

The analysis of data from wearable devices presents unique challenges, particularly when dealing with large volumes of multisensory data. The research will employ advanced data analysis techniques, including machine learning algorithms, to identify patterns and correlations in the data. Data visualisation tools will also be used to help interpret complex data sets and present findings in a clear and accessible manner.

To ensure the validity and reliability of the data, the research will implement rigorous data cleaning and preprocessing procedures. This includes filtering out noise, correcting for missing data, and normalising data across different sensors. By addressing these challenges, the research aims to produce robust and actionable insights that can inform the use of wearable technology in education.

1.12 Chapter Overview

The following chapters of this thesis will explore the detailed methodology and findings from the experiments conducted:

Chapter 2: State of the Art: This chapter provides a comprehensive review of the current literature on wearable sensors in education, with a particular focus on engineering education. It explores the history and market of wearable devices, theoretical frameworks relevant to attention and learning, and their integration into educational contexts. The chapter concludes with an identification of gaps in the current research and highlights potential future directions.

Chapter 3: Methodology: This chapter outlines the research design and experimental setup, including the data collection methods for wearable eye-tracking and multisensory approaches. It also details the system operation, data preprocessing, and machine learning techniques used for optimising sensor performance. The design and implementation of the multisensory device and its application in educational settings are discussed thoroughly.

Chapter 4: Results: This chapter presents the findings from the experiments, including the analysis of eye-tracking data for attention monitoring and mind-wandering detection. It also explores the results from the multisensory data analysis using machine learning algorithms and compares the performance of different sensors and classification models. Visualisations and statistical analyses are provided to support the results.

Chapter 5: Discussion and Conclusion: This final chapter discusses the implications of the experimental results for the field of educational technology. It synthesises the findings with existing literature, highlighting the contributions to knowledge, particularly the effectiveness of the multisensory approach in monitoring student engagement. The chapter also provides recommendations for future research and the practical application of wearable technology in enhancing engineering education.

Chapter 2

State-of-the-Art in Wearable Sensors for Education

2.1 Engineering Education

Engineering plays a pivotal role in shaping the modern world. From the infrastructure that supports cities to the technological advancements driving industries, engineering is an essential field that addresses a broad spectrum of human, social, and economic challenges. This diversity in application is reflected in the various branches of engineering, including civil, mechanical, electrical, chemical, and software engineering, among others. Each branch contributes uniquely to society, making engineering one of the most impactful professions globally. The term "engineer" itself is derived from the Latin word ingenium, meaning ingenuity, cleverness, or invention, which aptly captures the essence of the profession an art of problem-solving and innovation.

Engineering education, therefore, is not merely about imparting technical knowledge; it involves equipping students with the skills to solve complex problems, innovate, and apply scientific principles in real-world contexts. This process requires a strong foundation in mathematics and the sciences, coupled with practical experience and creativity. The goal is to prepare future engineers to address the critical challenges of our time, such as energy security, climate change, health, and sustainable development.

Despite the significance of engineering in addressing global challenges, the profession is often misunderstood by the general public. A study by Engineering UK revealed that nearly half of teenagers in the UK have little understanding of what engineers do, which contributes to a lack of interest in pursuing engineering degrees. This lack of awareness, coupled with stereotypes about engineering being complex or uncreative, has resulted in fewer students enrolling in engineering programs. The declining enrolment is concerning, especially in light of the increasing demand for engineers to tackle the technological and environmental challenges of the 21st century [33].

For instance, engineering education faces a significant challenge in attracting and retaining students in the United Kingdom. According to the Organisation for Economic Co-operation and Development (OECD), only about 8% of UK graduates receive degrees in engineering, compared to higher percentages in fields like arts (19%), business (19%), and natural sciences (17%) [34]. This disparity is alarming, especially considering that engineering graduates are essential for addressing critical global issues. The Royal Academy of Engineering's "Engineering Index" ranks the UK 14th globally, highlighting the need for a greater focus on producing more engineering graduates to maintain and enhance the country's competitiveness in the global economy [35].

The shortage of engineering graduates is not just a UK problem but a global issue. Countries worldwide are struggling to meet the growing demand for skilled engineers. The US, for instance, faces a similar challenge, with reports indicating that the number of engineering graduates is insufficient to meet the needs of industries such as technology, manufacturing, and infrastructure development. Similarly, in countries like Germany and Japan, there is a significant gap between the demand for engineers and the number of graduates entering the workforce [36].

Addressing this shortage requires a multifaceted approach. Firstly, there is a need to demystify the engineering profession and promote it as a creative and rewarding career path. Initiatives such as outreach programs, engineering clubs in schools, and mentorship opportunities can help spark interest in engineering from an early age. Secondly, engineering education itself must evolve to meet the needs of modern students. This includes incorporating innovative teaching methods, such as project-based learning, which allows students to work on real-world problems, and integrating emerging technologies like virtual reality (VR) and augmented reality (AR) into the curriculum to enhance learning experiences.

Moreover, the impact of emerging technologies on engineering education is profound and far-reaching. These technologies present significant opportunities to enhance student engagement, stimulate creativity, and better prepare students for the evolving demands of the workforce [37]. The COVID-19 pandemic further accelerated the integration of such technologies, mainly through the widespread adoption of online learning and remote educational practices. This shift has brought challenges and new possibilities to engineering education [38].

Furthermore, increasing emphasis is being placed on improving diversity within engineering disciplines. Initiatives aimed at attracting underrepresented groups, particularly women and minorities, into engineering programs are vital for expanding the talent pipeline and fostering a more inclusive and innovative environment. Research has shown that diverse teams are more creative and effective in problem-solving, reinforcing the importance of diversity as a core principle in engineering education [39, 40].

In conclusion, engineering education is at a crossroads. While the demand for skilled engineers is higher than ever, the number of students entering the field remains insufficient. By promoting engineering as a dynamic and creative profession, modernising curricula, and embracing diversity, educational institutions can help bridge the gap and prepare the next generation of engineers to tackle the challenges of the future.

2.2 Wearable Sensors in Education

Wearable devices, defined as small electronic devices worn or attached to the body, have gained significant traction in education. These devices offer new ways to monitor student engagement, health, and learning outcomes. This section explores the history, market trends, and educational applications of wearable sensors, highlighting their growing importance in shaping the future of education.

2.2.1 History of Wearable Sensors in Education

To provide a more detailed exploration of the history of wearable devices in education, it is important to understand how these technologies have evolved and gained traction over time. The development of wearable technology has been closely tied to advances in miniaturisation, computing power, and connectivity, which have enabled devices to become more portable, efficient, and helpful in various contexts, including education.

The earliest wearable device, as mentioned, was a cigarette pack-sized timing device designed by Edward Thorp and Claude Shannon in 1955. This device, which was hidden in a shoe to predict roulette wheels in casinos, was a precursor to the idea that technology could be seamlessly integrated into our daily lives without being obtrusive. It was not until 1966 that this concept was publicly introduced, sparking interest in the potential applications of wearable technology beyond gambling, such as in areas like health monitoring and communication [41].

The 1970s marked a significant period of growth for wearable technology, particularly with the introduction of calculator watches. These devices, such as the Pulsar Calculator Watch by Hamilton Watch Company in 1975, combined the functionality of a calculator with the convenience of a wristwatch. This innovation represented one of the first instances of a multifunctional wearable device that could be used in both professional and personal settings, highlighting the growing demand for portable, multipurpose technology [42]. The calculator watch's popularity laid the groundwork for future wearables, demonstrating that consumers were interested in compact devices that offered practical applications beyond timekeeping.

By the late 1970s and early 1980s, wearable technology had expanded into the entertainment industry with the introduction of the Sony Walkman in 1979. The Walkman revolutionised the way people consumed music, allowing them to listen to their favourite tracks on the go. This was a pivotal moment in the history of wearable devices, as it illustrated the potential for wearables to enhance personal entertainment experiences and shaped consumer expectations for future devices [43]. The success of the Walkman also influenced other companies to explore how wearable technology could be integrated into various aspects of daily life, from fitness to communication.

The 1990s saw further expansion of wearable technology into the workplace with the introduction of pager devices. These devices allowed for instant communication, particularly in professional environments where timely information exchange was critical. Wearable pagers became a staple in industries like healthcare, emergency services, and business, demonstrating how wearable technology could improve efficiency and productivity in professional settings [44]. The widespread adoption of pagers highlighted the importance of connectivity and communication in wearable devices, setting the stage for future innovations in this area.

However, the true boom in wearable technology occurred in the 2010s, driven by the convergence of advancements in wireless communication, sensor technology, and the Internet of Things (IoT). The introduction of smartwatches, such as the Apple Watch, and fitness trackers, like the Fitbit, marked a new era in wearable technology. These devices were not only capable of tracking fitness metrics but also integrated features like notifications, health monitoring, and even payment systems. This period also saw the rise of augmented reality (AR) and virtual reality (VR) headsets, which further expanded the scope of wearable technology into fields like education, gaming, and healthcare [45]. The evolution of these devices over the years is depicted in Figure 2.1.

As wearable technology continues to evolve, its applications in education are becoming increasingly apparent. From VR headsets that provide immersive learning experiences to smartwatches that track students' health and engagement, wearable devices are poised to play a significant role in shaping the future of education. The following section will delve into the current market trends for wearable devices in education and explore how these technologies are being integrated into learning environments.

An examination of the history of wearable sensors provides valuable insight into how technological advancements have facilitated their integration into educational contexts. This historical perspective highlights the potential of wearable technology to enhance learning experiences and improve educational outcomes across a range of disciplines.

2.2.2 Market of Wearable Sensors in Education

The education technology (edtech) industry has grown into a multi-trillion-dollar sector, with projections indicating continued expansion in the coming years. This growth is driven by increased public spending on education in many countries, particularly within the Organisation for Economic Co-operation and Development (OECD). OECD countries are dedicating over 10% of their public expenditure to education, reflecting the importance placed on fostering innovation and improving educational outcomes through technological advancements [46]. The COVID-19 pandemic further accelerated this growth, as it prompted educational institutions worldwide to adopt hybrid or fully remote learning models, leveraging emerging edtech solutions. Tech-

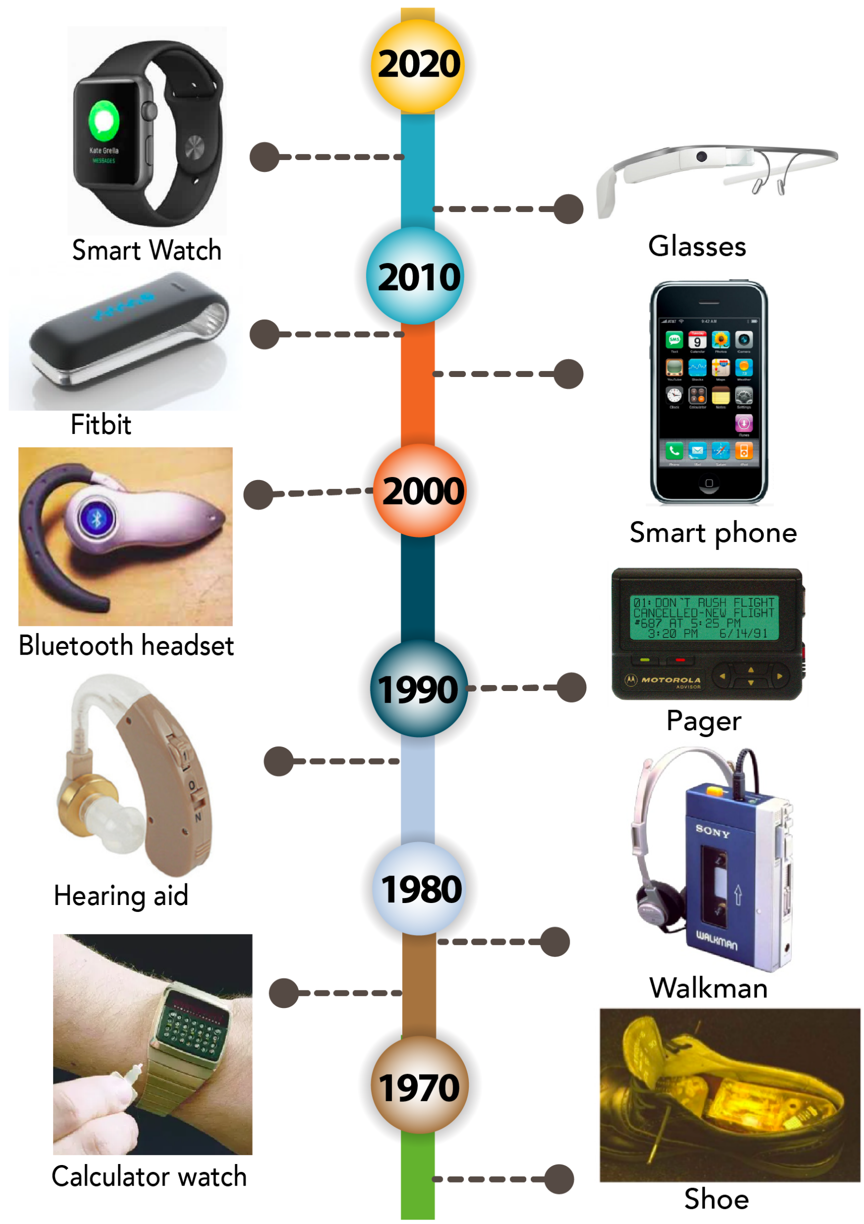

Figure 2.1: *Development of wearable devices during the past 50 years. Starting from the 1960s, the first wearable product was a centimetre-scale computer hidden inside shoes. Currently, advanced millimetre-scale systems are embedded on wrist-worn, chest-worn and head-worn platforms.*

nologies such as video conferencing tools, online learning management systems, and portable devices like laptops, tablets, and smartphones, which typically would have been adopted gradually, saw rapid integration into education systems due to the urgent need for alternative teaching methods during the pandemic [47]. This trend underscores the necessity for adaptable edtech solutions that can maintain educational continuity in the face of unexpected disruptions.

In the wake of these developments, there is a growing recognition of the importance of wearable devices within the edtech ecosystem. The integration of wearable technology in education is a relatively new frontier, yet it holds significant potential for enhancing the learning experience by providing real-time data on student engagement, performance, and well-being. Public spending on education, especially in low- and middle-income countries, is projected to rise from the current US$1.2 trillion per year to US$3 trillion [48]. Such investment will likely contribute to the broader adoption of wearable technology in educational settings. The Incheon Declaration, which calls for countries to allocate 4% to 6% of their gross domestic product (GDP) to education and at least 15% to 20% of public expenditure to education, further reinforces the importance of continuous investment in educational technologies [49]. This emphasis on funding will play a crucial role in driving the adoption of wearables, which can offer innovative solutions to both in-class and remote learning challenges.

The wearable technology market has seen a sharp increase in recent years, correlating strongly with the expansion of globally connected devices. The number of connected wearable devices was predicted to rise from 593 million in 2018 to 929 million by 2021, illustrating the growing demand for these technologies [50]. By 2020, the market for wearables was estimated to be worth US$5 billion, highlighting the significant financial interest in this sector [51]. This growth reflects not only consumer interest in wearable devices but also their potential applications across various industries, including education. A comprehensive database compiled by Vandrico INC in 2020 identified 266 companies producing 431 distinct wearable products. These devices were categorised into seven sectors: Entertainment, Fitness, Gaming, Industrial, Lifestyle, Medical, and Pets [52]. Interestingly, education was not included as a standalone category despite the increasing evidence supporting the use of wearables in educational settings. This omission underscores a gap in the current understanding and application of wearable technology within education, a gap that this research seeks to address.

Wearable devices have traditionally been concentrated in the lifestyle and fitness sectors, with products such as the SAMSUNG GEAR S3 [53], XIAOMI MI BAND 2 [54], and iHeart Internal Age [55] being particularly popular. The fitness sector has also seen significant growth, with products like the Garmin Vivosmart [56], Fitbit [57], and Withings Hybrid Smartwatch [58] leading the market. These devices have demonstrated the capability to monitor physical activity, health metrics, and even some cognitive functions, which opens up possibilities for their integration into educational environments. For instance, the use of wearable devices to track students' physical and cognitive well-being during classes could provide educators with valuable insights that could be used to tailor teaching methods and improve learning outcomes.

In the context of education, wearable devices offer several potential benefits. They can be used to monitor students' attention and engagement levels, track physical activity as part of health and physical education programs, and even support students with special needs by providing real-time feedback and interventions. Furthermore, the ability of wearable devices to collect and analyse data in real time makes them powerful tools for personalised learning, allowing educators to adjust their teaching strategies based on the needs and performance of individual students.

However, the integration of wearable technology into education is not without challenges. There are concerns related to privacy, data security, and the potential for over-reliance on technology at the expense of traditional teaching methods. Additionally, the cost of wearable devices could be a barrier to widespread adoption, particularly in low-income countries or underfunded school districts. These challenges highlight the need for further research and development to ensure that wearable devices are used effectively and ethically in educational settings.

Despite these challenges, the potential applications of wearable technology in education remain extensive. This research seeks to bridge existing gaps by exploring and categorising wearable technologies within the educational context, thereby expanding their applications beyond traditional sectors. In doing so, it contributes to the growing body of knowledge on wearable technology in education and offers insights that can support educators, policymakers, and technologists in effectively leveraging these devices to enhance learning outcomes.

This expansion into educational wearables represents a new frontier in both edtech and the broader wearable technology market. The challenge now lies in developing wearable devices that are not only effective but also accessible and sustainable, ensuring that they can be widely adopted and integrated into educational systems around the world. The following steps involve continuing to explore the potential of these devices, addressing the challenges they present, and working towards a future where wearable technology is a core component of educational practice.

2.2.3 Educational Applications of Wearable Sensors

Recent reviews have emphasised the role of wearable biosensors in assessing student cognitive and emotional states, supporting the integration of such sensors into educational settings [59]. Wearable technology has emerged as a transformative force in education, with potential applications across learning enhancement, assessment, engagement monitoring, and instructional evaluation. Although widely used in sectors like healthcare and entertainment, the educational use of wearables is still nascent. Nonetheless, early implementations provide essential insights into their capabilities and limitations. This section explores these domains critically.

Learning Enhancement

Wearable technologies such as smart glasses and head-mounted displays (HMDs) support immersive and experiential learning by integrating virtual or augmented environments into the curriculum. A hybrid model combining traditional pedagogy with wearable-enabled interactivity was particularly accelerated during the COVID-19 pandemic, allowing students to engage with simulations, remote labs, and adaptive learning modules from home [60].

Smartwatches and fitness trackers have also been employed in participatory simulations and contextual learning environments. In medical education, for example, wearable sensors are used to facilitate hands-on training by simulating real-time, authentic clinical scenarios [61]. Moreover, recent implementations of wearable technologies in remote learning have shown that physiological data such as heart rate and stress levels can be leveraged to assess students' cognitive engagement. This data-driven approach enables adaptive content delivery, allowing educational platforms to personalise learning experiences based on real-time feedback [62, 63].

Assessment

Wearable devices are increasingly being explored for their role in both formative and summative assessments. Physiological data such as skin conductance, heart rate variability, and gaze behaviour have been used to infer cognitive load, attentional focus, and stress levels during assessment tasks [64, 65]. These biometric signals offer additional layers of insight, helping educators develop a more comprehensive understanding of student performance beyond traditional test scores [66].

In specific educational settings, wearable technologies are used to monitor real-time engagement during testing activities, enabling immediate instructional feedback and adaptive interventions [67]. However, interpreting physiological signals remains complex due to individual differences and contextual variability. For example, an increased heart rate may indicate stress or excitement, requiring careful triangulation with other data sources for valid conclusions [68].

Monitoring and Engagement Tracking

One of the most promising applications of wearable sensors is the real-time monitoring of student engagement and well-being. Wearable devices placed on the wrist or head, such as smartwatches and eye-trackers, are capable of collecting continuous physiological and behavioural data, including heart rate variability and gaze fixation, which serve as proxies for cognitive engagement [68, 69].

The popularity of wearables among the 18–39 age group, as noted by Statista and the National Purchase Diary Panel Inc., underscores their viability in university settings [70, 71]. This demographic familiarity enhances acceptance and usability in higher education. Recent studies have shown that physiological data collected from wearable devices can be leveraged to assess students' cognitive and emotional states, enabling adaptive learning interventions and real-time feedback to support personalised educational experiences [63].

Wearables are also being explored in broader educational contexts to improve student accountability and participation. For instance, they have been implemented in pilot programs to facilitate attendance tracking and automate reminders, contributing to more consistent student engagement [72, 73].

Evaluation and Feedback

Beyond individual monitoring, wearable data can be aggregated to evaluate instructional effectiveness. Eye-tracking data, for instance, can identify which segments of a lesson sustain student attention and which are overlooked [74, 75]. Similarly, group-level physiological signals such as peaks in heart rate variability or galvanic skin response can indicate moments of cognitive overload or heightened engagement, informing pedagogical adjustments in real time [67, 76].

However, the interpretation of such data requires caution. Physiological indicators are inherently ambiguous; for instance, an elevated heart rate may reflect excitement, anxiety, or physical discomfort. As such, wearable-derived data should be triangulated with self-reports or observational measures to ensure meaningful educational insights [66, 68].

2.2.4 Location of Wearables on Body

Various state-of-the-art wearable devices have been explored for their effectiveness in educational contexts, with particular attention to how their physical placement on the body influences their functionality. These devices are commonly grouped into three categories: head-worn, wrist-worn, and chest-worn. Each type serves distinct educational purposes ranging from immersive learning and attention monitoring to emotional and social engagement analysis and comes with its own set of context-specific advantages and limitations. Table 2.1 presents a summary of these device categories, highlighting their educational applications alongside their respective benefits and challenges.

Head-Worn Devices

Head-worn devices or displays have evolved significantly since their conceptual introduction in the late 1960s [86, 87]. Over the past four decades, researchers have worked toward developing full-colour, see-through displays. With advances in microelectronics and the development of Light Emitting Diodes (LEDs), such capabilities are now feasible. Commercial examples include mixed-reality devices such as the Hololens [88].

In higher education, head-mounted displays have been shown to enhance learning by providing real-time information overlays [89]. EEG headsets, in conjunction with virtual reality

Table 2.1: *Advantages and disadvantages of wearable devices based on placement and educational application*

Device Type	Educational Applications	Advantages	Disadvantages
Head-worn (e.g., AR/VR, eye-trackers)	Immersive learning, visual attention tracking, cognitive load analysis	- Enables experiential and spatial learning - High accuracy in gaze data - Enhances engagement in simulations [77, 78]	- May cause cybersickness - Requires calibration - Raises privacy concerns [79, 80]
Wrist-worn (e.g., smartwatches, fitness bands)	Real-time physiological monitoring, stress and engagement tracking	- Discreet and easy to wear - Continuous data capture - Suitable for large-scale use [81]	- Accuracy may drop during movement - Context needed for valid interpretation [82]
Chest-worn (e.g., HRV monitors, sociometric badges)	Emotional state tracking, group interaction analysis	- High-fidelity heart rate and proximity data - Effective for collaborative learning research [83, 84]	- Can be perceived as invasive - May raise data privacy concerns [85]

platforms, have also been used to assess brain activity during spatial learning tasks [90]. For example, the Emotiv EPOC® system has been adopted for cognitive research in academic environments [91], and VR-based learning tools have demonstrated benefits for students in engineering programs [92].

Wearable glasses such as Google Glass have found applications in educational contexts ranging from surgical training [78, 93, 94] to the recording of first-person perspectives in simulation-based activities [95, 96]. Other use cases include live broadcasting of practical procedures to student groups [97] and interactive learning in fields like educational psychology and environmental sciences [80, 98, 99]. Studies have also employed smart glasses to enhance feedback for teachers and support social skills development in classroom settings [100].

Advantages of Head-Worn Wearable Devices in Education

Head-worn wearables offer alternate learning pathways, especially for visual and active learners [101, 102]. Technological advances have significantly expanded their capabilities, such as increasing the field of view in HMDs to over 100 degrees, enhancing realism and presence [103]. These features enable learners to engage with environments that are otherwise inaccessible, such as simulations in aerospace or medical scenarios [79, 104].

Disadvantages of Head-Worn Wearable Devices in Education

Despite their promise, head-worn devices pose privacy concerns due to their ability to record and stream data [80, 94]. Their complexity may also require training for both educators and learners [79]. High development and implementation costs further limit their scalability. In many cases, the available simulations are not tailored for instructional use, reducing their pedagogical value. Extended usage may also induce cybersickness in some users [79].

Wrist-Worn Wearable Devices

Wrist-worn devices have become prevalent in both commercial and educational contexts due to their unobtrusive design. These include wristbands, smartwatches, and wearable ECG sensors.

- **Wristbands:** Collect biometric signals for estimating student stress levels [81].
- **Smartwatches:** Facilitate skills training through motion-based feedback mechanisms [105].
- **ECG Sensors:** Measure student engagement and learning in engineering and biomedical courses [82].

Wearable activity trackers have also been incorporated into university curricula to support digital health education [106].

Advantages of Wrist-Worn Wearable Devices in Education

Wristbands are suitable for large-group deployment due to their ease of use and unobtrusiveness [81]. They enable real-time monitoring of physiological states like stress and engagement, which are critical for academic success and mental health awareness [107]. Moreover, students can collect and interpret their own data, promoting active engagement and self-regulated learning [82]. In training environments, wrist-worn sensors have replaced subjective assessment tools by providing objective feedback on skill proficiency [105].

Disadvantages of Wrist-Worn Wearable Devices in Education

These devices may suffer from connectivity issues that can affect data integrity during real-time use [81]. Placement and tightness of the wearable can influence sensor accuracy, and battery limitations may require frequent recharging [82]. Additionally, wearables positioned on the forearm may restrict movement, particularly in activities requiring physical agility.

Chest-Worn Wearable Devices

Chest-worn wearables have been applied in simulation-based medical training. One example includes a Tracheostomy Overlay System (TOS) used to teach clinical procedures to health science students [108]. Sociometric badges have also been developed to track social interactions, collaboration quality, and creative fluency among students [84].

Advantages of Chest-Worn Wearable Devices in Education

These wearables allow continuous monitoring of heart rate, HRV, respiration, and speech-related behaviours. Sociometric sensors incorporate multiple technologies, including infrared, accelerometers, and microphones, to capture body movement, vocal patterns, and social proximity [84]. They have been used to study stress responses and physiological dynamics in clinical training [83].

Disadvantages of Chest-Worn Wearable Devices in Education

The richness of the data collected by chest-worn devices can raise serious privacy concerns. Their acceptability largely depends on clear communication regarding data protection and ethical use of personal information [85].

2.3 Theoretical Framework

This research is grounded in several theoretical frameworks that inform the study of wearable technology and its application in education. These theories provide a foundation for understanding how wearable technology can influence learning outcomes and the factors that affect its adoption in educational settings.

2.3.1 Cognitive Load Theory (CLT)

Cognitive Load Theory (CLT) posits that learning effectiveness is impacted by the cognitive demands placed on a learner's working memory [109]. According to CLT, learners have a limited capacity for processing information, and when this capacity is exceeded, learning becomes less effective [109, 110]. CLT emphasises the need to balance intrinsic, extraneous, and germane cognitive loads to optimise learning outcomes [111, 112].

In the context of wearable technology, devices such as eye-trackers can play a pivotal role in reducing cognitive load by providing real-time feedback that helps students manage complex tasks more efficiently. For instance, by tracking eye movements, educators can identify moments when students are struggling and intervene promptly before cognitive overload occurs. This aligns with CLT's principles by helping to balance cognitive loads, thus maximising learning efficiency [113].

2.3.2 Attention Restoration Theory (ART)

Attention Restoration Theory (ART) suggests that cognitive fatigue can be mitigated through exposure to restorative environments, which help replenish depleted cognitive resources [114, 115]. In the realm of wearable technology, devices like Virtual Reality (VR) and Augmented Reality (AR) systems can create immersive environments that capture students' attention and reduce cognitive fatigue. By providing engaging and visually stimulating experiences, wearable devices can help restore students' focus on learning tasks, thereby enhancing overall academic performance [116, 117].

Integrating ART into educational interventions using wearable technology offers new opportunities for improving student engagement and well-being. For example, VR environments that simulate natural settings can be used during instructional breaks to help students recover from mental fatigue, thereby improving their focus and productivity when they return to learning tasks [118].

2.3.3 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) provides a framework for understanding how attitudes, subjective norms, and perceived behavioural control influence the adoption of new technologies [119]. TPB is particularly relevant to this research as it helps explain the factors influencing educators' and students' acceptance of wearable technology in the classroom [120]. According to TPB, an individual's intention to engage in a behaviour, such as adopting wearable technology, is influenced by their attitude toward the behaviour, the subjective norms surrounding it, and their perceived control over the behaviour [121]. In educational settings, these factors will all play a role in determining whether they choose to adopt it [122].

2.3.4 Self-Regulated Learning (SRL) Theory

Self-regulated learning (SRL) Theory posits that learners are active participants in their learning processes, capable of setting goals, monitoring progress, and adjusting strategies to achieve desired outcomes [123]. SRL is particularly relevant to the use of wearable technology in education, as wearable devices can provide learners with real-time feedback on their progress, enabling them to make informed decisions about their learning strategies [124]. For example, an eye-tracking device that alerts a student when their focus is waning could prompt them to take a break or switch tasks, thereby improving their self-regulation skills [125]. Similarly, a wearable device that tracks physiological indicators of stress could help students manage their emotions and maintain optimal arousal levels for learning [126].

2.3.5 Justification of Theoretical Choices

These four theories were deliberately selected and applied to guide distinct yet interconnected aspects of the research design. Each theory was operationalised through the development of tasks, data collection methods, and analysis strategies involving wearable technologies.

Cognitive Load Theory (CLT) informed the design of learning activities that were paired with wearable sensors (e.g., eye-trackers and GSR) to monitor learners' cognitive strain. This helped evaluate whether real-time feedback mechanisms reduced extraneous load during complex tasks.

Attention Restoration Theory (ART) supports the integration of immersive environments through head-mounted VR devices. These were used in experimental conditions to examine whether short exposure to restorative simulations improved attention and reduced fatigue, as measured via physiological signals.

Theory of Planned Behaviour (TPB) guided the survey instruments developed for the pre-study and post-study phases. These captured participants' attitudes, norms, and perceived control regarding wearable technology, enabling analysis of adoption intent and actual usage behaviour.

Self-regulated learning (SRL) was embedded in the study by providing participants with feedback from wearable data, such as attention lapse alerts or physiological stress indicators. This enabled them to reflect on and adjust their learning strategies, which was further examined through post-task reflections and behavioural logs.

In conclusion, the integration of CLT, ART, TPB, and SRL theories was not merely conceptual but directly informed the structure and methodology of this study. CLT and ART influenced the instructional and environmental design of the wearable-based interventions; TPB shaped the exploration of adoption behaviours; and SRL underpinned the feedback mechanisms and self-monitoring components embedded in the learning process. Together, these frameworks enabled a multidimensional investigation into how wearable technology can support engagement, reduce cognitive barriers, and empower learners in higher education contexts.

2.4 Integration of Multisensory Wearable Sensors

This section introduces the concept and implementation of multisensory wearable technologies within the context of educational research. The system developed in this study integrates three key physiological sensors: eye-tracking, photoplethysmography (PPG), and galvanic skin response (GSR), into a single wearable device. Each sensor contributes unique and complementary data that collectively support the monitoring and analysis of students' cognitive engagement, emotional arousal, and attentional focus during learning tasks. The following subsections detail the theoretical foundation, capabilities, and application of each sensor type.

2.4.1 Wearable Eye-Trackers

Although eye-tracking technology alone is not multisensory, it constitutes a foundational element of the integrated system proposed in this study. When combined with other physiological sensors such as PPG and GSR, it enables a multidimensional understanding of learners' cognitive and affective states. This subsection critically explores the application of eye-tracking in educational contexts, with a particular emphasis on its role in monitoring attention and detecting mind-wandering.

Eye-tracking technology has evolved from early psychophysical studies on reading to becoming a cornerstone of educational research. Portable, real-time eye-tracking systems now allow for naturalistic data collection, capturing where and for how long learners direct their gaze during instructional tasks [127–129]. These data offer valuable insights into cognitive load, visual processing, and engagement.

One emerging application of eye-tracking is in detecting mind-wandering, which is the drift of attention from task-relevant stimuli to internal thoughts. Studies have employed metrics such as blink frequency, gaze dispersion, and prolonged fixations on non-task areas to infer mind-wandering episodes [130, 131]. However, these measures vary across studies, and many rely on post-task self-reports for validation, which introduces subjectivity and recall bias [132]. Moreover, most experiments are conducted in controlled lab settings, limiting their ecological validity.

These limitations justify a more robust approach to attention monitoring, one that incorporates physiological correlates of attention lapse. The integration of eye-tracking with GSR and PPG in the present study aims to address these gaps, offering a synchronised, real-time method of identifying disengagement during learning.

Eye-tracking has also been applied to investigate the effectiveness of instructional design. Research has shown that longer fixation durations on relevant visual materials are often associated with improved learning outcomes, particularly when instructional visuals are clearly aligned with task objectives [133]. However, other studies have indicated that even with intense visual focus, learners may not necessarily achieve adequate comprehension, especially in cases where they lack prior knowledge or when the instructional visuals are poorly aligned with cognitive goals [134]. These findings suggest that gaze behaviour, while informative, is not always a reliable proxy for understanding or learning success.

Although these applications highlight the potential of eye-tracking in educational settings, they also reveal notable gaps in the literature, specifically, the absence of large-scale classroom implementations, standardised gaze-based feedback mechanisms, and longitudinal outcome measures. Consequently, this research approaches eye-tracking not as an isolated metric but as an integral component of a multisensory framework aimed at enhancing the detection of cognitive engagement and supporting adaptive learning environments.

2.4.2 Design and Implementation of a Multi-Sensory Wearable Device

To advance the measurement of cognitive and emotional states in educational settings, this research introduces a multi-sensory wearable device that integrates three key physiological sensors: eye-tracking, photoplethysmography (PPG), and galvanic skin response (GSR). These sensors are embedded in a single wearable system resembling smart glasses, designed to collect data on visual attention, heart rate variability, and emotional arousal, respectively.

The **eye-tracking module** forms the cognitive core of the system, enabling the capture of gaze direction, fixation points, and saccades. These metrics provide direct insight into attentional allocation and cognitive load during learning [135, 136]. The eye-tracking cameras are discreetly positioned around the lens rims to ensure continuous, accurate tracking while remaining unobtrusive.

The **PPG sensors**, embedded in the temples of the glasses, detect blood volume changes to infer heart rate variability (HRV), a physiological marker linked to mental workload, stress, and engagement [137, 138]. By providing real-time cardiovascular data, these sensors complement the visual attention information offered by the eye-tracker.

The **GSR sensors**, placed at the nose pads, measure skin conductance changes associated with sympathetic nervous system activity. GSR serves as an effective index of emotional arousal, enabling the detection of engagement, cognitive overload, or disengagement [139, 140].

This design prioritises both ergonomic comfort and sensor integration. The wearable device features a lightweight polycarbonate frame, adjustable nose pads and arms for stability, and a minimalist heads-up display (HUD) for user feedback. A single USB-C port is used for charging, with a built-in battery enabling prolonged experimental usage in classroom environments.

The integration of these three sensors is grounded in theories of multimodal engagement measurement. While each sensor offers partial insight into cognitive and affective states, their fusion allows for more comprehensive detection of attention dynamics and mind-wandering episodes [141, 142]. This multisensory approach addresses limitations in conventional, screen-based eye-tracking setups by enabling mobile, context-aware data collection in naturalistic learning settings [143].

By combining eye-tracking with PPG and GSR, this wearable system supports real-time monitoring of student engagement and lays the foundation for intelligent educational tools that adapt to learners' internal states. The next chapter presents the experimental validation of this system in real-world learning environments.

2.4.3 Data Collection and Co-Registration of Sensors

The integration of multiple sensors within a single wearable device demands meticulous attention to data collection and co-registration methodologies. Co-registration, which involves the simultaneous recording of various data streams, is essential to ensure that the physiological and cognitive data gathered from different sensors are synchronised and accurately reflect the user's state. This process is vital in multisensory systems, as the alignment of data across sensors allows for a comprehensive and coherent analysis of the user's responses.

Selecting an appropriate co-registration method is critical for ensuring the accuracy and reliability of the collected data. A single software solution is often employed when all sensors can be managed and analysed through a unified platform. This approach streamlines the process and maintains consistency across datasets. It is particularly effective for straightforward data analyses, facilitating real-time monitoring and immediate feedback in educational settings [144].

For more complex data environments involving heterogeneous sensors, a multiple-software solution may be more appropriate. In such cases, synchronisation is achieved through everyday events such as button presses or predefined stimuli that are simultaneously registered by all devices. This method allows for sensor-specific optimisation in recording and analysis [145].

The choice between single and multiple software solutions depends mainly on the study's complexity and the types of data being collected. In educational contexts, where the emphasis is on monitoring student engagement and cognitive load in real-time, a single software solution provides seamless integration and ease of deployment. In contrast, studies involving diverse physiological and neurological measures benefit from the flexibility of a multiple software setup, albeit with increased demands on coordination and calibration.

The importance of precise synchronisation cannot be overstated. Even minor misalignments in data streams can result in significant errors in interpreting the relationship between physiological indicators and cognitive states [146]. Accordingly, careful planning is essential to ensure that all data streams are temporally aligned, regardless of the chosen co-registration strategy.

In summary, the integration of multiple sensors in wearable systems for educational research requires a strategic approach to data collection and synchronisation. The decision between single and multiple software solutions should be informed by the study's objectives and the complexity of the data, with an emphasis on maintaining data integrity and analytical coherence.

2.4.4 Application in Educational Settings

The proposed multi-sensory wearable device, which integrates eye-tracking, galvanic skin response (GSR), and photoplethysmography (PPG) sensors, is designed to enhance educational experiences through real-time monitoring of attention, emotional states, and physiological responses. These capabilities enable a data-informed, adaptive approach to teaching, allowing educators to adjust their instructional strategies based on students' cognitive and affective engagement.

In conventional classroom environments, fluctuations in attention and engagement often go unnoticed. The integration of gaze tracking allows educators to identify moments when students disengage, while GSR and PPG data can offer physiological markers of emotional arousal and cognitive load. For example, an increase in GSR or a decrease in heart rate variability (HRV) may indicate stress, confusion, or mental fatigue [147]. This real-time insight enables educators to intervene promptly by modifying the pace, incorporating active learning techniques, or clarifying content. Such dynamic feedback loops have the potential to improve learning outcomes significantly [148].

The system's value extends beyond individual interventions to broader pedagogical analysis. Aggregated data can highlight trends in student engagement across specific lessons or teaching methods, supporting curriculum refinement. For instance, repeated patterns of mind-wandering during lecture-based content suggest the need for more interactive or multimodal instructional design. Additionally, the emotional arousal captured through GSR can be mapped to moments of high cognitive engagement or frustration, providing granular insights into how students experience the learning process.

The proposed system also offers specific advantages in remote and hybrid learning environments, where traditional behavioural cues are often absent. During online sessions, physiological data can provide proxy indicators of student engagement, compensating for the lack of visual and social feedback available to instructors [47]. This capacity for remote sensing becomes particularly critical in ensuring continuity of learning during disruptions, such as those experienced during the COVID-19 pandemic [149].

Unlike existing tools that focus solely on attention or require obtrusive setups, the proposed device offers a portable, minimally invasive, and comprehensive solution tailored for educational settings. Its integration of multiple sensing modalities into a single platform addresses the limitations of single-sensor systems by enabling cross-validation of attentional and emotional states. Moreover, its design supports ethical deployment by allowing data to remain on local devices or be anonymised before analysis, in alignment with privacy standards in educational technology.

In summary, the application of this multi-sensory wearable device represents a critical advancement in responsive teaching. By delivering continuous multimodal data on learner states, the device supports adaptive instruction, fosters emotional regulation, and enhances student well-being, which are key goals for next-generation educational environments.

2.4.5 Future Directions and Challenges

While the conceptual design of the multi-sensory wearable device marks a significant step forward in educational technology, several limitations must be acknowledged to ensure its practical and ethical deployment. This thesis addresses key challenges related to sensor integration, data synchronisation, and ethical data handling, which are examined in the subsequent experimental chapter.

Integrating eye-tracking, photoplethysmography (PPG), and galvanic skin response (GSR) sensors into a unified platform presents technical challenges, including potential signal interference and calibration complexity. These issues are tackled through a synchronisation strategy and a co-registration framework aimed at ensuring temporal alignment and data accuracy during real-time use.

Ethical considerations are paramount in educational contexts involving physiological monitoring. Concerns such as data privacy, informed consent, and the secure handling of sensitive biometric information are incorporated into the system design through anonymisation protocols and transparent participant communication [150].

Beyond the scope of this thesis, further developments could explore the integration of additional modalities, such as electroencephalography (EEG) or respiratory sensors, to deepen insights into cognitive states [151]. These additions, however, would require advances in sensor miniaturisation and unobtrusive form factors.

Scalability and long-term deployment present further opportunities for refinement. Adapt-ing the system for large-scale classroom use or asynchronous online learning environments will involve hardware optimisations and intelligent data analysis models capable of automated interpretation.

Ongoing interdisciplinary collaboration will be vital for extending this work into fully adaptive, context-aware learning systems that balance technological potential with ethical responsibility.

2.5 Identified Gaps in the Literature

In parallel with the design challenges noted above, several broader research gaps remain in the application of wearable technologies in education particularly within engineering disciplines. This section identifies underexplored areas that directly inform the aims and methods of this thesis.

2.5.1 Underexplored Applications in Engineering Education

Although wearable technologies have been widely explored in domains such as healthcare, sports, and cognitive psychology, their use in engineering education remains comparatively underdeveloped. Existing literature tends to focus on general education or broader STEM contexts, often overlooking the unique cognitive demands of engineering learning environments. Engineering students are frequently required to engage with abstract, technically dense material that demands sustained attention and conceptual reasoning. These are precisely the areas where physiological and behavioural data captured through wearable sensors could provide meaningful insights into learner engagement and cognitive load.

Despite this potential, there is limited empirical research applying wearable technologies specifically to monitor or enhance engagement within engineering classrooms. This gap presents a critical opportunity for targeted investigation and application.

2.5.2 Need for Multisensory and Integrated Approaches

Many existing studies rely on single-sensor or mono-modal data, such as eye-tracking or self-reported engagement, without fully leveraging the capabilities of integrated, multisensory systems. The combination of modalities like eye-tracking, photoplethysmography (PPG), and galvanic skin response (GSR) offers the potential for a more nuanced understanding of learners' cognitive and emotional states. These integrated perspectives are particularly valuable when assessing attention, cognitive load, and emotional arousal in real-time.

However, studies that employ multimodal sensor fusion are still rare, especially in naturalistic or classroom-based engineering settings. Furthermore, there is a lack of scalable frameworks that link sensor-derived metrics to actionable pedagogical strategies. Without such frameworks, it remains challenging for instructors to meaningfully interpret and apply data from wearable systems in support of teaching and learning.

By addressing these gaps, this study contributes both empirical findings and a practical framework for deploying multisensory wearable technologies in engineering education. The following chapter outlines the methodology used to explore these issues.

Chapter 3

Methodology

This chapter outlines the methodological framework adopted to investigate how wearable technology can enhance cognitive and emotional monitoring in higher education learning environments. The study employs a sequential explanatory mixed-methods design, combining quantitative and qualitative approaches to explore attention, emotion, and mind-wandering among students during authentic learning tasks.

Wearable technologies such as eye-trackers, galvanic skin response (GSR) sensors, and photoplethysmography (PPG) devices are central to this research. These tools enable the continuous, non-invasive capture of physiological and behavioural signals that reflect cognitive engagement. By leveraging the multimodal nature of these data, the study aims to uncover student attention and disengagement patterns that are often imperceptible through conventional educational assessments.

This chapter is structured into several sections. It begins with a literature-informed rationale for the methodological approach and a review of relevant studies to support sensor and design choices. The subsequent sections detail the research design, participant recruitment, experimental procedures, and ethical considerations. The chapter describes the data collection protocols and analysis techniques, including integrating machine learning models for real-time engagement detection. The chapter concludes by discussing methodological limitations and the practical implications of system implementation.

3.1 Literature Review and Study Selection

To inform the methodological design of this study, a targeted literature review was conducted focusing on the application of wearable devices in educational contexts, particularly in attention tracking, emotion detection, and cognitive engagement. The aim was to identify relevant technologies, sensor configurations, and experimental designs that could be adapted for higher education settings.

The following research questions guided the review:

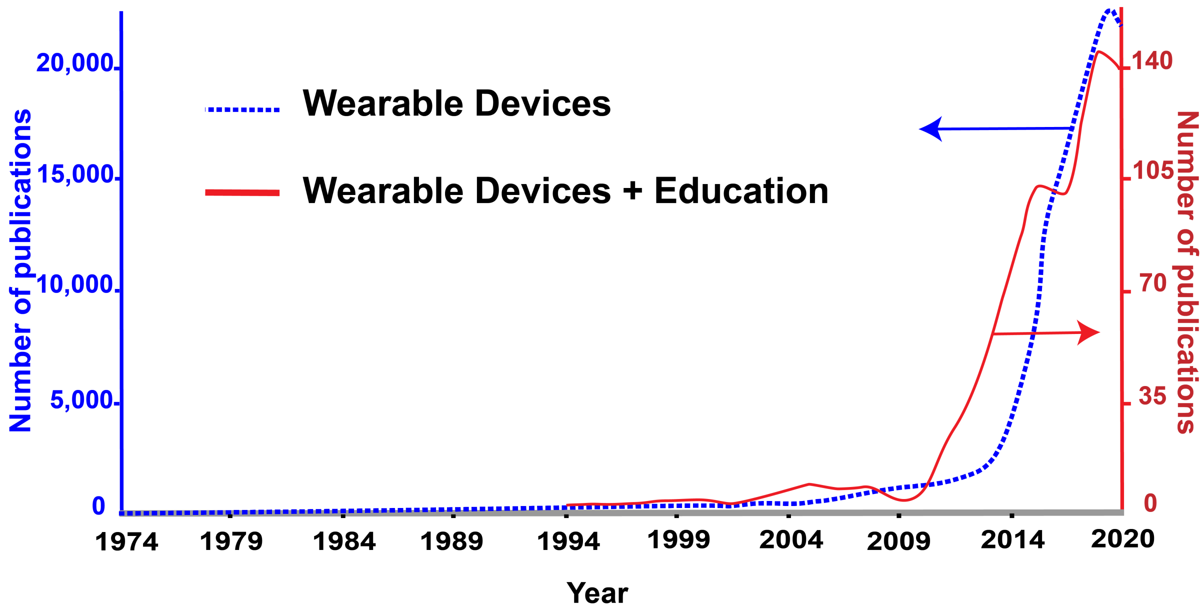

Figure 3.1: *Research publications in the field of wearable devices (blue y-axis, left) and wearable devices in education (red y-axis, right) since 1974. Data was retrieved from the Web of Science using keywords such as "wearable devices", "wearable", and "education".*

What types of wearable devices have been applied in higher education to support cognitive, emotional, or behavioural tracking?

Which sensor modalities and body placements are most effective in terms of data reliability, comfort, and usability for educational wearables?

Relevant literature was sourced from Web of Science and Google Scholar, using search descriptors such as "wearable technology", "higher education", "attention monitoring", and "cognitive engagement". Table 3.1 presents the descriptors and synonyms used in the search process.

Table 3.1: *Descriptors and Synonyms Used in the Literature Review*

Descriptor	Definition	Synonyms
Wearable Technology	Electronic devices worn on the body to monitor physiological, cognitive, or behavioural states in real time.	Smart wearables, body-mounted sensors
Higher Education	Formal post-secondary education, including undergraduate, postgraduate, and doctoral programmes.	Tertiary education, university-level education
Undergraduate	Education undertaken after secondary school and prior to postgraduate study, typically leading to a bachelor's degree.	Bachelor's level, first degree

Studies were included if they met the following criteria:

- Focused on the use of wearable devices in teaching and learning contexts within higher education.

Table 3.2: *Wearable Devices in Higher Education and Main Features*

Main Category	Subcategory	Application Targets	References
Head-worn	Head-mounted and Glasses	Cognitive training, simulation-based learning, immersive learning in environmental sciences, medical training	[78, 80, 89–93, 95–100, 152]
Wrist-Worn	Smartwatches, Wristbands	Stress monitoring, physical activity tracking, real-time feedback in clinical education	[81, 82, 105, 106]
Chest-Worn	Sensor Patches	Heart rate and respiration monitoring, collaboration tracking, cognitive load assessment	[84, 108]

- Involved undergraduate or postgraduate students.
- Published in English and peer-reviewed.
- Employed physiological or behavioural sensing for educational purposes.

Excluded were studies that:

- Treated smartphones as wearable devices.
- Used wearables exclusively for medical or clinical diagnosis.
- Investigated learning in informal, non-accredited, or training contexts.

The search identified a growing interest in wearable technologies for education, particularly from 2010 onward. As shown in Figure 3.1, the number of publications in this area has increased in parallel with broader trends in wearable technology adoption. A key finding from the literature was the categorisation of wearables by body placement, namely, head-worn (e.g., eye-trackers and smart glasses), wrist-worn (e.g., fitness bands), and chest-worn (e.g., ECG patches), each offering distinct benefits for specific educational objectives.

Table 3.2 summarises the main categories of wearable devices and their reported applications in higher education, forming a basis for selecting appropriate technologies for this study's experimental framework.

3.2 Research Design

The research design of this thesis is grounded in a mixed-methods approach, combining quantitative and qualitative data collection techniques to address the research questions comprehensively. This approach was selected for its capacity to offer a nuanced understanding of the phenomenon under investigation, enabling data triangulation and the integration of multiple perspectives. The quantitative phase was used to identify patterns in physiological and behavioural engagement, while the qualitative phase contextualised and enriched these findings by capturing participants' subjective experiences.

The decision to employ a mixed-methods approach is rooted in the recognition that both qualitative and quantitative data are necessary to fully capture the complexity of engineering education enhanced by wearable technology. Quantitative data provides measurable outcomes that can be generalised, while qualitative data offers depth and context to those outcomes. By integrating these two approaches, the research gains both breadth and depth, enabling a more holistic understanding of how wearable devices can impact the understanding of students' engagement and learning process. Quantitative methods allow for the statistical analysis of engagement levels and cognitive states, while qualitative methods, such as questionnaires, provide insights into the participants' subjective experiences. This combination ensures that the findings are robust, reliable, and reflective of the diverse ways students interact with wearable technology. The following section provides a detailed description of the procedures and instruments used across both phases, including the experimental design, wearable systems employed, and data collection protocols.

3.2.1 Detailed Description of Methods

This study followed a sequential explanatory mixed methods design, beginning with quantitative data collection through wearable sensor systems, followed by qualitative inquiry to contextualise and enrich the findings. The research was conducted in a controlled laboratory environment and involved engineering students engaging with educational tasks designed to elicit varying levels of cognitive load and attention.

Quantitative Phase: Participants were equipped with a multisensory wearable device comprising three integrated components: an eye-tracker, a photoplethysmography (PPG) sensor, and a galvanic skin response (GSR) sensor. Each participant completed a learning task using multimedia materials that included visual, auditory, and textual content. During these sessions, eye movements were tracked to record gaze behaviour, while physiological signals were simultaneously captured to monitor arousal and engagement. The experimental setup ensured consistent lighting, seating distance, and screen configuration to reduce variability in the data collection environment.

Qualitative Phase: To supplement the quantitative data, participants completed pre- and post-experiment questionnaires aimed at capturing their prior knowledge, perceived engagement, and learning experience. In addition, semi-structured interviews and small focus groups were conducted with a subset of participants. These qualitative components were designed to provide insight into user perceptions of the wearable system and the learning experience, including usability, comfort, and perceived impact on attention.

All sessions followed a consistent protocol, beginning with a briefing and device calibration, followed by the learning task and concluding with a debrief and qualitative data collection. With the experimental framework established, the next section outlines how participants were recruited and the ethical safeguards implemented to ensure responsible conduct throughout the study.

3.2.2 Participant Selection and Ethical Considerations

Participants were selected using purposive sampling to ensure relevance to the study's objectives. Specifically, the sample consisted of 15 postgraduate engineering students enrolled at the University of Glasgow, all with prior exposure to cognitively demanding coursework. This background made them suitable for investigating attention, engagement, and mind-wandering in a controlled educational setting.

Participants were divided into two groups: eight in the probe-caught condition and seven in the self-caught condition. Gender balance was not considered in the recruitment process, but efforts were made to ensure the representation of both male and female students.

This study adhered strictly to the university's ethical guidelines. Ethical approval was obtained from the institutional review board. Informed consent procedures included a detailed explanation of the study's purpose, procedures, and data usage, including the deployment of wearable sensors. Participants were informed of their right to withdraw at any time.

All collected data were anonymised to protect participant identity and stored securely in accordance with GDPR and university data protection protocols. A debriefing session followed each experiment to address any participant concerns and to provide additional context about the research.

3.2.3 Data Analysis Techniques

Following data collection, distinct analysis procedures were applied to the quantitative and qualitative datasets to extract meaningful insights relevant to the research objectives.

Quantitative Data: Raw physiological and behavioural data from the wearable devices were preprocessed to remove artefacts and synchronised across modalities. Eye-tracking data were filtered to exclude blinks and outliers, while physiological signals (GSR and PPG) were smoothed and normalised for consistency. Feature extraction was performed to derive relevant indicators of attention and cognitive engagement, including fixation duration, saccade frequency, pupil dilation, skin conductance response, and heart rate variability (HRV).

These features formed the basis of subsequent statistical and computational analyses. Descriptive statistics were used to summarise data distributions, and inferential methods such as t-tests and ANOVA were used to explore differences across experimental conditions. Correlation analysis was conducted to examine relationships among physiological variables and task-related measures.

Qualitative Data: Responses from questionnaires were transcribed and analysed using thematic analysis. An inductive approach was used to identify emerging patterns in participants' narratives, particularly around usability, emotional responses, and the perceived educational value of the wearable technology. Initial coding was conducted manually, with themes refined through iterative review. Triangulation with quantitative findings supported a comprehensive understanding of the learner experience.

More advanced analysis techniques, including machine learning classification models for mind-wandering detection and engagement prediction, are described in detail in Section 3.5. While the analysis methods ensured rigour and interpretability, it was also necessary to apply specific inclusion and exclusion criteria to maintain data quality and consistency, as discussed below.

3.2.4 Justification for Exclusion Criteria

Certain data points and participants may be excluded from the final analysis based on predefined criteria. For example, participants who do not complete the full experiment or whose data is incomplete due to technical issues may be excluded to ensure the reliability of the findings. Additionally, outliers in the data that are determined to result from external factors unrelated to the study (e.g., health issues affecting physiological responses) are carefully considered and documented.

3.2.5 Limitations of the Research Design

While the mixed-methods approach offers comprehensive insights, there are limitations to this research design. One potential limitation is the reliance on wearable technology, which, despite its advantages, may introduce biases such as discomfort or awareness of being monitored, potentially affecting natural behaviour. Additionally, the qualitative data, while rich in detail, may be influenced by participants' willingness to share openly, particularly in focus group settings. These limitations are acknowledged, and efforts are made to mitigate them, such as ensuring participant comfort and confidentiality throughout the study.

3.3 System Operation and Implementation

The various wearable sensors used in this thesis were selected based on their ability to capture essential physiological biosignals. These sensors play a critical role in monitoring the physiological states of students, providing valuable insights into their cognitive and emotional engagement during educational activities. The technical specifications for these sensors, including their signal frequency and parameter range, are summarised in Table 3.3. These specifications ensure that the sensors can accurately detect and monitor the necessary biosignals required for the educational studies conducted. Following the description of the wearable system's hardware and software components, the next section outlines how these technologies were implemented in controlled experiments to monitor attention and detect mind-wandering during educational tasks.

Table 3.3: *Technical specifications for various wearable sensors used to collect physiological biosignals relevant to educational studies, namely electrocardiogram (ECG), heart rate variability (HRV), electromyogram (EMG), and electroencephalogram (EEG).*

Sensor Type	Signal frequency	Parameter range
Chest-worn e.g. ECG sensor	250 Hz	0.5-4 mV
Wrist-worn e.g. EMG sensor	10-5000 Hz	0.01-15 mV
Head-worn e.g. EEG sensor	0.5-60 Hz	0.0003 mV

3.3.1 Wearable Device Components

Wearable devices are composed of several intricate components, each playing a vital role in gathering physiological and psychological data essential for educational studies. These components include sensors, data processing electronics, communication modules, power management systems, and energy harvesters. Each part of this system must work harmoniously to ensure accurate, reliable, and continuous data collection.

Sensors are the primary interface between the human body and the wearable device. Depending on the objectives of the study, different types of sensors are strategically placed on various parts of the body, such as the head, wrist, or chest. For instance, head-mounted EEG sensors capture brainwave activity to assess cognitive states [153], while chest-worn ECG sensors monitor heart rate variability and detect subtle physiological changes associated with stress or engagement levels [154].

The electronic units within wearable devices are tasked with processing the raw signals from the sensors. These units often include microcontrollers or digital signal processors (DSPs) that filter out noise, such as motion artefacts, which could otherwise compromise data quality. For example, during a classroom experiment, students might move their hands or adjust their posture, which could introduce unwanted fluctuations in the sensor readings. Advanced signal processing techniques, such as adaptive filtering, are applied to ensure that only relevant physiological data is captured.

Moreover, these electronics are optimised for speed and efficiency, allowing real-time data processing. This is crucial in educational settings where immediate feedback can significantly enhance the learning experience [155]. For instance, if a student is detected to be disengaged or experiencing cognitive overload, interventions can be deployed swiftly.

Communication modules, typically based on Bluetooth Low Energy (BLE) or Wi-Fi, are

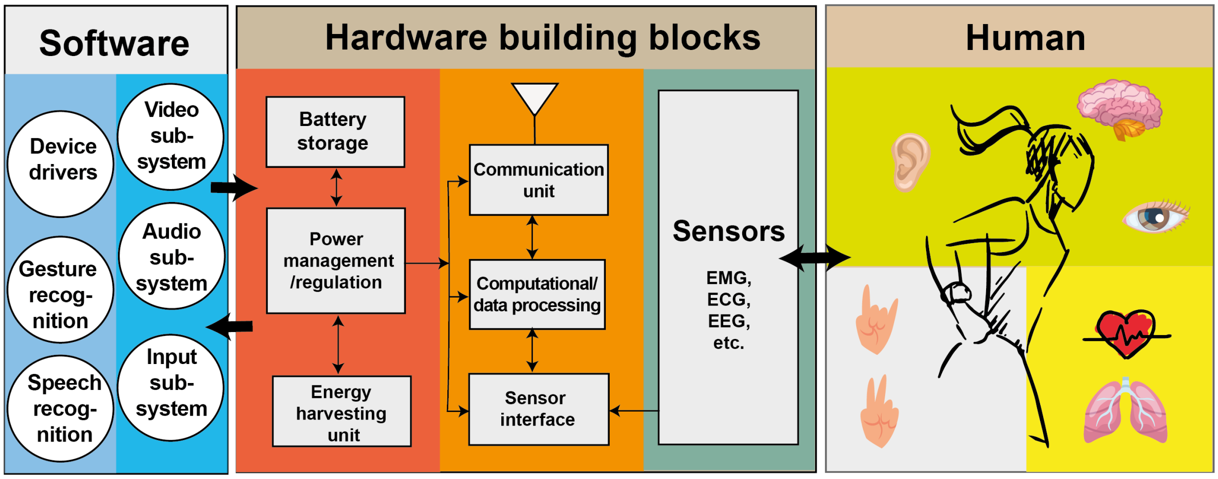

Figure 3.2: *Concept diagram showing the software and hardware building blocks of wearable devices for educational purposes. The main hardware building blocks of a wearable device are the sensors, readout circuit interface, energy harvester, and power management and telecommunications units. The software component can be programmed to drive the wearable devices' hardware according to different subsystems and inputs from sensors, e.g., video, audio, gestures, and speech.*

integral to the operation of wearable devices. These modules ensure that the processed data is transmitted securely and efficiently to a central data repository, where it can be further analysed. In some cases, devices may also include Near Field Communication (NFC) capabilities for short-range data exchange, especially in scenarios where quick data transfer is needed without establishing a continuous connection [156].

In educational environments, these communication modules allow for the seamless integration of wearable devices with existing learning management systems (LMS). For instance, data from wearable sensors can be directly uploaded to an LMS, where it is analysed alongside traditional academic performance metrics, providing a more holistic view of student progress [157].

One of the critical challenges in wearable technology is ensuring that devices remain operational for extended periods without frequent recharging. Power management systems are designed to optimise battery life, balancing the energy consumption of sensors, processors, and communication modules. Techniques such as duty cycling, where sensors are powered down during periods of inactivity, are commonly employed to conserve energy.

Additionally, energy harvesting technologies are being increasingly integrated into wearable devices [158]. These technologies capture energy from the user's movements, body heat, or ambient light, providing a supplementary power source that can extend the operational lifespan of the device. For instance, piezoelectric materials embedded in the device can generate electricity from the natural motion of the user, reducing the reliance on traditional battery power [159].

The software subsystems within wearable devices are responsible for analysing the collected data and providing real-time feedback to both students and educators. These subsystems often include machine learning algorithms that can detect patterns in the data, such as signs of cognitive fatigue, stress, or disengagement. For instance, a machine learning model might be trained to recognise specific physiological signatures associated with mind-wandering during lectures [160].

In real-time applications, such as in classroom settings, this software can alert educators to intervene when necessary. For example, if the system detects that a significant portion of the class is disengaged, the educator can adjust their teaching approach on the fly, perhaps by introducing a more interactive element or altering the pace of the lesson [157].

The integration of wearable devices with educational systems goes beyond data collection. These devices can be part of a larger ecosystem that includes visual and auditory feedback mechanisms. For instance, a wearable device might be paired with a visual display that shows a student's engagement level during a lesson or with auditory cues that remind students to refocus when their attention drifts [161].

Furthermore, these systems can be linked with virtual or augmented reality environments, where the physiological data collected by the wearable devices enhance the immersive experience. For instance, in a virtual engineering lab, a student's stress levels could influence the difficulty of the tasks presented, creating a dynamic learning environment that adapts to the student's current state [162].

Figure 3.2 illustrates the overall architecture of the wearable devices, detailing the interaction between the software and hardware building blocks that make up the system.

3.4 Data Collection and Experimental Setup

3.4.1 Wearable Eye-Tracking System

Eye-tracker for attention monitoring

An experiment was conducted to evaluate the effectiveness of Pupil Core eye-tracking glasses in detecting attention lapses among students. To enhance the accuracy of the evaluation, a comparative analysis was performed between the Pupil Core eye-tracking glasses and a desktop-based eye-tracker to identify instances of student disengagement, as illustrated in Figure 3.3.

Before beginning the data collection, the dedicated setups for both wearable and webcam-based eye-trackers must be studied. Learners are seated at a predefined distance of 70 cm from a laptop screen [163]. A Pupil Core headset is worn on the learner's head to track and collect eye movement data. The data collection process for wearable and desktop-based eye-trackers is illustrated in Figure 3.4.

Each participant completed the experiment individually using both the Pupil Core eye-tracking glasses and the desktop-based eye-tracker in separate sessions. Before each session, participants received a brief introduction to the experiment and its procedures.

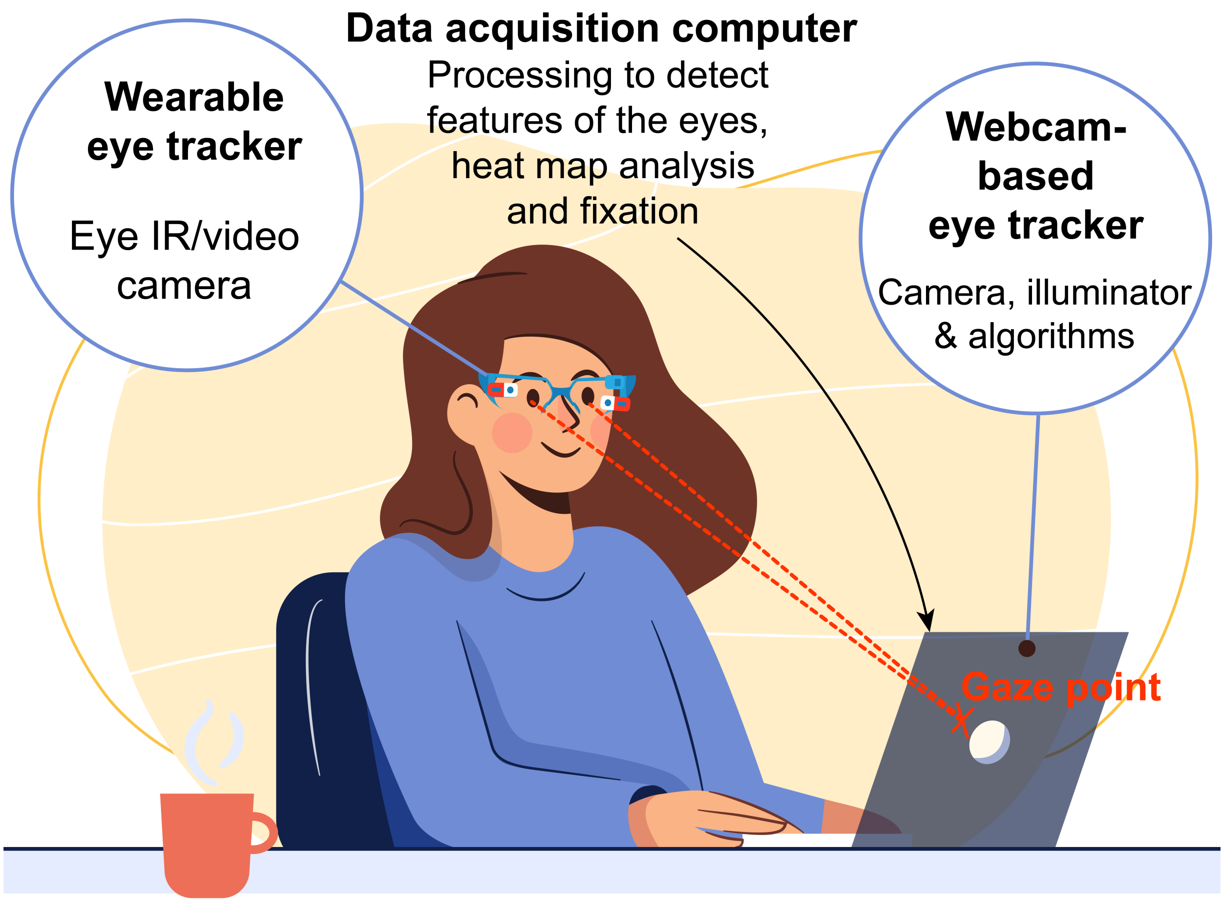

Figure 3.3: *The system-level architecture of wearable and webcam-based gaze-aware attention monitoring systems*

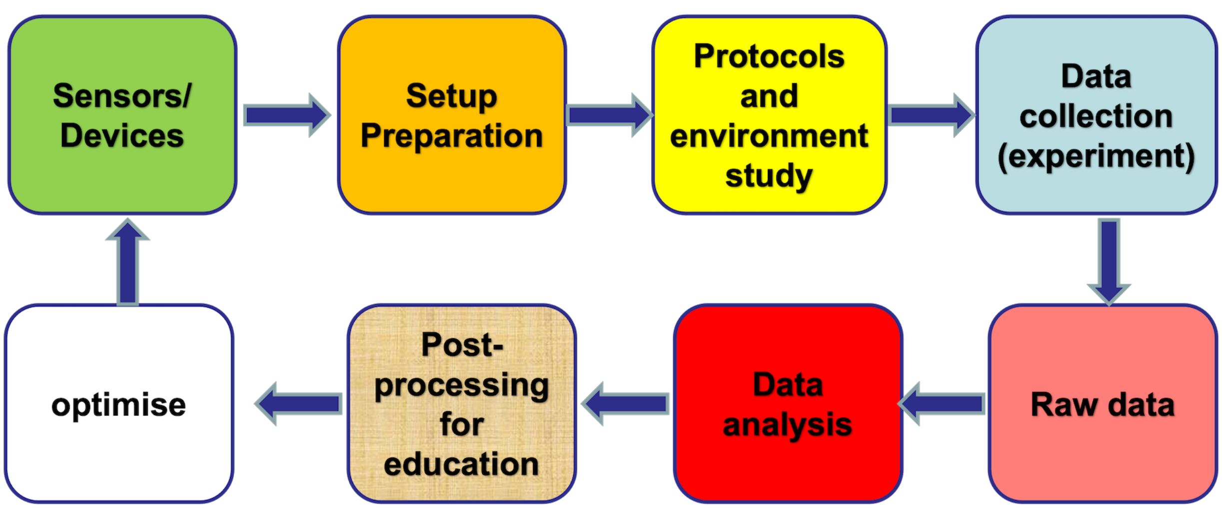

Figure 3.4: *Steps for data collection and experimental plan for attention monitoring using an eye-tracker*

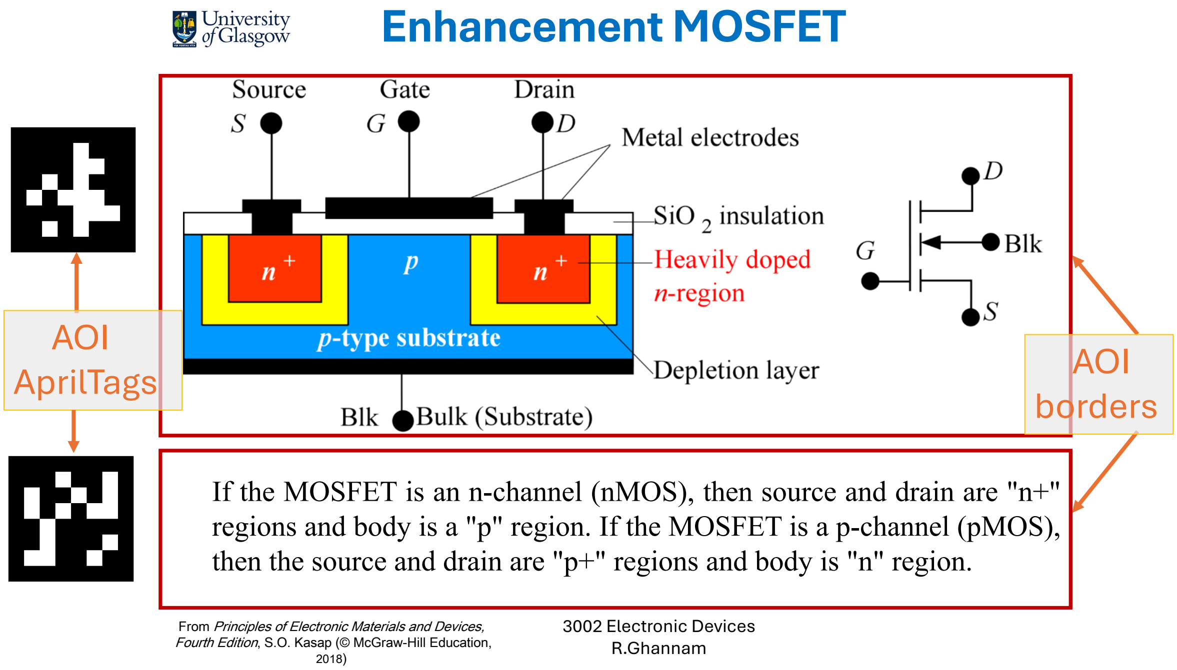

Figure 3.5: *A sample lecture slide used in the experiment, with predefined areas of interest (AOIs) using AprilTags.*

Setup and Calibration: The Pupil Core glasses were adjusted to ensure a comfortable and accurate fit for each participant. The device's world camera captured the participant's visual environment, while infrared cameras tracked ocular movements. Collected eye gaze data was stored in dedicated files. Pupil Core's software suite, encompassing Pupil Capture and Pupil Player, facilitated data acquisition and processing.

A dual pupil detection algorithm, operating in both 2D and 3D planes, enhanced the system's accuracy. To delineate areas of interest (AOIs), surface tracker plug-ins were integrated into each page, utilising text or image [164], as shown in Figure 3.5. The Pupil Core interface was activated on the participant's computer, initiating live face and gaze detection upon headset initialisation, as visualised in Figure 3.6.

Calibration and Validation: To establish accurate gaze point estimation, participants underwent a calibration process involving thirty fixed screen points. Participants clicked on each point while the system recorded the corresponding gaze position. Ridge regression was employed to calculate gaze coordinates. A subsequent four-point validation check assessed the system's accuracy in determining real-time gaze points. Due to the webcam's sensitivity to head movement and lower sampling rate (30 samples per second compared to Pupil Core's 200 samples per second), recalibration was frequently required to maintain data precision.

Once calibration was complete, data collection commenced for both eye-tracking systems. The Pupil Core system captured comprehensive gaze data, including fixation points, gaze positions, heatmaps, and gaze distribution. Fixation data was timestamped and included details

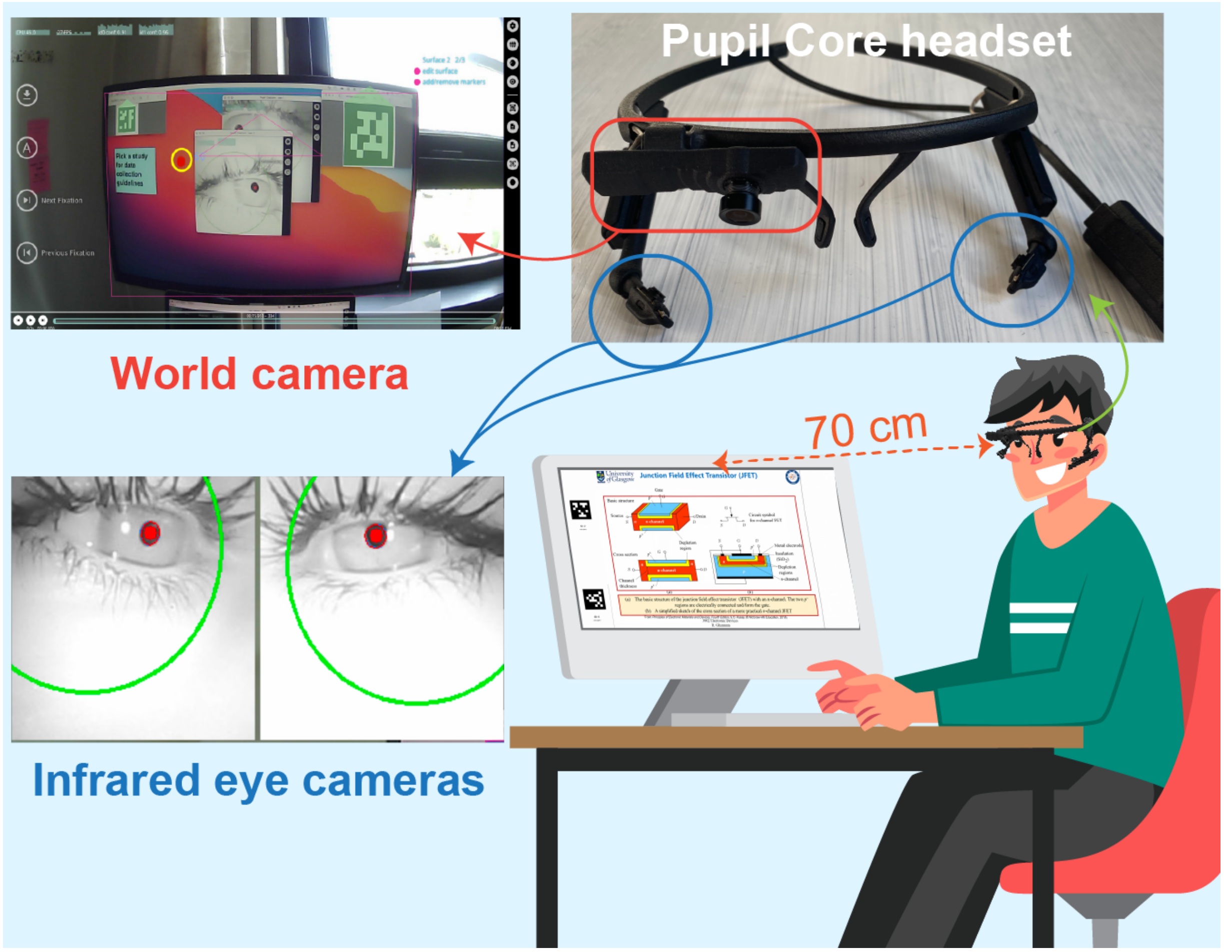

Figure 3.6: *The experimental setup for the wearable eye-tracker. It shows the Pupil Core headset (top right) with its view from the world camera (top left) and pupil detector camera (down left).*

such as fixation ID, duration, dispersion, and normalised x and y coordinates. Conversely, the desktop-based system recorded simpler data, consisting solely of 2D screen coordinates of the gaze point and corresponding timestamps.

Eye-tracker for mind-wandering monitoring

The data collection process for this experiment followed a systematic approach, beginning with the setup preparation and calibration of eye-tracking glasses, followed by data collection from participants. The data collected was analysed using Python, and further statistical analysis was conducted in RStudio. Finally, the results were interpreted, and potential future directions were identified. Figure 3.7 illustrates this step-by-step process, providing a clear overview of the entire procedure from setup to results.

An 18-minute video lecture on International Comparisons in Education was used as the stimulus [29]. Participants completed pre- and post-experiment questionnaires and responded to

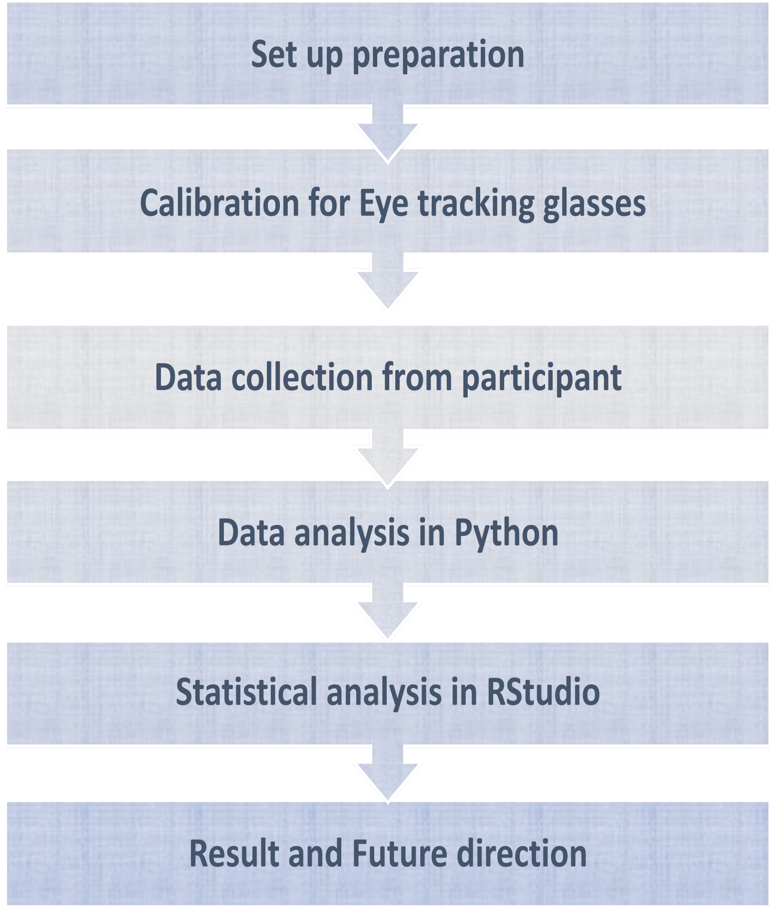

Figure 3.7: *Data collection process from setup preparation to result presentation*

probe questions during the video. Areas of Interest (AOIs) were defined to differentiate between the slide and teacher content.

The experiment was conducted using the OpenSesame platform [165]. Participants viewed the video on a 1920x1080 pixel monitor from approximately 60 cm distance. Eye-tracking data was synchronised with participant responses using timestamps.

The study employed two experimental conditions: self-caught and probe-caught. Fifteen participants were divided into two groups (n=8 for probe-caught, n=7 for self-caught).

Before the experiment, participants received a brief explanation about mind-wandering. Participants were seated in a comfortable position to minimise head movement. A 9-point calibration process was conducted using eye-tracking glasses. The experiment began with pre-test questions, followed by the video lecture, and concluded with post-experiment questions and engagement ratings. Pop-up questions were presented at four intervals in the probe-caught condition, and participants responded by pressing a key to confirm or dismiss, as shown in Figure 3.8.

After the video lecture concluded, participants completed the post-experiment questionnaire to evaluate their learning outcomes. Additionally, participants rated their engagement level by answering two questions regarding their interest in the lecture material and their engagement

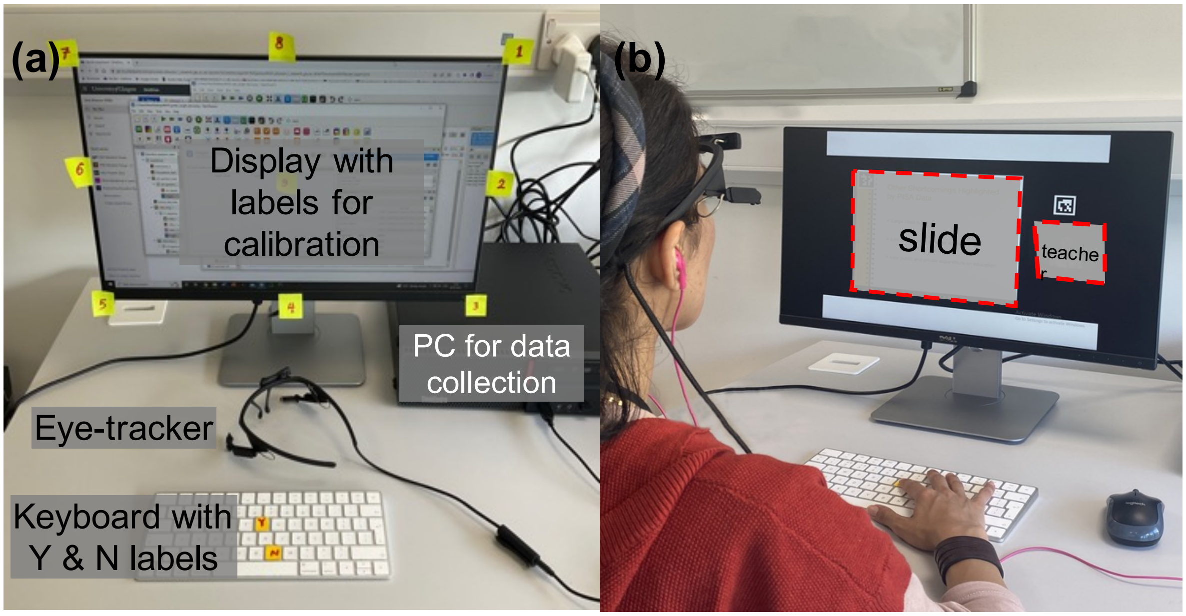

Figure 3.8: *The experimental setup for the wearable eye-tracking device. (a) The calibration procedure and the Pupil Core headset, (b) a participant taking the test.*

during the video lecture. The responses were used to calculate participants' overall engagement levels.

Fixation data was extracted separately for each AOI and experimental condition. To analyse mind-wandering, 50-second pre-mind-wandering and 15-second post-mind-wandering segments were divided into 13 five-second bins. The relationship between mind-wandering and other variables was examined through correlation analysis. Fixation durations were analysed across AOIs, with longer durations potentially indicating mind-wandering [166].

3.4.2 Multisensory Mind-Wandering Detection

The detection of mind-wandering during an educational task is crucial for understanding how effectively learners are engaged with the material. Mind-wandering, a common phenomenon where attention drifts away from the task at hand, can significantly impact learning outcomes by reducing the amount of information retained. By monitoring and detecting instances of mind-wandering, educators and researchers can gain deeper insights into the cognitive engagement levels of students, allowing for more personalised and adaptive learning experiences.

A multisensory approach to mind-wandering detection utilises diverse wearable sensors to capture a wide spectrum of physiological and behavioural signals. Wearable galvanic skin response (GSR) sensors, for example, measure the electrical conductance of the skin, which varies with sweat gland activity, a response linked to emotional and attentional states. Photoplethysmography (PPG) sensors measure blood flow and heart rate, providing data on physiological arousal that can indicate changes in attention levels. Eye-trackers, on the other hand, moni-

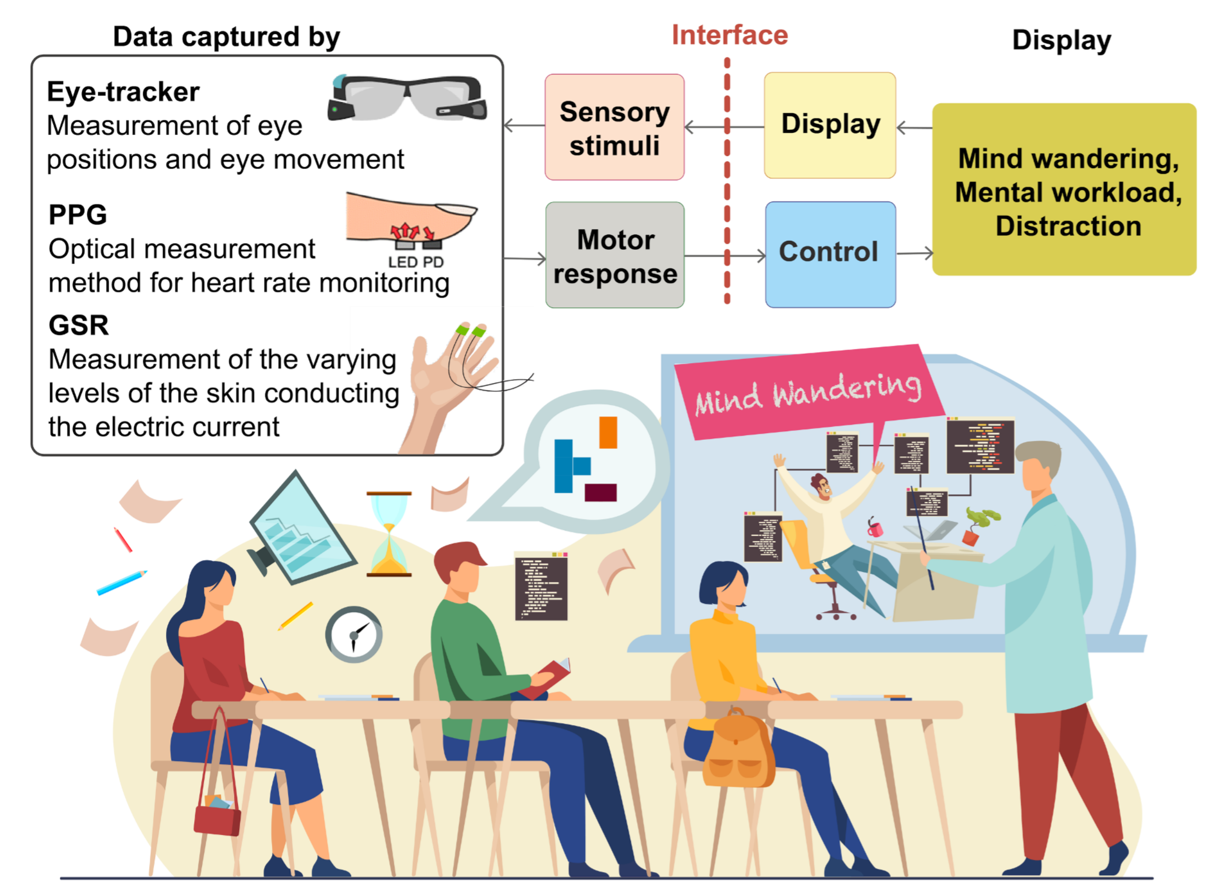

Figure 3.9: *Conceptual schematic of a multisensory methodology for mind-wandering detection and a block diagram showing measurements collected using PPG, GSR, and eye-trackers.*

tor eye movements and gaze patterns, which are directly related to where and how attention is focused during a task.

When these sensor modalities are combined, they provide a comprehensive picture of a learner's cognitive and emotional state. Machine learning algorithms can be applied to this rich dataset to identify patterns and predict instances of mind-wandering in real-time. This technology is particularly advantageous because it allows for continuous, non-invasive monitoring that is comfortable for the wearer, making it suitable for use in naturalistic educational settings.

As illustrated in Figure 3.9, the integration of these sensors with machine learning enables rapid data analysis, facilitating real-time feedback and interventions. For instance, if a student is detected to be mind-wandering during a lesson, adaptive learning systems could pause or adjust the material to re-engage the learner, thereby improving educational outcomes. This combination of wearable technology and advanced data analytics represents a powerful tool in the pursuit of more effective, personalised education.

In this experiment, a multisensory approach was employed to detect mind-wandering during an 18-minute lecture, leveraging multiple physiological and behavioural sensors. Sensors were utilised to capture comprehensive data from ten postgraduate engineering students as they watched a lecture video. Combination of these sensors allowed for a richer understanding of the participants' cognitive states by simultaneously examining physiological arousal, heart rate variability, and gaze behaviour.

GSR is a widely recognised method for measuring changes in the skin's electrical conductance, which occurs due to the activity of sweat glands. This physiological response is closely tied to the autonomic nervous system and is influenced by emotional arousal. The GSR signal is particularly sensitive to fluctuations in emotional states such as stress, excitement, or disengagement, making it a valuable indicator of cognitive load and mind-wandering. When a participant becomes disengaged from a task or experiences an increased cognitive load, the activity of sweat glands changes, which is detected by the GSR sensor as a variation in skin conductance. In this experiment, GSR sensors were placed on the non-dominant hand's fingers, capturing these subtle changes during the lecture.

PPG is a non-invasive optical technique that measures the blood volume changes in the microvascular bed of the peripheral circulation. In educational settings, PPG is particularly useful for tracking heart rate and heart rate variability (HRV). HRV, which reflects the variation in the time interval between heartbeats, is a key indicator of autonomic nervous system activity. Increased HRV has been associated with mental effort, cognitive engagement, and attention, while decreased HRV may indicate stress, fatigue, or mind-wandering. By capturing these metrics through PPG sensors attached to the participant's fingers, the study aimed to correlate physiological responses with cognitive states. This sensor, often used in cardiovascular assessments, provided critical data on the participants' emotional arousal and mental workload during the lecture.

Eye-tracking technology is essential for understanding visual attention and gaze patterns during learning tasks. In this experiment, wearable eye-tracking glasses were employed to monitor where and how long participants focused their gaze on specific elements of the lecture video. Eye-tracking data, such as fixation duration and saccades, can provide insights into the participants' level of engagement and instances of mind-wandering. For example, prolonged fixations on irrelevant stimuli or excessive saccades might indicate a loss of focus. By combining eye-tracking data with GSR and PPG metrics, the study aimed to identify moments when participants' attention drifted away from the lecture content.

The integration of GSR, PPG, and eye-tracking allowed for a comprehensive analysis of the physiological and behavioural indicators of mind-wandering. By examining these data streams simultaneously, the study sought to create a more accurate and nuanced understanding of the participants' cognitive states during the learning task. The multimodal approach enabled the detection of subtle shifts in attention and cognitive load that might not have been captured by a single modality. For example, a decrease in heart rate variability (as measured by PPG) combined with an increase in skin conductance (as measured by GSR) and a lack of focused gaze (as measured by eye-tracking) would strongly suggest an episode of mind-wandering.

Setup and Calibration:

The experimental setup involved a controlled environment where participants were asked to view an 18-minute lecture video on international education [29]. The lecture content was carefully chosen to ensure it was engaging but also complex enough to challenge the participants, thereby increasing the likelihood of mind-wandering. Prior to the lecture, participants completed a pre-lecture questionnaire consisting of five questions designed to assess their prior knowledge of the lecture's topic. This baseline assessment allowed for a comparison of cognitive engagement levels before and after the lecture.

Upon completing the pre-lecture questionnaire, participants were positioned comfortably in front of a computer monitor. The experimental setup, as shown in Figure 3.10, comprised the following components:

Eye-Tracking Glasses: The Pupil Core headset was used for eye-tracking, a device known for its high accuracy and ease of use in educational research. The glasses were carefully calibrated for each participant to ensure that the gaze data accurately reflected where they were looking during the lecture. Calibration involved asking participants to fixate on specific points on the screen while the system adjusted to their unique eye movements.

GSR Sensors: The GSR sensor was attached to the participants' fingers on their non-dominant hands. The placement of the sensor on the non-dominant hand minimised interference with natural movements and ensured that the data collected was as unobtrusive as possible. The sensor continuously monitored the skin conductance throughout the lecture.

PPG Sensor: A single Shimmer PPG sensor was also attached to the non-dominant hand and positioned to allow for accurate measurement of heart rate and HRV without interfering with the GSR sensors. The PPG sensor was calibrated to ensure that it captured the full range of heart rate variability during the experiment.

During the setup phase, participants were briefed on the procedure, including how to use the equipment and what to expect during the experiment. They were also instructed on how to interpret and report instances of mind-wandering during the post-experiment questionnaire.

Once the setup and calibration were complete, participants were instructed to focus on the lecture video. The system continuously monitored their physiological and behavioural responses throughout the 18-minute session. After the lecture, participants were asked to complete a post-experiment questionnaire, which included eighteen questions assessing their understanding of the lecture material and two additional questions about their overall experience, including their perceived instances of mind-wandering.

The combination of pre-and post-experiment assessments, along with real-time physiological monitoring, provided a robust dataset for analysing the relationship between cognitive engagement and mind-wandering. This approach allowed the study to explore not only the physiological signatures of mind-wandering but also how these episodes affected learning outcomes.

The collected sensor data were subsequently used to develop machine-learning models ca-

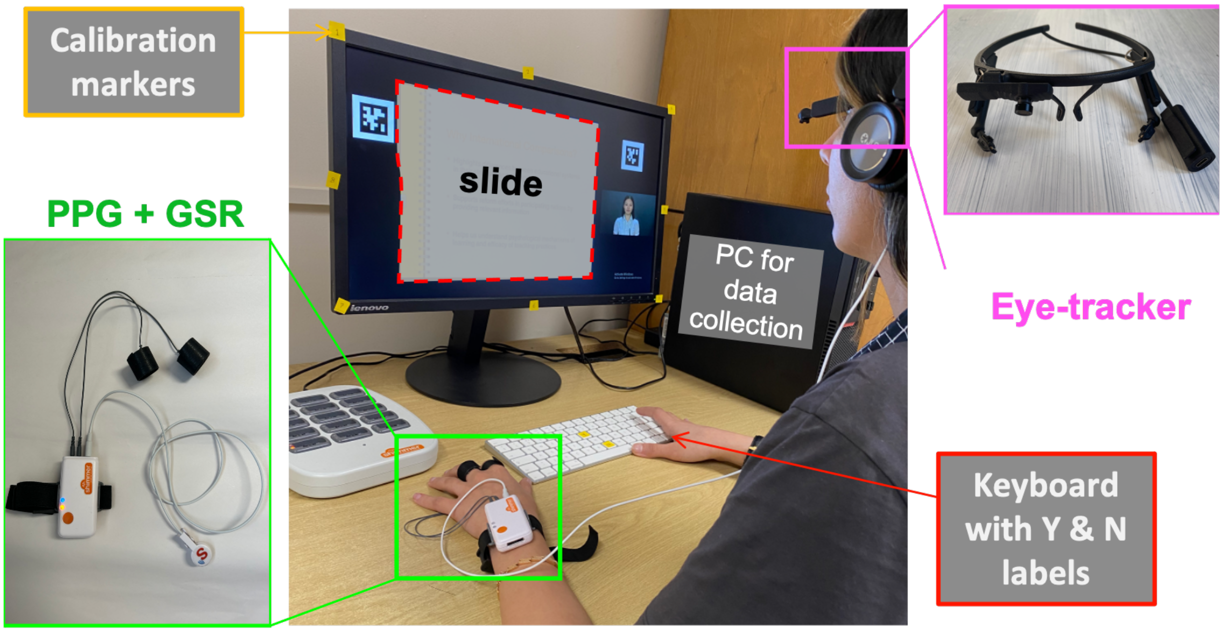

Figure 3.10: *The multisensory experimental setup for detecting mind wandering, which combines eye-tracking, GSR, and PPG sensors. The setup includes the calibration procedure, the placement of the Pupil Core headset, Shimmer GSR and PPG sensors, and a participant taking the test.*

pable of classifying cognitive states and predicting learner engagement. The following section outlines the machine learning pipeline, from preprocessing to model training and evaluation.

3.5 Machine Learning

To classify and predict cognitive states such as mind-wandering and engagement, a series of supervised machine-learning models were applied to the extracted features from the multisensory wearable device. The input features included eye-tracking metrics (e.g., fixation duration, saccade amplitude), galvanic skin response (e.g., skin conductance peaks), and heart rate variability derived from PPG signals. These features were selected based on their documented relevance to attention and arousal in cognitive and affective computing literature.

The modelling pipeline involved data normalisation, feature selection, and training validation using standard classification algorithms. Models implemented include Support Vector Machines (SVM), Random Forest (RF), and Gated Recurrent Units (GRU) for temporal sequence classification. The GRU model was particularly suited for time-series physiological data due to its capacity to retain long-term dependencies without overfitting on short fluctuations.

Data were split using stratified k-fold cross-validation (with $k = 5$) to ensure balanced evaluation across conditions. Model performance was assessed using standard classification metrics including accuracy, precision, recall, and F1-score. To prevent overfitting, hyperparameter tuning was conducted using grid search within each training fold. Feature importance was also computed in ensemble models to identify the most predictive physiological indicators of engagement and mind-wandering.

All modelling and analysis were conducted in Python using libraries such as Scikit-learn, TensorFlow, and Keras. Further interpretation of model outputs and their implications for engagement monitoring are presented in Chapter 4.

3.5.1 Data Preprocessing and Feature Extraction

The journey from raw sensor data to valuable insights begins with data preprocessing and feature extraction, two critical steps in the machine learning pipeline. The raw data collected from wearable sensors, such as eye-tracking, GSR, and PPG, often contain noise, inconsistencies, and irrelevant information that can obscure underlying patterns.

Preprocessing involved several techniques designed to clean and prepare the data for analysis. Normalisation was applied to scale the data within a consistent range, enabling comparability across different participants and sensor modalities. Smoothing techniques, such as moving averages, helped reduce fluctuations and highlight broader signal trends. Additionally, filtering was used to reduce artefacts from blinks, movement noise, or sensor irregularities, ensuring that only relevant physiological and behavioural signals were retained.

Once the data were preprocessed, relevant features were extracted, specific attributes that serve as inputs for machine learning models. In the context of eye-tracking, features such as fixation duration, saccade velocity, and pupil dilation were used to capture visual attention and cognitive load. For GSR data, skin conductance level (SCL) was extracted to indicate emotional arousal and stress. Heart rate variability (HRV) and pulse amplitude were key features derived from PPG data, offering insight into cardiovascular activity and cognitive effort. The quality and relevance of these features directly impacted the performance of subsequent machine learning models.

3.5.2 Classification and Regression Models

Once the relevant features had been extracted, they were used as inputs for various machine-learning models designed to solve classification and regression tasks.

Classification models were employed to categorise the data into predefined classes, enabling the identification of distinct cognitive or emotional states. For example, Support Vector Machines (SVM) were particularly effective in binary classification tasks, such as distinguishing between "focused" and "mind-wandering" states. The SVM algorithm works by finding the optimal hyperplane that separates data points belonging to different classes, ensuring high classification accuracy even in high-dimensional feature spaces. Additional models, such as random forests and k-nearest neighbours (k-NN), were also considered for their respective strengths in handling noisy data, computational efficiency, and interpretability.

Regression models, on the other hand, were used to predict continuous outcomes based on the extracted features. These models were particularly suited for estimating variables like cognitive load or emotional arousal on a continuous scale. Techniques such as linear regression, Support Vector Regression (SVR), and Neural Networks were applied, enabling the modelling of relationships between sensor-based features and outcome measures. These models were especially valuable in scenarios where a nuanced understanding of cognitive and emotional states was required beyond simple binary classification.

By employing both classification and regression approaches, the machine learning framework was able to capture a broad spectrum of cognitive and affective dynamics during learning tasks.

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3.5.3 Model Training and Validation

The effectiveness of machine learning models depends heavily on the quality and diversity of the training data. In this study, data were collected from a diverse group of participants performing various educational tasks under controlled conditions. The dataset was curated to capture a wide range of physiological and behavioural responses, ensuring that the models could generalise well across different individuals and learning contexts.

To evaluate model performance, the dataset was divided into training and testing subsets. The training set was used to develop the models, while the testing set provided an independent assessment of their generalisability. This separation prevented overfitting and ensured that the models performed reliably on unseen data.

Cross-validation techniques, specifically k-fold cross-validation, were employed to evaluate generalisability further. In this approach, the dataset was split into k equally sized folds, and the model was trained k times, each time using a different fold as the validation set and the remaining $k-1$ folds for training. This procedure helped reduce variance in performance estimates and offered a more robust assessment of the model's predictive ability.

Hyperparameter tuning was conducted using grid search and random search techniques to optimise model performance. Parameters such as the regularisation strength in SVMs and the number of trees in Random Forests were fine-tuned to maximise evaluation metrics, including accuracy, precision, recall, and F1-score. This ensured that the models struck an effective balance between sensitivity and specificity.

Feature selection techniques were applied to eliminate irrelevant or redundant features, thereby improving model efficiency and generalisability. Additionally, dimensionality reduction methods such as Principal Component Analysis (PCA) were used to reduce complexity without sacrificing essential information. These techniques helped streamline the models, reduced computational overhead, and, in some cases, improved predictive accuracy.

3.5.4 Sensor Fusion and Multimodal Learning

One of the key innovations of this study is the use of a sensor fusion approach, which involves combining data from multiple wearable sensors to develop a more comprehensive and accurate representation of students' cognitive and emotional states. By integrating data from eye-tracking, GSR, and PPG sensors, the models could leverage the unique strengths of each modality while compensating for their individual limitations.

For example, eye-tracking data provided direct indicators of visual attention and focus yet lacked sensitivity to emotional or physiological arousal. Conversely, GSR and PPG sensors offered valuable insights into autonomic nervous system activity, capturing arousal, stress, and heart rate variability, but did not reflect specific cognitive attentional patterns. Through sensor fusion, it became possible to simultaneously assess behavioural, emotional, and physiological dimensions of engagement.

This integration supported the development of multimodal learning models capable of identifying complex interactions between sensor signals. Deep learning architectures, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), were explored due to their ability to learn non-linear relationships across high-dimensional data streams. These models were particularly effective in capturing temporal and spatial dependencies within multimodal signals, allowing for more accurate and context-aware predictions.

By combining signals at either the feature level (early fusion) or decision level (late fusion), the modelling pipeline could flexibly adapt to different experimental configurations and data quality constraints. This multimodal framework provided a richer understanding of how learners engage with content over time.

3.5.5 Implementation and Real-Time Monitoring

The ultimate goal of this research was to implement the developed machine learning models within a real-time monitoring system for use in educational environments. This system was designed to continuously assess students' attention and engagement during learning activities, offering immediate, actionable feedback to both learners and instructors.

In practice, the system was capable of detecting instances of mind-wandering, cognitive overload, or disengagement as they occurred, enabling timely pedagogical interventions. For example, if the system identified a sustained drop in attention or an increase in physiological stress, it could prompt the instructor to adjust their teaching strategy such as incorporating an interactive element or modifying the pacing of content delivery.

The system was engineered for scalability and adaptability across various educational settings, including traditional classrooms, online learning platforms, and hybrid environments. The machine learning models were optimised for low-latency processing to ensure that feedback could be delivered rapidly enough to influence real-time decision-making.

Furthermore, the system was developed with interoperability in mind, allowing it to integrate with existing learning management systems (LMS) and educational technologies. This flexibility supports broader adoption and the potential for long-term improvements in personalised learning, instructional design, and engagement monitoring.

3.5.6 Theoretical Framework

The design of the multi-sensory wearable device is grounded in the theoretical premise that combining multiple physiological and behavioural sensors enables a more accurate and holistic understanding of learners' cognitive and emotional states. By integrating eye-tracking, photoplethysmography (PPG), and galvanic skin response (GSR) sensors into a single system, the framework leverages the strengths of each modality to monitor attention, engagement, and arousal in a complementary fashion.

This approach aligns with contemporary theories in cognitive science and educational psychology, which emphasise the importance of multi-dimensional monitoring to enhance learning outcomes. Attention, emotion, and cognitive load are interrelated processes that influence how students interact with instructional content. Simultaneous monitoring of these processes offers a more nuanced understanding of the learning experience.

Embedding this multi-sensory framework into a wearable device allows for real-time, continuous data collection in authentic learning environments. The resulting insights can inform adaptive teaching strategies, support personalised learning, and improve the detection of disengagement or cognitive overload. As such, this framework supports the broader goal of using technology not just to observe learning but to enhance it actively.

3.5.7 Implementation and Potential Applications

The conceptual design of the multi-sensory wearable device holds significant potential for application in educational settings. By providing continuous, detailed assessments of student engagement and attention, the system can support the adaptation of instructional content to meet individual learning needs, thereby enhancing the overall learning experience.

One potential application is in real-time learning analytics, where engagement metrics derived from the device could be used to tailor teaching strategies dynamically. For example, instructors could receive live feedback on when students are losing focus or experiencing cognitive overload, enabling immediate pedagogical adjustments.

In addition to classroom use, the device could be employed in online and hybrid learning environments to compensate for the lack of in-person observation. It offers a means of detecting disengagement or emotional stress remotely, supporting more personalised interventions in digital learning contexts.

Future development could include the creation of a fully functional prototype based on the current design, followed by iterative testing in real-world educational environments. Further refinement would ensure that the device meets the practical requirements of both educators and learners. Integrating advanced machine learning algorithms would also enhance the system's ability to detect complex patterns and deliver more accurate, timely feedback on engagement and cognitive state.

3.6 Conclusion

This chapter outlined the comprehensive methodology employed across three studies to explore the application of wearable technology in higher education. Through the integration of multi-sensory data, including GSR, PPG, and eye-tracking sensors, this Thesis aims to enhance the educational experience by providing a holistic approach to real-time attention monitoring and mind-wandering detection.

The conceptual design of a novel multisensory device, which combines these three sensors into a single wearable form factor, represents a significant advancement in the ability to measure and analyse cognitive and emotional states during learning activities. By employing advanced machine learning techniques, this research seeks not only to monitor but also provide actionable insights that can be used to optimise teaching strategies and improve student engagement.

This methodology sets the foundation for future developments in educational technology, particularly in the design and implementation of multisensory devices that can offer a more comprehensive understanding of student behaviours and learning processes in real time.

Chapter 4

Experiments and Results

4.1 Introduction

The aim of this chapter is to present the experimental procedures and results obtained in this thesis, focusing on the use of eye-tracking and multisensory data to monitor and enhance cognitive engagement in educational settings. In modern education, maintaining student attention and engagement poses significant challenges, especially with the increasing prevalence of digital distractions. Understanding how students interact with learning materials and identifying moments of disengagement are crucial in addressing these challenges.

To tackle these issues, this thesis explores two primary approaches: eye-tracking technology and multisensory data integration. Eye-tracking provides an objective measure of where students direct their visual attention during learning activities, offering insights into their focus and engagement levels. On the other hand, multisensory data combining eye-tracking with physiological signals such as Galvanic Skin Response (GSR) and Photoplethysmography (PPG) allows for a more comprehensive assessment of students' cognitive states, particularly mind-wandering.

This chapter is structured as follows: First, the results of the eye-tracking experiments are presented, detailing how visual attention patterns were monitored and analysed to assess student engagement. This is followed by exploring the use of multisensory data and machine learning models to classify episodes of mind-wandering and non-mind-wandering. Throughout the chapter, the methods employed, the data collected, and the key findings are discussed, ultimately highlighting the potential of these technologies to enhance educational outcomes through real-time feedback on student engagement.

The experiments and results presented in this chapter provide valuable insights into how emerging technologies can be harnessed to address critical challenges in education, offering new opportunities for personalised learning and intervention strategies.

4.2 Eye-Tracking experimental results

Maintaining student attention and engagement is a critical challenge in modern education, especially given the increasing prevalence of digital distractions. To address this challenge, our research explored the application of eye-tracking technology to monitor and enhance student attention during learning activities. Eye-tracking technology provides an objective measure of where and how long students direct their visual focus, offering valuable insights into their attentional patterns and cognitive engagement with the material.

4.2.1 Eye Tracking for Attention Monitoring

In this experiment, two types of eye-tracking devices were employed: wearable eye-trackers and desktop-based eye-trackers. Each device offers specific advantages that make it suitable for different aspects of the research.

Wearable Eye-Tracker (Pupil Core):

The wearable eye-tracker utilised in this experiment was the Pupil Core, a state-of-the-art, lightweight, and portable device designed to capture naturalistic gaze behaviour in dynamic environments. Operating at a high sampling rate of 120 Hz, the Pupil Core ensures that even rapid eye movements are accurately recorded, making it particularly effective for studies where precision is critical. The portability of this device allows it to be used in more varied and realistic educational settings, such as live classroom environments or during field exercises, where traditional stationary equipment would be impractical. The ability to capture gaze data in these diverse contexts is invaluable, as it reflects more naturalistic interactions between students and their learning materials.

One of the significant advantages of the Pupil Core wearable device is its capacity to track gaze in dynamic contexts. This is particularly relevant in educational settings where students frequently shift their attention between different stimuli, such as a lecturer, presentation slides, and their notes. The Pupil Core's high temporal resolution allows researchers to pinpoint exactly when and where a student's focus shifts, providing detailed insights into their attentional processes. This level of granularity in data collection is critical for understanding the nuances of student engagement and for identifying patterns of attention and distraction that may not be apparent through other means.

Desktop-Based Eye-Tracker:

In contrast, the desktop-based eye-tracker used in this experiment operates at a slightly lower sampling rate of 60 Hz but offers a higher degree of stability and precision in controlled environments. This device is ideally suited for experiments where the participant is seated and engages directly with on-screen content, such as reading exercises, problem-solving tasks, or interactive simulations. The controlled nature of the desktop-based setup ensures consistent data quality, making it particularly useful for tasks that require sustained attention on a single, static display. This high precision is crucial when analysing detailed interactions with digital content, where even minor variations in gaze can indicate significant differences in cognitive processing.

The desktop-based eye-tracker's design allows for a detailed examination of micro-level gaze patterns, which can reveal how students process and comprehend complex information. For instance, by tracking how long a student fixates on a particular word or image, educators can infer the difficulty or interest level of that content. Additionally, this device is particularly effective in studies aiming to compare different instructional designs or content layouts, as the controlled environment reduces the influence of external variables, ensuring that the data reflects the impact of the content itself rather than extraneous factors.

Integration of Both Devices:

By employing both wearable and desktop-based eye-trackers, this experiment achieved a balanced and comprehensive approach to analysing student attention. The wearable device provided insights into how students interact with educational content in real-world settings, capturing the fluid and dynamic nature of attention. Meanwhile, the desktop-based tracker offered high-resolution data in controlled environments, allowing for precise measurement of gaze behaviour during specific tasks. This dual approach ensures that the findings are robust and applicable across various educational contexts, from traditional classroom settings to more flexible, modern learning environments.

The combination of these two types of devices enabled the study to cover a wide spectrum of learning scenarios. For instance, the wearable eye-tracker could capture how students navigate physical learning spaces, such as labs or workshops, while the desktop-based device provided detailed data on how students engage with digital learning materials. This comprehensive coverage is essential for developing a holistic understanding of student attention and for designing educational interventions that are effective in both physical and digital realms.

Experimental Setup:

To systematically analyse attentional patterns in an educational setting, this study meticulously designed an experimental setup that utilised both wearable and desktop-based eye-tracking devices. The primary objective was to create an environment that closely mirrors typical classroom conditions while ensuring the collection of accurate and reliable data on student attention and engagement. The setup was consistent across all sessions to minimise external variables that could influence the results. Participants were seated in a manner that allowed them to view the presentation materials comfortably, simulating a typical learning posture and environment.

Device Integration:

The wearable eye-tracker was used to monitor gaze behaviour in a more naturalistic and flexible manner, allowing students to move their heads and bodies as they would in a real classroom. This flexibility is crucial for capturing authentic gaze patterns that reflect how students naturally engage with content. In contrast, the desktop-based eye-tracker provided a more stable and controlled measurement of gaze behaviour, which is particularly useful for analysing detailed interactions with on-screen content in a fixed position.

Areas of Interest (AOIs):

For each learning activity, specific Areas of Interest (AOIs) were meticulously predefined within the presentation slides. These AOIs were strategically chosen to represent critical regions on the screen, such as key sections of text, important images, or interactive elements like graphs and charts, where student focus is most crucial for effective learning. The selection of AOIs was informed by educational theories and previous research on attention and cognition, ensuring that these regions were relevant to the learning objectives.

By defining these AOIs, the study aimed to not only quantify but also visualise the distribution of students' gaze points across these key areas. This method allows for a detailed and nuanced understanding of how students interact with different types of content. For instance, by analysing gaze duration and fixation counts within each AOI, researchers could determine which parts of the content were most engaging, which elements captured students' attention most effectively, and which parts were potentially overlooked.

Gaze Data Collection and Analysis:

The collection of gaze data involved recording where and for how long students focused their attention on specific elements of the instructional material. The eye-tracking devices captured continuous data streams that detailed the sequence of visual fixations, saccades (quick eye movements) and blinks. This data was then processed to create visual representations such as gaze plots and heatmaps, which provided intuitive and informative insights into student attention patterns.

For example, gaze plots offered a visual representation of the scan paths, showing the sequence and direction of eye movements across the screen. This allowed researchers to track how students navigated through the content, revealing patterns in how they processed the information presented to them. Heatmaps, on the other hand, illustrated the intensity of gaze concentration within the AOIs, highlighting areas where students spent the most time looking. These visualisations are crucial for understanding not just what students are looking at but also how they allocate their cognitive resources during learning activities.

Experimental Protocol:

Participants were guided through the experimental process to ensure consistency and reliability in data collection. Prior to each session, calibration was performed using the eye-tracking devices to ensure accurate gaze tracking. This process involved asking participants to focus on specific points on the screen, allowing the system to adjust to each individual's unique eye characteristics.

During the learning activities, participants were instructed to engage with the content as they normally would in a classroom setting, without any specific instructions that might alter their natural gaze behaviour. The learning activities included a variety of content types, such as text-heavy slides and multimedia elements.

Data Integrity and Validation:

To ensure the validity and reliability of the data, several measures were taken. Data from the eye-trackers was continuously monitored during the experiments to detect and address any potential issues such as signal loss or calibration drift. After the sessions, the data underwent a thorough validation process, where it was cross-checked for accuracy and completeness. Any anomalies, such as unusually long fixations due to blinking or other interruptions, were identified and corrected to maintain the integrity of the data.

Data Visualisation:

Data visualisation played a crucial role in this study by transforming raw eye-tracking data into meaningful insights that can be easily interpreted. The data collected from the eye-tracking devices were processed and visualised using advanced analytical techniques, such as gaze plots, heatmaps, and temporal analysis charts. These visualisation methods are essential for understanding how students engage with educational content and for identifying patterns in their attention and cognitive processes.

As summarised in Figure 4.1, the study employed various methods to visualise the eye-tracking data. Each method offers unique insights into the students' visual attention and engagement, allowing researchers to explore different aspects of gaze behaviour. These visualisations are not just static representations; they are dynamic tools that can reveal the temporal and spatial patterns of attention, providing a comprehensive picture of how students interact with learning materials.

Gaze Plot Visualisation:

The gaze plot is one of the most powerful tools used in this study to represent the sequence and direction of eye movements across the screen. It provides a visual representation of the scan paths taken by students as they interacted with the content. This visualisation method is

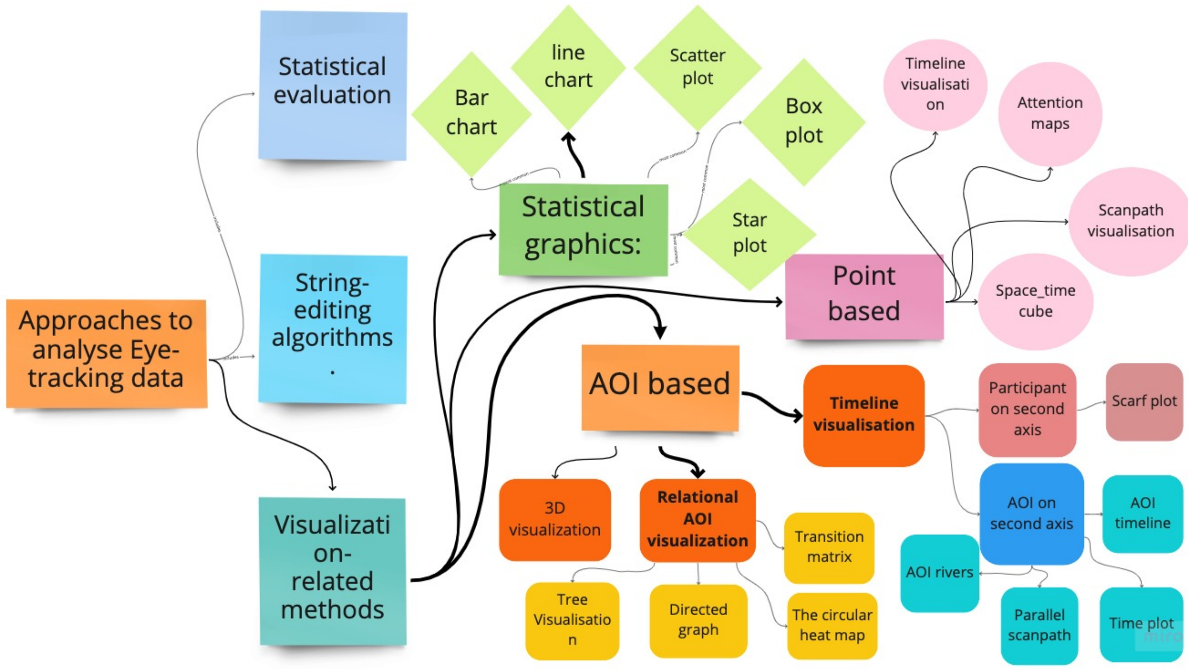

Figure 4.1: *Overview of Eye-Tracking Data Visualisation Methods*

particularly useful for understanding the order in which students process information, how their gaze shifts between different Areas of Interest (AOIs), and how quickly they move from one element to another.

For instance, Figure 4.2 illustrates a fixation plot scan path using the Pupil Core eye-tracker. The red line traces the learners' gaze path during a specific segment of the experiment, offering a detailed view of how their attention shifted throughout the task. This type of visualisation is invaluable for identifying which parts of the content captured the students' attention first, how they navigated through the material, and where they spent the most time. It also reveals moments where students' attention may have faltered, allowing educators to pinpoint areas that may need instructional reinforcement or redesign.

Heat-Map Visualisation:

Heatmaps provide another layer of insight by illustrating the intensity of gaze concentration across the AOIs. These visualisations highlight the areas where students focused the most during the learning session, offering a clear and intuitive understanding of which parts of the content were most engaging. The heatmap aggregates data from multiple participants, creating a visual representation of collective gaze behaviour.

Figure **??** displays a heatmap generated from the wearable eye-tracker, while Figure **??** shows a heatmap from the desktop-based eye-tracker. Comparing these heat maps reveals interesting differences in gaze distribution. The wearable eye-tracker provided a broader and more detailed representation of participant gaze, capturing more diverse and naturalistic engagement

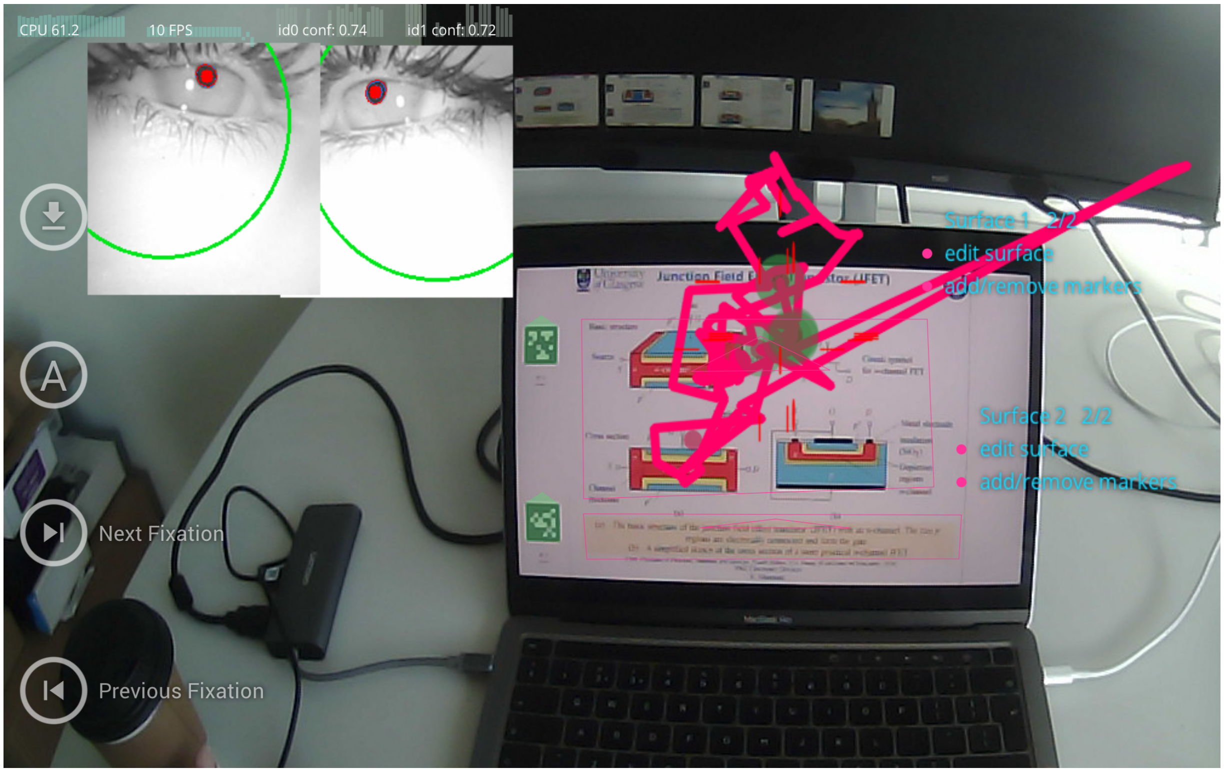

Figure 4.2: *The fixation plot scan path using the Pupil Core eye-tracker*

patterns. In contrast, the desktop-based eye-tracker, due to its lower sampling rate and fixed setup, recorded a more concentrated but restricted distribution of gaze data, focusing primarily on written text. This comparison highlights the importance of choosing the right tool for the specific research context and underscores the value of combining multiple data sources to gain a fuller understanding of student attention.

Data Processing and Machine Learning Integration:

Initially, the data captured by the eye-trackers appears in raw format, which requires significant processing before it can be used for meaningful analysis. Advanced devices, such as the Pupil Core, facilitate this process by enabling data to be exported into structured datasets. To further refine this data, the study utilised Machine Learning algorithms, which allowed for a series of steps, including data inspection, cleaning, transformation, and visualisation.

By applying Machine Learning techniques, the study could uncover valuable insights and produce more nuanced interpretations from the gathered data. For instance, algorithms were used to identify patterns in the gaze data that might not be immediately apparent through simple visual inspection. This process also involved clustering gaze points to detect common behaviours among participants, categorising different types of eye movements, and correlating these movements with cognitive engagement levels.

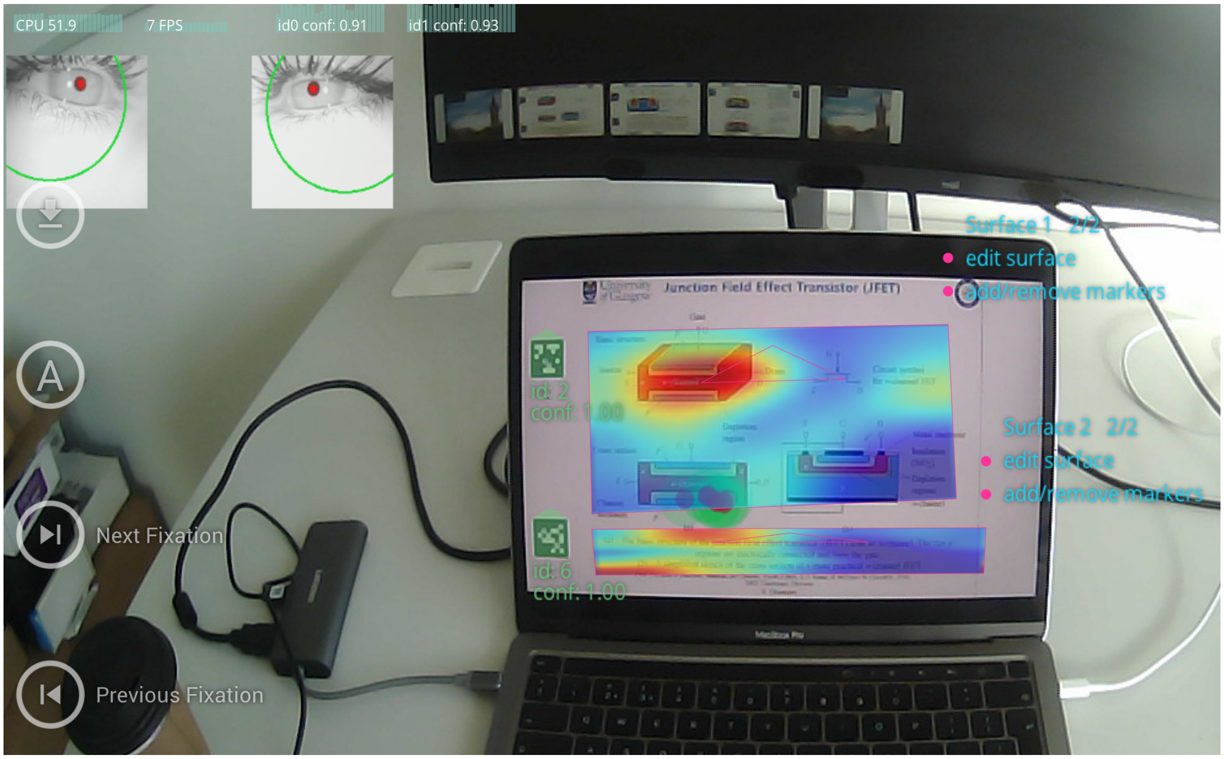

Figure 4.3: *The heat-map for the wearable eye-tracker*

Bar Chart Analysis of Gaze Distribution:

For a more detailed analysis, the raw gaze data from the Pupil Core glasses was exported to Python, where gaze counts for each participant were plotted. Figure 4.5 presents a comprehensive analysis of the gaze distribution across six Areas of Interest (AOIs) for six individual participants during a learning session. This bar chart is critical for understanding how visual attention was distributed among the different AOIs and how engagement levels varied among participants.

The data depicted in Figure 4.5 indicates that Surface One attracted the highest number of gaze points, suggesting it was the most engaging and attention-capturing area for the participants. This observation is significant for instructional design, as it highlights the parts of the content that were either more visually appealing or cognitively demanding, leading to higher concentrations of visual focus. Conversely, Surface Six recorded the fewest gaze points, indicating a drop in participant engagement as the session progressed. This trend could be attributed to several factors, such as cognitive fatigue, difficulty of the material, or diminishing interest, all of which are critical considerations in educational settings where sustained attention is necessary for effective learning.

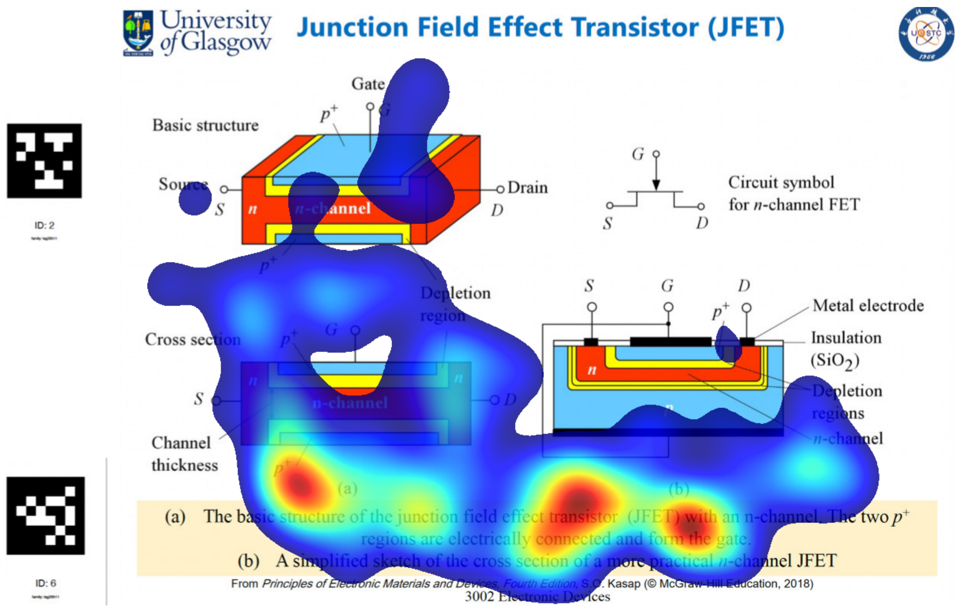

Figure 4.4: *The heat-map for desktop-based eye-tracker*

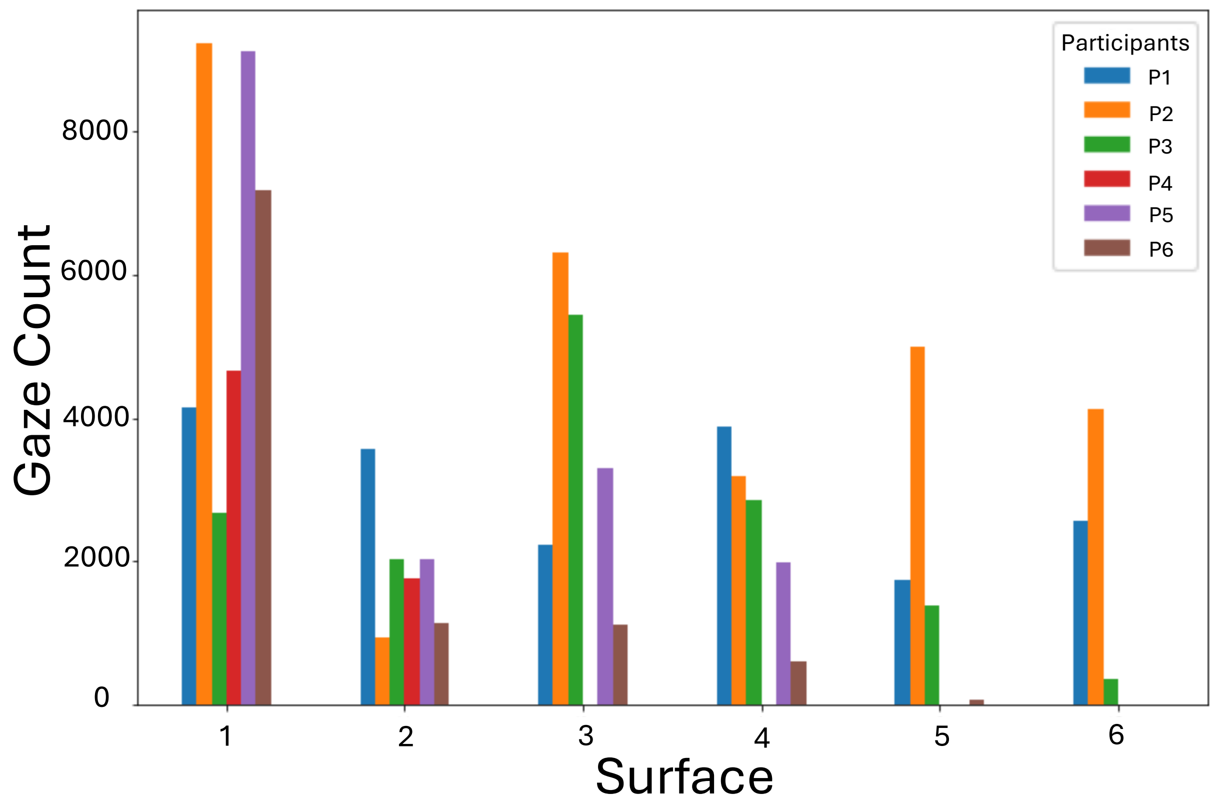

Figure 4.5: *The gaze plot for each individual participant in each AOI*

Temporal Analysis through Line Charts:

Understanding how attention evolves over time is just as important as knowing where it is focused. The line chart in Figure 4.6 offers a temporal analysis of gaze behaviour, capturing the

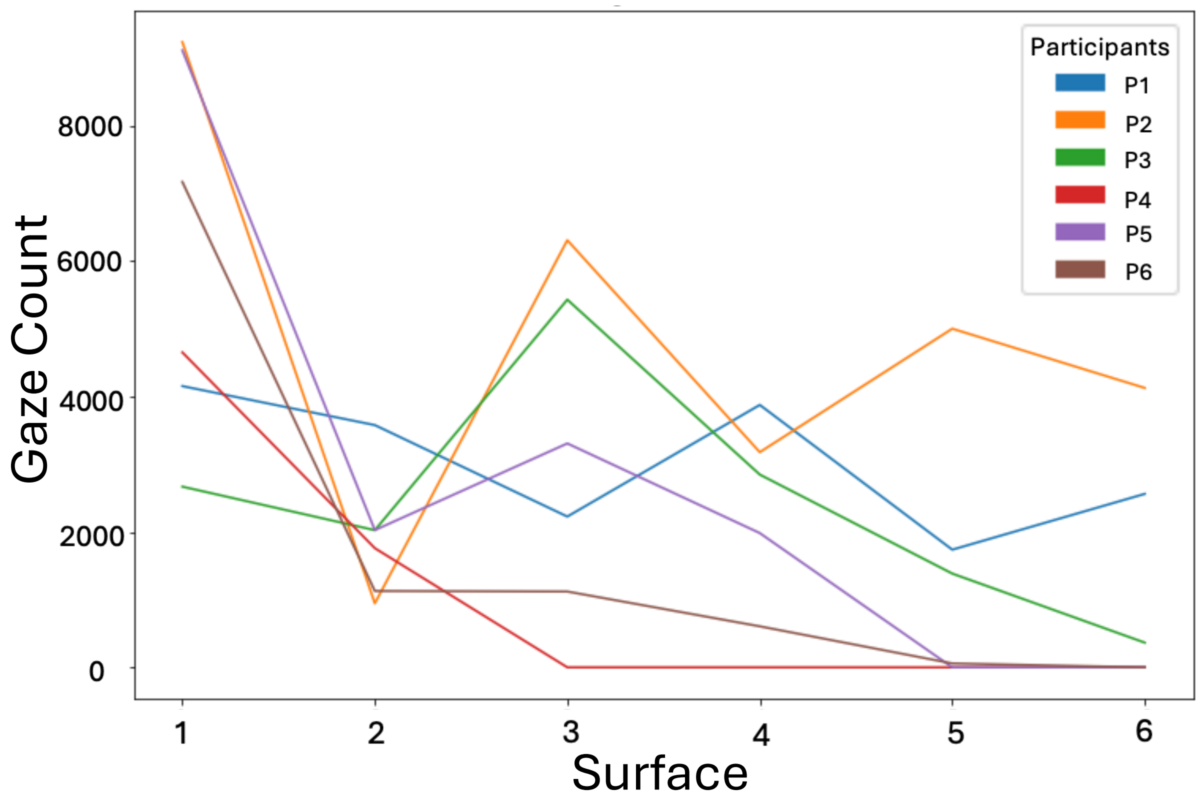

Figure 4.6: *Visual indication of similar changes in the gaze behaviour of participants over time*

evolution of gaze points across the six AOIs for each participant as the session progressed. This visualisation is particularly valuable for identifying common patterns in attention, as well as significant deviations or outliers that may warrant further investigation.

One of the key insights from Figure 4.6 is the observable trend of decreasing gaze points over time for most participants. This decline suggests that attention levels gradually diminished as the session progressed, likely due to factors such as cognitive fatigue, decreasing engagement with the content, or the complexity of the material. Such findings are significant for educational contexts as they highlight the need for instructional strategies that sustain student engagement over extended periods. For example, introducing interactive elements, multimedia content, or periodic breaks could help to re-engage students and counteract the natural decline in attention.

Implications for Instructional Design and Personalised Learning:

The visualisations presented in this study provide deep insights into the cognitive processes of students during learning activities. For educators, these insights are invaluable for improving instructional design. For instance, the data suggests that certain areas of content are more engaging and should be emphasised, while other areas may need to be redesigned to capture and maintain student attention. Additionally, understanding the temporal dynamics of attention can inform the structuring of learning sessions, ensuring that content is paced in a way that aligns with students' cognitive capacities.

For instructional designers, detailed gaze distribution and temporal analysis can guide the development of future learning materials. By analysing which content areas consistently attract attention, designers can create materials that maximise engagement and minimise disengagement. Furthermore, these findings could influence the timing and placement of interactive elements or multimedia components, helping to sustain attention and foster a more immersive learning experience.

Conclusion:

The eye-tracking data, when visualised effectively, reveals important trends in student attention that can be leveraged to enhance educational outcomes. By analysing gaze patterns, educators and instructional designers can identify which parts of the content are most engaging, where attention wanes, and how attention evolves over time. These insights provide actionable information for improving instructional materials and strategies, ultimately leading to more effective and engaging learning experiences.

4.2.2 Eye tracking to monitor mind-wandering

Mind-wandering, defined as a shift in attention away from the task at hand toward unrelated thoughts or concerns, is a prevalent and well-documented challenge in educational contexts. This phenomenon can significantly impede learning by disrupting cognitive processes essential for comprehension, retention, and academic performance. To address this issue, the present study employed eye-tracking technology to monitor and quantify mind-wandering episodes in real-time. This approach aimed to provide an objective measure of attentional lapses and to examine their impact on learning outcomes.

Understanding Mind-Wandering in Educational Settings:

Mind-wandering is often involuntary and can occur without the individual's awareness, making it particularly challenging to manage in educational settings. It typically emerges during tasks that are monotonous, cognitively demanding, or perceived as lacking personal relevance, resulting in reduced engagement and diminished learning outcomes. In response to the need for a deeper understanding of this phenomenon, the present study investigated the relationship between visual attention, cognitive engagement, and mind-wandering. By leveraging eye-tracking data, the research aimed to identify patterns that could inform strategies to mitigate the negative effects of mind-wandering in learning environments.

Probe-Caught and Self-Caught Techniques:

Two complementary methods were employed to monitor mind-wandering: the probe-caught and self-caught techniques. Each method offers distinct advantages in capturing the nuances of mind-wandering behaviour, thereby providing a comprehensive understanding of how and when attentional shifts occur.

Probe-Caught Method: In the probe-caught method, participants were periodically interrupted by randomly timed pop-up questions asking them to report whether they were focused on the task or mind-wandering at that precise moment. This method is particularly effective in capturing spontaneous episodes of mind-wandering, as it provides real-time feedback on the participants' attentional state. The timing of these probes was carefully designed to be unpredictable, ensuring that participants could not anticipate them and thus providing a more accurate representation of natural mind-wandering occurrences.

Self-Caught Method: In the self-caught method, participants were instructed to self-report whenever they noticed their minds had wandered. This approach relies on the participants' metacognitive ability to recognise and acknowledge their own attentional shifts, making it a valuable complement to the probe-caught method. Self-caught reports provide insight into the participants' awareness of their cognitive state, which is crucial for understanding how self-regulation can impact the ability to refocus attention after a lapse. The combination of these two techniques allowed us to capture both spontaneous and self-recognised episodes of mind-wandering, offering a more nuanced view of this complex behaviour.

Continuous Eye-Tracking Data Collection:

During the learning sessions, eye-tracking data was continuously collected to capture detailed information on participants' gaze patterns, fixation durations, and saccadic movements. By analysing this data alongside self-reports and probe-caught responses, the study identified specific visual indicators associated with episodes of mind-wandering. For instance, prolonged fixations on non-informative areas of the screen or erratic scanning patterns were frequently correlated with reported instances of attentional drift. These visual cues provided objective evidence of when and how participants' attention shifted away from the learning material.

Correlation Between Mind-Wandering and Engagement:

A key focus of this study was to explore the correlation between mind-wandering and engagement levels. Engagement was assessed through a combination of self-reports and post-experiment questionnaires, where participants rated their perceived level of focus during the task. This subjective data was then compared with the objective eye-tracking data and mind-wandering reports to identify any significant relationships. The analysis revealed a strong correlation between mind-wandering and reduced engagement, as shown in Table 4.1.

Table 4.1: *The correlation between MW level, engagement and post-experiment result*

Report method	MW level	SD	MW-engagement[1]	MW-post-exp	MW-post-exp -Pre-exp
Probe-caught	.62	.22	-0.59(<.001)***	-0.009(0.568)	-0.04 (0.003)**
Self-caught	138.89	87.77	0.37(<.001)***	0.06(<.001)***	0.07(<.001)***

[1] Pearson Correlation coefficient (P-value)
[2] ***p < .001; **p < .01.

Findings from Probe-Caught and Self-Caught Methods:

In the probe-caught condition, a significant negative correlation was observed between mind-wandering and engagement (r = –0.59, p < 0.001). This finding suggests that higher levels of mind-wandering were associated with lower reported engagement, aligning with existing literature on the detrimental effects of mind-wandering on cognitive performance. These results underscore the importance of sustained attention during learning activities, as frequent attentional lapses can disrupt the learning process and negatively impact outcomes.

In contrast, the self-caught method revealed a more nuanced relationship. While there was still a significant correlation between mind-wandering and engagement (r = 0.37, p < 0.001), the positive correlation suggests that participants who were more aware of their mind-wandering episodes tended to report higher engagement levels overall. This could be due to the fact that self-recognition of mind-wandering allows participants to refocus their attention more effectively, thereby mitigating some of the negative effects on engagement. This self-awareness might enable students to recover from attentional lapses more quickly, minimising the impact on their overall cognitive performance.

Impact of Mind-Wandering on Learning Outcomes:

To further investigate the impact of mind-wandering on learning outcomes, the relationship between mind-wandering frequency and post-experiment performance was examined. The post-experiment assessed participants' retention and comprehension of the material presented during the session. In the self-caught condition, a significant but small positive correlation was found between mind-wandering and post-experiment scores (r = 0.06, p < 0.001). This finding suggests that participants who were able to recognise and correct their own mind-wandering episodes may have maintained adequate levels of performance despite occasional attentional lapses. The ability to self-regulate attention appears to be a critical factor in mitigating the negative effects of mind-wandering on learning outcomes.

However, in the probe-caught condition, no significant correlation was found between mind-wandering and post-experiment results (r = -0.009, p = 0.568), indicating that mind-wandering had a more detrimental effect when participants were not consciously aware of their attentional

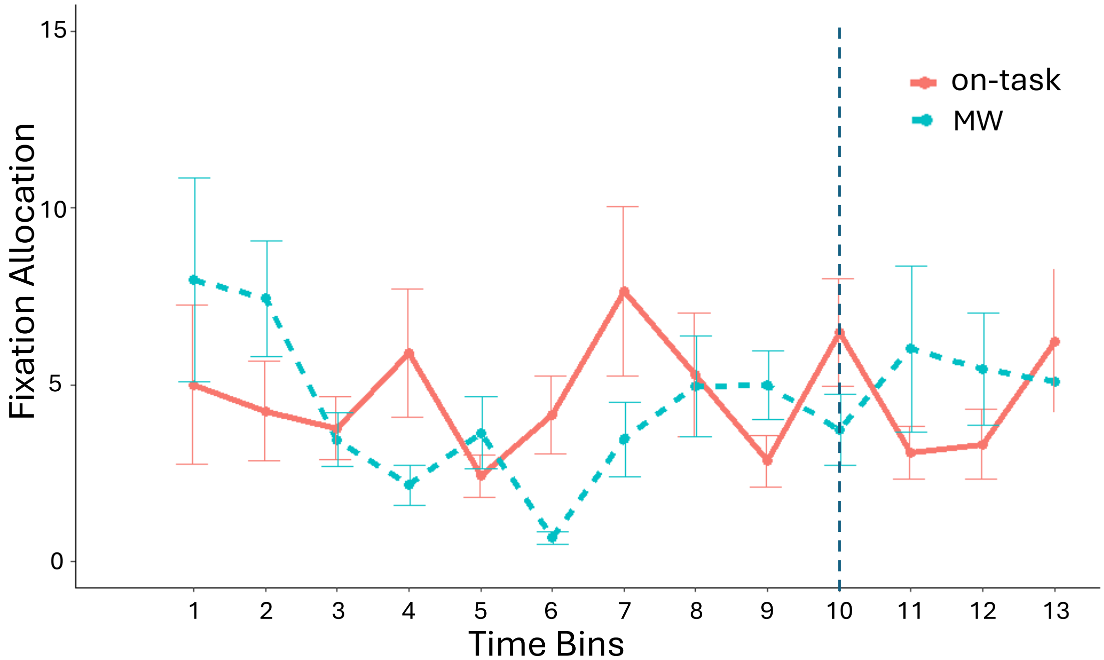

Figure 4.7: *The time trend of fixation allocation in the moments leading to MW in the self-caught condition. The x-axis represents the time bins, and the y-axis represents fixation allocation. The blue dotted line represents the MW (mind-wandering) condition, and the red line represents the on-task condition. Error bars show the mean standard error.*

lapses. When controlling for the pre-experiment effect, a significant relationship emerged in both conditions, with partial correlations of -0.04 ($p = 0.003$) and 0.07 ($p < 0.001$) in the probe-caught and self-caught methods, respectively. This suggests that mind-wandering, particularly when unrecognised, can negatively affect learning outcomes. However, self-awareness of attentional lapses can help mitigate these effects, highlighting the importance of metacognitive skills in educational contexts.

Temporal Analysis of Eye Movement Patterns:

A temporal analysis of eye movement patterns offered additional insights into the dynamics of mind-wandering during the learning session. By segmenting the session into discrete time bins, changes in fixation patterns were observed in the moments preceding reported episodes of mind-wandering. This approach enabled a more detailed understanding of the attentional shifts that occur over time.

Fixation Allocation and Mind-Wandering: Fixation allocation refers to how participants distribute their visual attention across different areas of interest during a learning session. In the context of mind-wandering, changes in fixation allocation provide crucial information about the onset and progression of attentional drift.

Self-Caught Condition: In the self-caught condition, as shown in Figure 4.7, participants' fixation frequency tended to increase before the onset of mind-wandering, particularly in the

10 seconds leading up to the reported episode. This pattern suggests that participants may have attempted to refocus their attention before ultimately recognising that their minds had wandered. The data indicates a proactive, albeit unsuccessful, effort to maintain cognitive engagement. Conversely, the on-task trend exhibited a sharp increase and subsequent decrease in fixation frequency within the same time frame, indicating a shift in attention away from the task as mind-wandering set in.

Probe-Caught Condition: In the probe-caught condition, as shown in Figure 4.8, the data revealed an initial increase in fixation frequency, followed by a sudden drop, typically around 7 seconds before the mind-wandering report. This pattern highlights the unpredictable nature of mind-wandering episodes, where participants may appear focused before abruptly losing attention. The on-task trend in this condition showed a more gradual decline, further emphasising the challenge of detecting mind-wandering without real-time feedback. This suggests that mind-wandering can occur suddenly and without conscious awareness, making it difficult to predict and prevent.

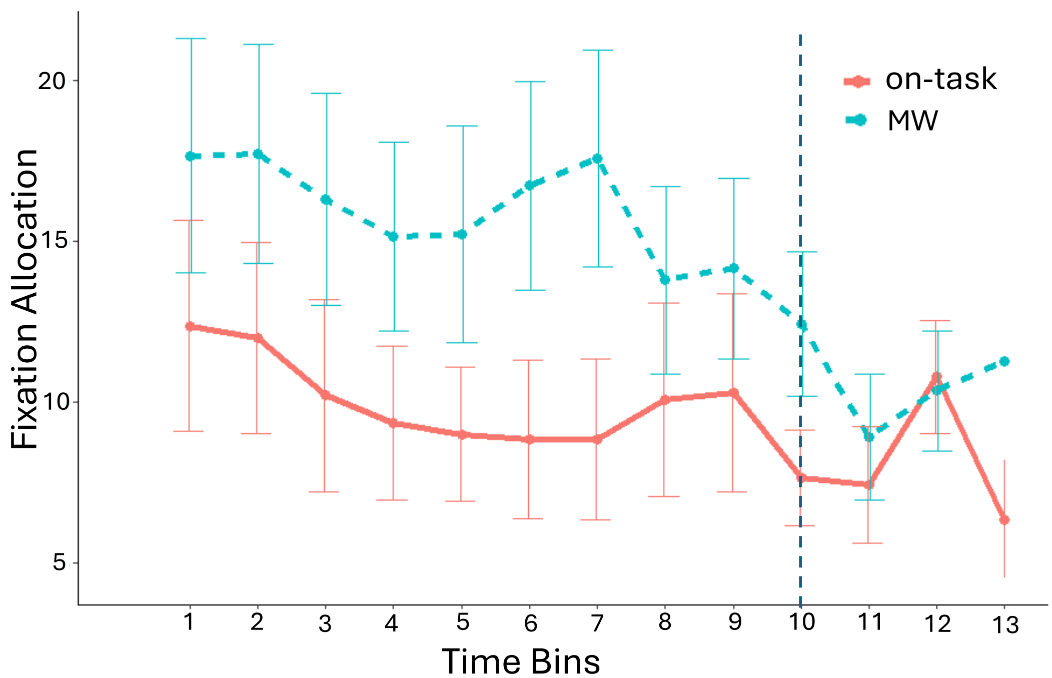

Figure 4.8: *The time trend of fixation allocation in the moments leading to MW in the probe-caught condition. The x-axis represents the time bins, and the y-axis represents fixation allocation. The blue dotted line represents the mind-wandering (MW) condition, and the red line represents the on-task condition. Error bars show the mean standard error.*

Fixation Duration and Mind-Wandering:

Fixation duration refers to the length of time participants maintain their gaze on specific areas of interest during a learning session. In the context of mind-wandering, changes in fixation

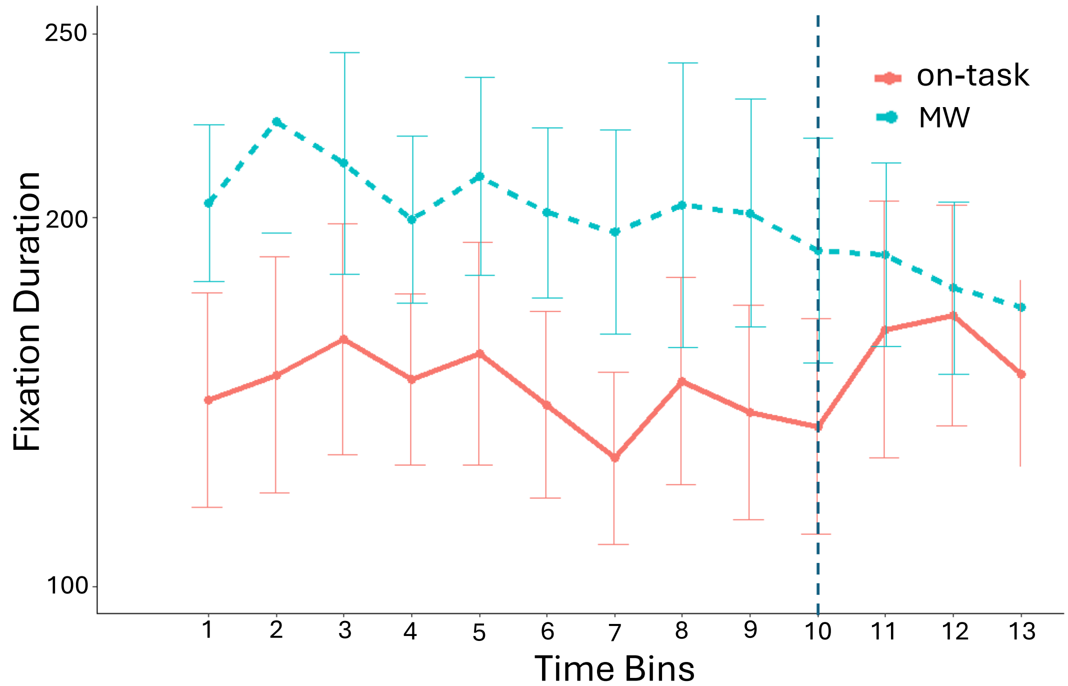

Figure 4.9: *The time trend of fixation duration in the moments leading to MW in the self-caught condition. The x-axis represents the time bins, and the y-axis represents fixation duration. The blue dotted line represents the mind-wandering (MW) condition, and the red line represents the on-task condition. Error bars show the mean standard error.*

duration provide valuable insights into the nature of attentional lapses. The analysis of fixation durations on slides revealed that mind-wandering correlated with longer fixation durations on written text over time.

Self-Caught Condition: Figure 4.9 illustrates the results of the self-caught experiment, where mind-wandering gradually decreased towards the end, whereas the on-task trend increased from the same bin. This suggests that as participants became more aware of their mind-wandering, they were able to regain focus, leading to shorter and more effective fixations on relevant content.

Probe-Caught Condition: In contrast, Figure 4.10 depicts the probe-caught condition, where fixation duration peaked at bin 9 and gradually decreased, though not as sharply as the on-task trend. This pattern indicates that in the absence of conscious awareness, mind-wandering leads to prolonged but less effective fixations, reflecting a state of cognitive disengagement where attention is misallocated to less relevant stimuli.

Implications for Educational Practice:

The findings from this study have significant implications for educational practice. The ability to monitor mind-wandering in real-time through eye-tracking offers educators a powerful tool for identifying moments of disengagement and intervening to re-engage students. By recognising the visual cues associated with mind-wandering, educators can design more effective instruc-

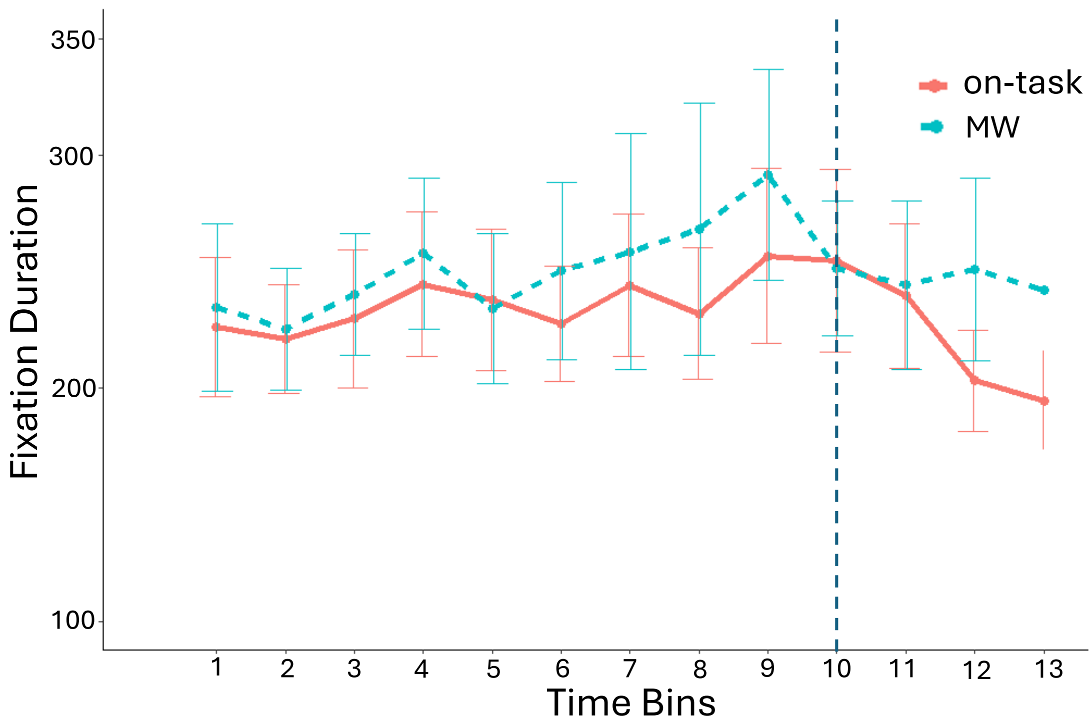

Figure 4.10: *The time trend of fixation duration in the moments leading to MW in probe caught condition. The x-axis represents the time bins, and the y-axis represents fixation duration. The blue dotted line represents the mind-wandering (MW) condition, and the red line represents the on-task condition. Error bars show the mean standard error.*

tional strategies that minimise cognitive drift and promote sustained attention.

For example, incorporating interactive elements or brief cognitive breaks at strategic points during a lesson could help mitigate the effects of mind-wandering and improve overall learning outcomes. Additionally, fostering self-awareness among students regarding their attentional states could empower them to better manage their focus and reduce the frequency of mind-wandering episodes. Educators could also use this data to personalise learning experiences, tailoring instruction to the attentional profiles of individual students.

Conclusion:

In conclusion, eye-tracking technology proved to be an invaluable tool for monitoring and understanding mind-wandering during learning activities. The ability to visualise and analyse gaze patterns in relation to self-reported and probe-caught mind-wandering episodes provides deep insights into how students interact with content. These insights can be leveraged to enhance instructional materials, design more engaging learning experiences, and ultimately improve educational outcomes by addressing mind-wandering as one of the most pervasive challenges in learning.

4.3 Multi-sensory experimental results

The integration of multisensory data has emerged as a powerful approach for improving the accuracy and depth of cognitive state monitoring, particularly in complex environments such as education, where understanding student engagement is essential. In this study, a multisensory approach was employed by combining data from eye-tracking, galvanic skin response (GSR), and photoplethysmography (PPG) sensors. This combination enabled the capture of a comprehensive profile of students' physiological and attentional states during learning activities. By integrating these diverse data streams, the study aimed to develop a holistic understanding of how various physiological signals correlate with cognitive engagement, especially during episodes of mind-wandering.

Rationale for Multisensory Integration:

The rationale for employing multisensory data lies in the complementary nature of the various signals collected. While eye-tracking provides precise information regarding the location and duration of visual attention, it does not capture the underlying emotional or physiological responses associated with attentional shifts. Galvanic skin response (GSR), which measures changes in skin conductance, offers insights into autonomic nervous system activity and serves as a reliable indicator of emotional arousal and stress. Photoplethysmography (PPG), in contrast, tracks heart rate variability, providing information related to stress levels, cognitive load, and overall physiological state. By integrating these modalities, the study aimed to construct a more comprehensive view of the cognitive and emotional factors that influence learning, thereby enhancing the accuracy and sensitivity of mind-wandering detection.

Experimental Design and Data Collection:

The multisensory experiment was conducted in a controlled environment designed to closely simulate a typical classroom setting. Participants were equipped with the Pupil Core eye-tracker, Shimmer GSR sensors, and PPG sensors, all of which continuously recorded data throughout the session. This setup was chosen to reflect a realistic learning environment, ensuring that the results would be applicable to actual educational contexts.

The learning materials were presented on a screen, and participants were instructed to engage with the content as they would in a typical classroom setting. The session was structured to include a variety of tasks such as reading, problem-solving, and interactive activities, each designed to elicit varying levels of cognitive engagement and physiological responses. By incorporating a diverse range of task types, the study aimed to capture a broad spectrum of attentional and emotional states, which is essential for understanding how different cognitive demands influence both mind-wandering and engagement.

Synchronisation and Data Processing:

A critical aspect of the study involved the synchronisation of data from each sensor to ensure temporal alignment. This synchronisation was essential for accurately capturing the physiological changes associated with attentional shifts, particularly during transitions between mind-wandering and focused states. For example, by aligning the timing of gaze shifts with concurrent changes in skin conductance and heart rate variability, the study was able to identify specific moments of attentional drift and correlate them with physiological markers of cognitive load and emotional arousal.

The raw data from each sensor was then processed using advanced machine-learning algorithms to classify episodes of mind-wandering and non-mind-wandering. This processing involved several steps, including noise reduction, feature extraction, and the application of classification models that could distinguish between the different cognitive states based on the integrated sensory data.

Analysis of Raw Data: Insights from Multisensory Signals:

Figure 4.11 presents the raw data collected from the three key sensors used in the study: the Pupil Core eye-tracker, Shimmer GSR, and PPG sensors. This figure provides a visual comparison of the physiological and attentional signals recorded during episodes of mind-wandering (left side) and non-mind-wandering (right side). By juxtaposing these two cognitive states, the figure

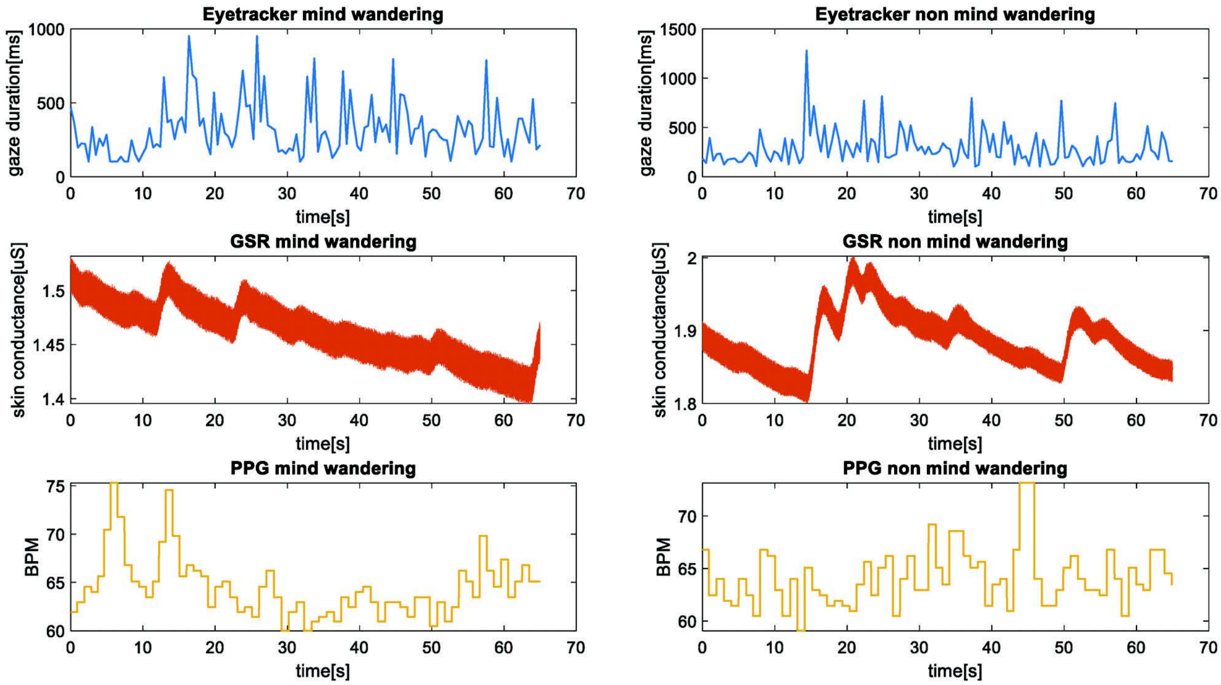

Figure 4.11: *The raw data were collected from each sensor of the Pupil Core eye-tracker, Shimmer GSR and PPG sensors, respectively. Graphs on the left show the collected data with mind-wandering, whereas the graphs on the right are for data with non-mind-wandering.*

highlights the differences in the data captured by each sensor, offering insights into how these signals vary with changes in attention and engagement.

Eye-tracking data: The eye-tracking data, shown in the top panels of Figure 4.11, captures the participants' gaze behaviour during both mind-wandering and non-mind-wandering episodes. During mind-wandering, the eye-tracker data often reveals a reduction in gaze fixation on key areas of interest, as indicated by more erratic and dispersed gaze patterns. This suggests that participants' visual attention is less focused and more scattered during these episodes. The data highlights moments where participants' gaze shifts unpredictably, potentially scanning non-relevant areas of the screen or even off-screen, indicating a cognitive drift away from the task at hand. In contrast, the non-mind-wandering data demonstrates more consistent and concentrated fixations on areas of interest, indicative of higher cognitive engagement and task-focused attention. This focused attention is crucial for effective learning, as it reflects the participants' active processing of the presented material.

GSR Data: The middle panels of Figure 4.11 display the GSR data, which measures changes in skin conductance associated with emotional arousal and stress. During mind-wandering episodes, GSR readings typically show lower levels of arousal, reflecting a state of reduced cognitive effort and disengagement. This decrease in skin conductance suggests that as attention drifts, the participants' emotional and physiological engagement with the task diminishes, potentially leading to a decrease in learning effectiveness. Conversely, during non-mind-wandering periods, GSR levels are generally higher, indicating that participants are more emotionally and cognitively engaged with the learning material. This heightened arousal is often associated with increased focus and effort, signalling that the participant is actively involved in the learning process.

PPG Data: The bottom panels of Figure 4.11 illustrate the PPG data, which tracks heart rate variability as an indicator of physiological state. During mind-wandering episodes, the data typically shows increased heart rate variability, which is often associated with a more relaxed and less focused state. This suggests that participants may be in a more passive cognitive state, with reduced attentional resources dedicated to the task. Increased heart rate variability during these periods can indicate a shift towards a more autonomic, rather than a cognitively controlled, state. On the other hand, the non-mind-wandering data indicates more stable heart rates, reflecting a heightened state of concentration and cognitive load. A stable heart rate with lower variability is often linked to sustained attention and active engagement, which are critical for effective cognitive processing and learning.

Machine Learning for Classification and Analysis: The visual distinctions presented in Figure 4.11 provided a foundation for advanced analysis and classification tasks. By processing these raw signals using machine learning algorithms, models were trained to detect episodes of mind-wandering with high accuracy. The integration of multiple data streams enabled the development of complex feature sets capable of capturing subtle variations in physiological and attentional states patterns that are often challenging to identify through any single modality alone.

For instance, the machine learning models used in this study were trained to recognise patterns associated with cognitive disengagement by analysing the synchronised data from all three sensors. These models could then classify new data streams, identifying moments when a participant was likely to be mind-wandering versus fully engaged. This capability is particularly valuable in educational settings, where real-time detection of disengagement can enable immediate interventions to redirect attention and improve learning outcomes.

Implications for Educational Practice and Future Research: The findings from this multisensory experiment have significant implications for educational practice. By providing a comprehensive view of the physiological and attentional states that accompany learning, this approach offers educators new tools for monitoring and enhancing student engagement. The ability to detect mind-wandering in real-time, based on multisensory data, opens up possibilities for developing adaptive learning systems that can respond to students' cognitive states, providing prompts, breaks, or alternative content when disengagement is detected.

Furthermore, this research contributes to the growing body of evidence supporting the use of multisensory data in cognitive science and education. Future research could explore the integration of additional sensors, such as electroencephalography (EEG) for brain activity monitoring or facial expression analysis for emotional state detection, to further refine our understanding of cognitive engagement. Additionally, studies could investigate the application of this multi-sensory approach in diverse educational settings, including remote and online learning environments, to assess its effectiveness across different contexts.

Conclusion: In conclusion, the integration of eye-tracking, GSR, and PPG data provided a rich, multi-dimensional perspective on student engagement during learning activities. The ability to monitor both attentional focus and physiological arousal in real-time offers powerful insights into the dynamics of mind-wandering and cognitive engagement. By leveraging these insights, educators and researchers can develop more effective strategies to enhance learning, ensuring that students remain focused and engaged throughout their educational experiences.

4.3.1 Data Analysis using Machine-Learning

The raw data collected from the sensors was extensive, capturing minute-by-minute fluctuations in gaze patterns, skin conductance levels, and heart rate variability. To interpret this data effectively, feature extraction techniques were applied to reduce its complexity while preserving the most relevant information for classification. As shown in Table 4.2, key features extracted included statistical measures such as mean, standard deviation, and skewness, alongside more advanced features such as signal energy and autocorrelation.

Table 4.2: *List of numerical features extracted from raw sensor data.*

Features	
Mean	Skewness
Standard deviation	Kurtosis
Median	Minimum
Median Absolute Deviation (MAD)	Range
25^{th} quantile	Mean of the autocorrelation
75^{th} quantile	Std. deviation of lagged autocorrelation
Interquartile range	Total Signal Energy

For eye-tracking data, features such as fixation duration, saccade length, and gaze entropy were calculated to quantify visual attention and scanning patterns. GSR data was processed to extract features related to the intensity and frequency of skin conductance responses, which are indicative of emotional arousal and stress levels. PPG data was analysed to derive heart rate variability metrics, including the standard deviation of normal-to-normal intervals (SDNN) and the root mean square of successive differences (RMSSD), both of which are commonly used to assess autonomic nervous system function.

The extracted features were then used as inputs for the machine learning models, with the goal of classifying episodes of mind-wandering and non-mind-wandering based on the combined sensory data.

To classify the collected data, two machine learning models were employed: Support Vector Machine (SVM) and Gated Recurrent Unit (GRU) networks. These models were selected based on their respective strengths in handling different characteristics of the dataset.

SVM is a robust classification algorithm that excels in separating data into distinct classes based on the distribution of features. It constructs a hyperplane that maximises the margin between different classes, making it particularly effective for binary classification tasks such as mind-wandering detection. In this study, a quadratic kernel function was employed to map features into a higher-dimensional space, enabling the construction of a linear boundary to separate mind-wandering from non-mind-wandering instances. The SVM model was trained on the extracted features from all three sensors, allowing it to leverage the full spectrum of multisensory data.

The mathematical representation of a linear SVM hyperplane and its objective function is given as follows [167]:

$$h : x'W + b = 0 \tag{4.1}$$

$$\min_{W,b,\xi_i} \left\{ \frac{1}{2}\|W\|^2 + C\sum_{i=1}^{n} \xi_i \right\}, \text{ with } C > 0, \xi_i \geq 0 \tag{4.2}$$

Where W denotes the normal vector to the hyperplane and b is the bias value. C refers to the regularisation parameter, also known as the penalty factor, which is highly correlated with the tolerance of misclassification. The penalty factor is always greater than zero, and the larger factor will create a hard margin and vice versa (soft margin); its value needs to be determined carefully since a hard margin may result in overfitting of the classifier. In this study, the penalty factor is set as one in the training of the classification model.ξ_i represents the slack variable related to the classification error, the SVM algorithm automatically allocates a slack variable for the feature points between the hyperplane and its margin, whereas the value of slack variable($0 \leq \xi_i \leq 1$) is proportional to the distance of feature points to the hyperplane. In the circumstance that the feature points beyond the hyperplane (misclassification), the slack variable is larger than one.

If a linear hyperplane is not able to separate the feature points, the features can be mapped to a higher-dimensional space through a kernel function, where a linear boundary is available. The conventional kernel function includes higher-order polynomials (quadratic, cubic) and the Gaussian function, whereas the choice of the kernel function depends on the data distribution and the optimal hyperplane to separate them. In this study, the quadratic kernel function was selected. SVM algorithm is suitable to implement on a multi-class problem by utilising multiple binary classifiers via the 'one vs one' approach; for instance, if there are N classes to distinguish, $N(N-1)/2$ times binary SVM will be computed to construct hyperplanes between each individual class.

GRU is the improved version of the regular recurrent neural network (RNN) [168–170]. A

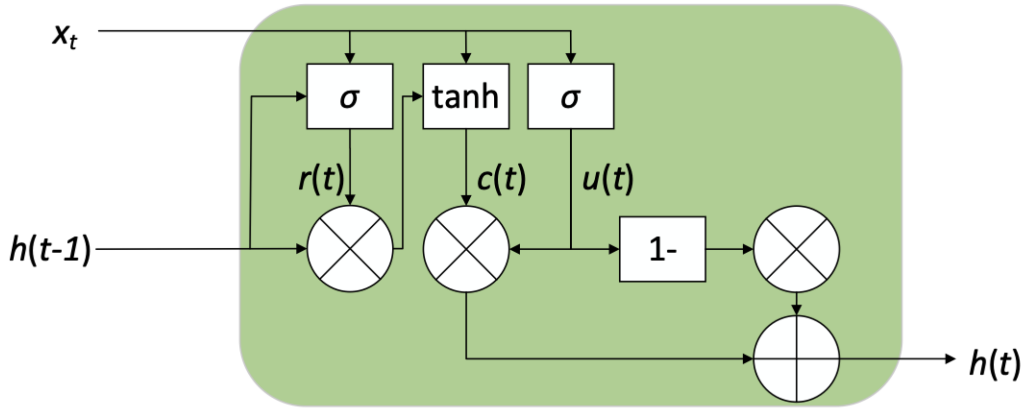

Figure 4.12: *The block diagram of a simple GRU to process the recorded raw data with faster processing speed and less memory cost.*

standard GRU consists of two different gates, namely, the update gate and reset gate; compared to other variants of RNN, such as Long Short Term Memory (LSTM), GRU has comparable performance with a simpler architecture, faster processing speed and less memory cost. The block diagram of a simple GRU is illustrated in Figure 4.12, and the mathematical expression of GRU is given below [168, 169]:

$$r(t) = \sigma(W_{rh}h_{t-1} + W_{rx}x_t + b_r) \tag{4.3}$$

$$u(t) = \sigma(W_{uh}h_{t-1} + W_{ux}x_t + b_u) \tag{4.4}$$

$$c(t) = \tanh(W_{ch}(r(t) \odot h(t-1)) + W_{cx}x_t + b_c) \tag{4.5}$$

$$h(t) = z(t) \odot c(t) + (1 - z(t)) \odot h(t-1) \tag{4.6}$$

Where $r(t)$ and $u(t)$ represent the output of the reset and update gate, respectively. σ denotes the sigmoid activation function. W refers to the weight index of gated units, whereas b is the bias value. refers to the Hadamard product of two vectors. $c(t)$ represents the output of the tanh operator, which receives a linear combination of the current input x(t) and the result of the Hadamard product between $r(t)$ and $h(t-1)$. $h(t)$ represents the current output of the GRU. The update gate $u(t)$ controls the ratio of current input information and historical information. When $u(t)$ is close to 1, most of the historical information is forgotten, and a larger volume of input information is taken from the current moment, and vice versa. In this paper, as GRU has the ability to extract useful time-dependent information from raw data, the input of GRU is a time-series signal rather than features.

The confidence level of the classifier is a probability matrix with its size equal to nXm, $n$is the number of samples and m is the number of classes. It is used to measure the certainty of classifier decision-making, whereas, for each sample, the class yielding the highest confidence level will be chosen as the output class. The value of the confidence level is converted from the normalised classifier output through a softmax function 4.7.

$$P_c = \frac{e_c}{\sum_{k=1}^{K} e_k} \tag{4.7}$$

where class c is the class of interest, Pc the confidence level of class c, ec and ek denote the unnormalised classifier output of class c and class $k(k \leq K)$, respectively, and k is the number of classes. In this study, a decision-level fusion method was developed to combine the confidence levels derived from all sensing approaches. The fusion process [171, 172] is depicted in equation 4.8

$$\sum_{i=1}^{L} P_n \log \frac{1}{P_n} \tag{4.8}$$

Where P_n denotes the confidence level matrix for classifier n, P_{Fusion} is the confidence level matrix after fusion. s refers to the index of samples, and c indicates the class number. The confidence level matrix of different sensors shares the same dimension. The fusion of data from multiple sensors is the straightforward accumulation of their respective output confidence level matrices. The new prediction label is the class with the highest fusion confidence level. In our paper, n equates to 3, representing g classification results from eye-tracker, GSR and PPG, respectively. It is important to notice that the fusion of data is unrelated to the acquisition frequency of sensors because data fusion occurs at the decision level following classification.

The results of the classification models are presented in Figures 4.13 and 4.14, which show the performance of SVM and GRU models, respectively. The SVM model achieved classification accuracies of 80.97%, 76.81%, and 76.39% for GSR, eye-tracking, and PPG data, respectively, with a combined sensor fusion accuracy of 86.53%. These results indicate that sensor fusion significantly improves the model's ability to accurately classify mind-wandering episodes, as it allows the model to draw on multiple sources of information.

Figure 4.14 demonstrates the GRU model with even higher performance, with classification accuracies of 85.69%, 81.67%, and 80.42% for GSR, eye-tracking, and PPG data, respectively, and a sensor fusion accuracy of 89.86%. The superior performance of the GRU model can be attributed to its ability to capture temporal dependencies in the data, making it particularly effective for detecting patterns that unfold over time.

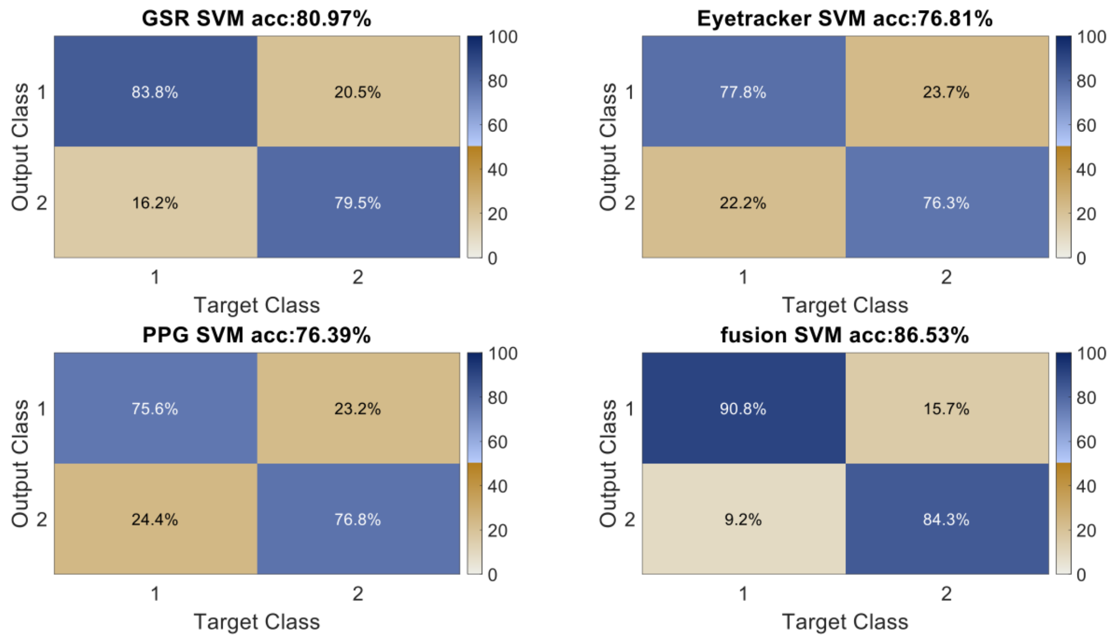

Figure 4.13: *The SVM classification for GSR, eye-tracker, PPG and fusion. Class 1 notes mind-wandering, and class 2 indicates non-mind-wandering.*

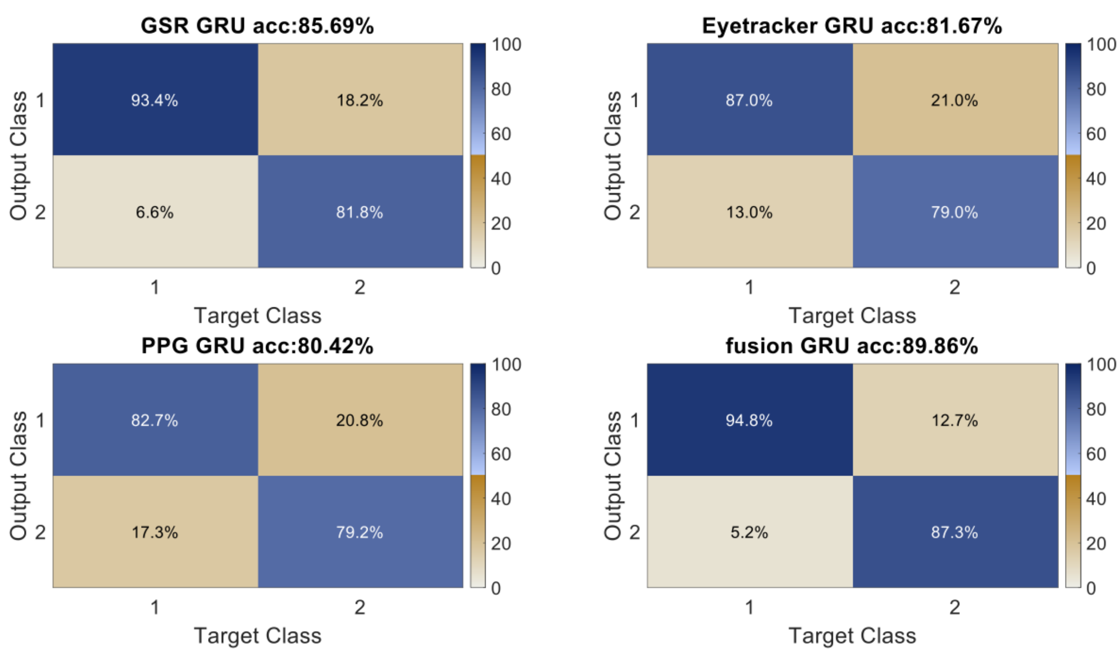

Figure 4.14: *The GRU classification for GSR, eye-tracker, PPG and fusion. Class 1 notes mind-wandering, and class 2 indicates non-mind-wandering.*

4.3.2 Boxplot Analysis

Figure 4.15 visualises the variability and distribution of the performance metrics across the 10 iterations of training and testing. The boxplot provides a summary of the key metrics, such as accuracy, precision, recall, and F1 score, for each model and sensor combination, enabling a clear comparison of their performance.

The boxplot graphically depicts the distribution of the performance metrics through their quartiles. The central line within each box represents the median value, while the edges of the box correspond to the first (Q1) and third quartiles (Q3), effectively capturing the interquartile range (IQR). The whiskers extend to the minimum and maximum values, excluding outliers, which are plotted as individual points beyond the whiskers. This visualisation helps to identify the range, central tendency, and any potential outliers in the model's performance across different iterations.

Figure 4.15 illustrates the boxplot of the 10 iterations of 'training and testing'. The blue circle represents the mean value of 10 different classification results, whereas the red line in the middle of the 'box' represents the median value. The upper and lower boundaries denote the maximum and minimum accuracy values of 10 iterations of 'training and testing' separately.

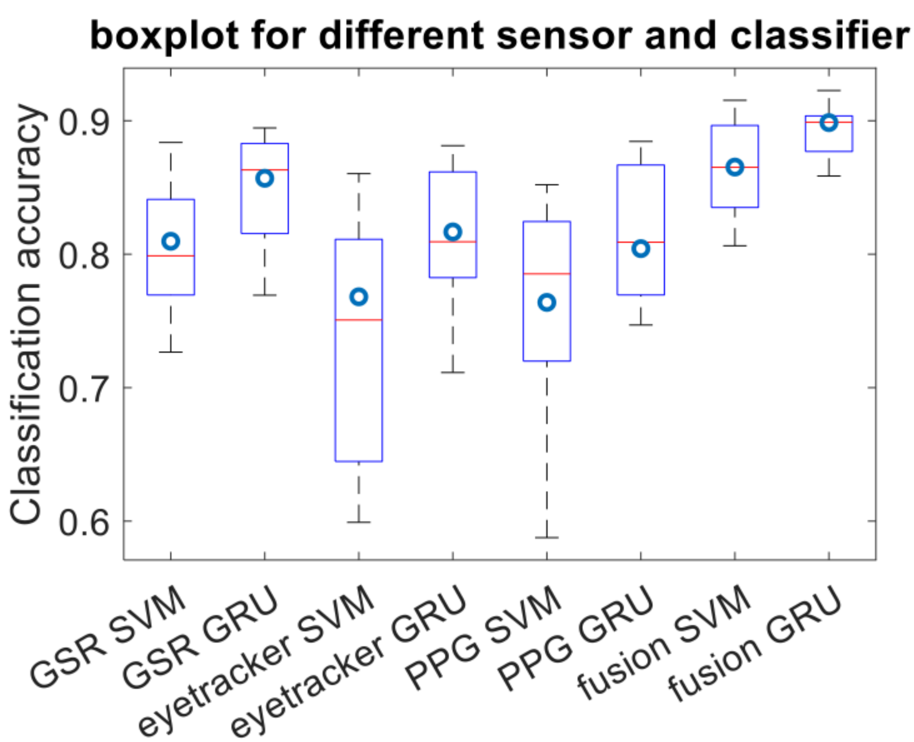

Figure 4.15: *Boxplot of 10 iterations of training and testing using each individual sensor and their fusion using SVM and GRU*

The edges of the blue 'box' in the boxplot represent the 25th percentile (lower quartile) and the 75th percentile (upper quartile) of the classification results, which collectively encapsulate the middle 50% of the data. This range, known as the interquartile range (IQR), provides a concise summary of the central tendency and variability in the classification performance across the 10 iterations. In this context, the narrowness or width of the IQR reflects the consistency of the model's performance narrower boxes indicate more stable performance, while wider boxes suggest greater variability.

It is observed that the fusion of data from multiple sensors, combined with both SVM and GRU classifiers, not only enhances the mean classification accuracy but also reduces the variance in the classification results. This reduction in variance indicates an improvement in the stability and robustness of the classification system, thanks to the fusion process. The fusion of multiple sensor inputs provides the model with a richer and more comprehensive dataset, allowing it to better capture the nuances of mind-wandering versus non-mind-wandering states. As a result, the model is less sensitive to fluctuations in individual sensor data, leading to more consistent performance across different iterations.

Moreover, when comparing the SVM classifier to the GRU-based recurrent neural networks, the GRU models demonstrate a higher gain in both the mean and variance of classification accuracy across the 10 iterations of training and testing. This suggests that GRU models are better suited for capturing the temporal dynamics of the data, allowing them to make more accurate predictions over time. The GRU's ability to retain and leverage information from previous time steps is particularly beneficial in this context, where changes in cognitive states (such as transitions between mind-wandering and focused attention) may occur gradually rather than abruptly. Consequently, GRU models can provide a more refined classification by incorporating these temporal dependencies, leading to higher overall accuracy and more stable results across iterations.

The fluctuations in performance, as depicted by the wearable sensors in Figure 4.15, result from the classifier's exposure to different datasets during the training and testing phases of each iteration. Since the classifier is trained and tested on varying segments of the data in each of the 10 iterations, its performance is inherently influenced by the quality and representativeness of the data segments it encounters. When the classifier is trained on favourable data segments, those that clearly distinguish between mind-wandering and non-mind-wandering states, it achieves higher classification accuracy. Conversely, when the classifier encounters less favourable data segments, where the distinctions between the two cognitive states may be more subtle or ambiguous, its performance tends to decline. This variability underscores the importance of data selection and highlights the role of sensor fusion in mitigating the impact of less favourable data segments by providing a more comprehensive and robust input for the classifier.

In summary, the combination of sensor fusion and advanced classifiers like GRU not only enhances the mean classification accuracy but also contributes to more stable and consistent performance across multiple iterations. This stability is crucial for developing reliable wearable systems capable of accurately monitoring cognitive states in real-time educational settings.

Furthermore, the observed fluctuations in performance underscore the significance of data selection, reinforcing the value of incorporating multiple sensor inputs to ensure robust and reliable classification results, even when faced with varying data quality.

4.3.3 Benchmarking with Related Work

The multisensory system developed in this study achieved a detection accuracy of 89.86% using a Gated Recurrent Unit (GRU)-based classification model. This level of performance is competitive with, and in several cases surpasses, previously reported results in the field of cognitive state monitoring and mind-wandering detection using both unimodal and multimodal approaches.

In studies utilising only eye-tracking data, classification accuracies typically range between 67% and 72% for binary mind-wandering detection tasks, with F1-scores as low as 0.59 in authentic classroom environments [173, 174]. These results highlight the limitations of relying solely on visual attention metrics to infer internal cognitive states.

EEG-based systems, though rich in signal content, have demonstrated moderate detection performance. For example, entropy-assisted feature extraction combined with random forest classifiers achieved an AUC of approximately 0.712, indicating potential but requiring more invasive sensor placement and complex signal processing [175].

Compared to these approaches, the integration of eye-tracking, galvanic skin response (GSR), and photoplethysmography (PPG) in this study provided a richer, multimodal representation of attentional and emotional states. The adoption of a temporal deep learning framework, particularly GRU, further enhanced the model's ability to capture sequential dependencies and transient fluctuations in physiological signals, leading to more stable and accurate classification outcomes.

Table 4.3 summarises the performance of different sensor modalities and modelling techniques reported in the literature, positioning the current study within this broader research landscape.

Table 4.3: *Benchmarking performance with prior studies on mind-wandering detection*

Approach	**Sensor Modality**	**Model Type**	**Performance Metric**
This study	Eye-tracking, GSR, PPG	GRU	89.86% accuracy
Prior work on eye-tracking only [173]	Eye-tracking	SVM	67–72% accuracy
Classroom-based gaze tracking [174]	Eye-tracking	Logistic Regression	F1-score: 0.59
EEG-based entropy features [175]	EEG	Random Forest	AUC: 0.712

These comparisons underscore the methodological contribution of this thesis, particularly the value of integrating multimodal physiological data with temporal deep learning. The findings support the feasibility and effectiveness of real-time, wearable-based cognitive monitoring systems in educational contexts.

Chapter 5

Discussion and Conclusion

5.1 Overview of Findings

This research set out to explore the effectiveness of wearable sensors, particularly eye-tracking devices, in monitoring attention and detecting mind-wandering in educational settings. Initially, an experimental plan was established to compare the performance of wearable eye-tracking glasses (Pupil Core) with a desktop-based eye-tracker to detect loss of attention in students. The findings indicated that both systems can monitor attention, but the wearable eye-tracker provided more accurate and detailed data. Building on these insights, the study progressed to explore a multisensory approach by integrating Galvanic Skin Response (GSR), Photoplethysmography (PPG), and eye-tracking sensors to enhance the accuracy of detecting mind-wandering.

5.2 Contributions to Knowledge

This research contributes to the growing field of educational technology in several ways:

Wearable Eye-Trackers for Engagement Measurement: This study demonstrates the effectiveness of wearable eye-trackers in monitoring student engagement. It expands the understanding of how these devices can be used beyond traditional educational tools to offer real-time feedback on students' attention. Unlike screen-based eye-trackers, which are often limited to stationary environments, wearable eye-trackers provide more flexibility, capturing data in dynamic learning settings and proving more practical for diverse educational contexts.

Multisensory Approach for Cognitive Awareness: Integrating GSR and PPG sensors with eye-tracking technology allowed for a richer analysis of cognitive states. The findings confirmed that physiological markers such as skin conductance and heart rate variability can complement eye-tracking data, offering a more nuanced understanding of students' attention and mind-wandering patterns. This comprehensive sensor fusion approach contributes to a more holistic assessment of student engagement, addressing the limitations of using eye-tracking data alone.

Mind-Wandering Detection in Educational Settings: This research achieved high accuracy in detecting mind-wandering instances during lectures by implementing machine learning models to process multisensory data. This finding is particularly significant for enhancing learning outcomes, as it highlights the potential of real-time intervention strategies that can re-engage students when their attention wanes.

5.3 Design and Integration of a Multisensory Device

The research also contributes to conceptualising and integrating a multisensory device that incorporates all three sensors (GSR, PPG, and eye-tracking). The envisioned device would offer a seamless and non-intrusive means of collecting and analysing physiological and neurological data in real time. The design considerations for this device include the following key aspects:

Sensor Integration: The device would integrate GSR sensors to measure skin conductance as an indicator of emotional arousal, PPG sensors to track heart rate variability as a proxy for cognitive load, and eye-tracking sensors to monitor visual attention and gaze patterns. These sensors would be embedded within a comfortable, wearable form factor, such as a headset or glasses, ensuring ease of use and minimal disruption to the learning process.

Data Fusion and Analysis: The device would employ advanced data fusion techniques to combine the signals from the three sensors, providing a holistic view of the user's cognitive and emotional state. Machine learning algorithms could be used to process and interpret the data, enabling the device to detect instances of mind-wandering or lapses in attention with high accuracy.

Real-Time Feedback: One of the innovative features of this multisensory device would be its ability to provide real-time feedback to students and educators. For instance, the device could alert students when their attention is waning, prompting them to re-engage with the material. Similarly, educators could use the data to identify which parts of the lesson are most engaging or where students are most likely to lose focus.

User Interface Design: The device would also include a user-friendly interface that displays key metrics in an accessible manner. This interface could be integrated with existing educational platforms, allowing educators to track student engagement over time and adjust their teaching strategies accordingly.

5.4 Implications for Educational Technology

The integration of a multisensory device into educational settings has the potential to revolutionise how attention and engagement are monitored. This research highlights the possibility of designing tools that observe cognitive states and actively contribute to improving learning outcomes. The multisensory approach could be particularly valuable in remote learning environments, where traditional cues for monitoring student engagement are less effective.

Moreover, the ability to detect mind wandering in real-time opens up new avenues for personalised learning. Educators can tailor their instruction to better meet individual needs by identifying when and why students lose focus, potentially improving retention and understanding. The findings from this research also suggest that such a device could play a crucial role in addressing some of the key challenges in education today, such as maintaining student engagement in increasingly digital learning environments.

5.5 Interdisciplinary Impacts

While this thesis's findings focus on engineering education, they have the potential to influence several other disciplines. Wearable technology, particularly when combined with multisensory data and machine learning algorithms, provides valuable insights into cognitive processes such as attention, engagement, and mind-wandering. These insights are not limited to the context of engineering education but can be applied to a wide range of fields, including psychology, healthcare, workplace training, and even the arts.

Psychology and Cognitive Science: In psychology, wearable technologies such as eye-trackers and GSR sensors could be used to study attention, cognitive load, and emotional responses more precisely. For example, wearable devices can enhance research into cognitive states like mind-wandering or focus, providing real-time physiological data that enriches traditional experimental designs. This could lead to more accurate models of how people process information, react to stimuli, and manage their cognitive resources in various contexts.

Healthcare and Neurofeedback: The ability to monitor physiological signals such as heart rate variability and skin conductance in real-time has precise applications in healthcare, particularly in mental health and neurofeedback. Wearable devices could be used in therapy or rehabilitation settings to monitor patient engagement during treatment, identify moments of distraction, or track progress in attention-related disorders such as ADHD. Furthermore, multisensory wearables could assist in neurofeedback training, where patients learn to regulate their physiological responses to improve cognitive or emotional control.

Workplace Training and Professional Development: The use of wearable technology to monitor attention and engagement could be extended to workplace training and professional development programs. In corporate environments, training sessions often face challenges similar to those in classrooms, with participants becoming disengaged or distracted. By using wearable sensors, organisations could assess the effectiveness of training programs in real time, allowing trainers to adapt their methods or content dynamically to maintain engagement. This could lead to more effective training sessions, higher retention of information, and improved employee performance.

Figure 5.1: *Acceptability route to implementing wearable devices in a higher educational setting*

Creative Arts and Design: In disciplines such as creative arts, wearable technology could offer new methods for understanding how individuals interact with artistic or design elements. For instance, eye-tracking could study how audiences engage with visual art, film, or architecture, providing insights into which aspects capture attention and provoke emotional responses. This data could inform the design of more engaging and immersive artistic experiences, both in physical and digital formats.

Education Across Disciplines: Beyond engineering, other fields of education could benefit from the insights provided by wearable technology. For example, in medical education, wearable devices could be used to monitor student performance during hands-on procedures, offering real-time feedback on stress levels, focus, and decision-making. In disciplines such as history or literature, virtual or augmented reality wearables could immerse students in historical settings or narrative environments, enhancing learning through experiential engagement.

Overall, the interdisciplinary impacts of this research demonstrate that wearable technologies, particularly when paired with multisensory data collection, offer a wide range of possibilities for enhancing education and professional practices. As these technologies evolve, their applications across disciplines will likely expand, offering new ways to understand and improve human performance and engagement in various contexts.

5.6 Conceptual Design of a Multisensory Device

The development of the multisensory device followed a structured approach that included three key steps: content validation, feasibility analysis, and implementation. These steps ensured that the device was not only theoretically sound but also practical and effective in an educational setting. Figure 5.1 illustrates the process flow from initial problem analysis to final implementation.

5.6.1 Introduction to the Design

In the pursuit of improving cognitive and emotional monitoring in educational environments, this research explores the conceptual design of a multisensory device that integrates GSR, PPG, and eye-tracking sensors. This design aims to create a more comprehensive and accurate system for detecting and analysing students' attention and mind-wandering during learning activities. By combining these sensors into a single wearable device, the design seeks to leverage the strengths of each sensor to provide a holistic understanding of the learner's physiological and cognitive states.

5.6.2 Design Specifications

Based on the findings of this PhD research, a conceptual design for a wearable multisensory device was developed. While the device has not yet been physically prototyped, its technical architecture and functional components are grounded in the experimental data and practical constraints observed throughout this study. The specifications aim to guide future implementation and testing in real educational settings.

Frame and Material: The device features a lightweight polycarbonate frame with a matte black finish. Designed for long-term wear in academic environments, the total weight is estimated at under 60 grams to ensure user comfort.

Eye-Tracking Cameras: Dual infrared cameras embedded in the lens rims track eye movements at 200 Hz, including gaze direction, fixation duration, and saccades, to monitor visual attention.

PPG Sensors: Placed within the temple arms, these sensors record blood volume changes at 50 Hz to derive heart rate and heart rate variability (HRV), supporting cognitive load analysis.

GSR Sensors: Located on the nose pads, GSR sensors measure skin conductance at 10 Hz, detecting changes in emotional arousal associated with attentional shifts and stress.

Adjustability and Comfort: Customisable nose pads and extendable arms accommodate various facial structures. The design is intended for all-day use without causing discomfort or fatigue.

Charging and Connectivity: The device includes a discreet USB-C charging port and uses Bluetooth Low Energy (BLE) for data transmission to external devices or cloud platforms.

User Interface: A minimal heads-up display (HUD) is embedded in one lens to provide real-time feedback and engagement alerts without obstructing the user's field of vision. Touch-sensitive controls on the frame allow intuitive interaction with device functions.

Performance Targets: To ensure effectiveness and usability in real-world scenarios, a set of Key Performance Indicators (KPIs) has been defined. These are informed by experimental results, literature benchmarks, and usability expectations and are summarised in Table 5.1.

This conceptual specification lays the foundation for future prototyping and empirical vali-

Table 5.1: *Key Performance Indicators (KPIs) for the conceptual multisensory wearable device*

Performance Metric	**Target Value**
Attention Detection Accuracy	>85% (based on ML model results in Chapter 4)
Mind-Wandering Detection Latency	<3 seconds after onset
Sensor Synchronisation Error	<20 milliseconds across modalities
Battery Life	Up to 8 hours continuous use
User Comfort Score	≥4.0 out of 5.0 (subjective feedback scale)
Sampling Rates	Eye-tracker: 200 Hz, PPG: 50 Hz, GSR: 10 Hz

dation. It balances technical performance with ergonomic design to support seamless integration into educational workflows.

5.7 Future Research Directions

While this research has demonstrated the benefits of wearable technology in educational settings, several areas warrant further investigation:

Longitudinal Studies: Future research should explore the long-term effects of using wearable technology on student engagement and learning outcomes. Longitudinal studies help determine whether these technologies have a lasting impact on student's cognitive development and academic performance.

Broader Application Across Disciplines: While this study focused on engineering education, the application of wearable technology could be expanded to other disciplines. Future research could investigate how wearable devices can be used in fields such as humanities, social sciences, and art education, where different types of cognitive engagement may be required.

Refinement of Machine Learning Models: The machine learning algorithms used to detect mind wandering can be further refined. Future research could explore using more sophisticated models and larger datasets to improve the accuracy and reliability of mind-wandering detection systems.

Ethical Considerations: As wearable devices become more integrated into educational environments, future research must address ethical concerns, such as data privacy and the potential for over-monitoring students. Studies should investigate how to implement these technologies in ways that protect students' rights while maximising their educational benefits.

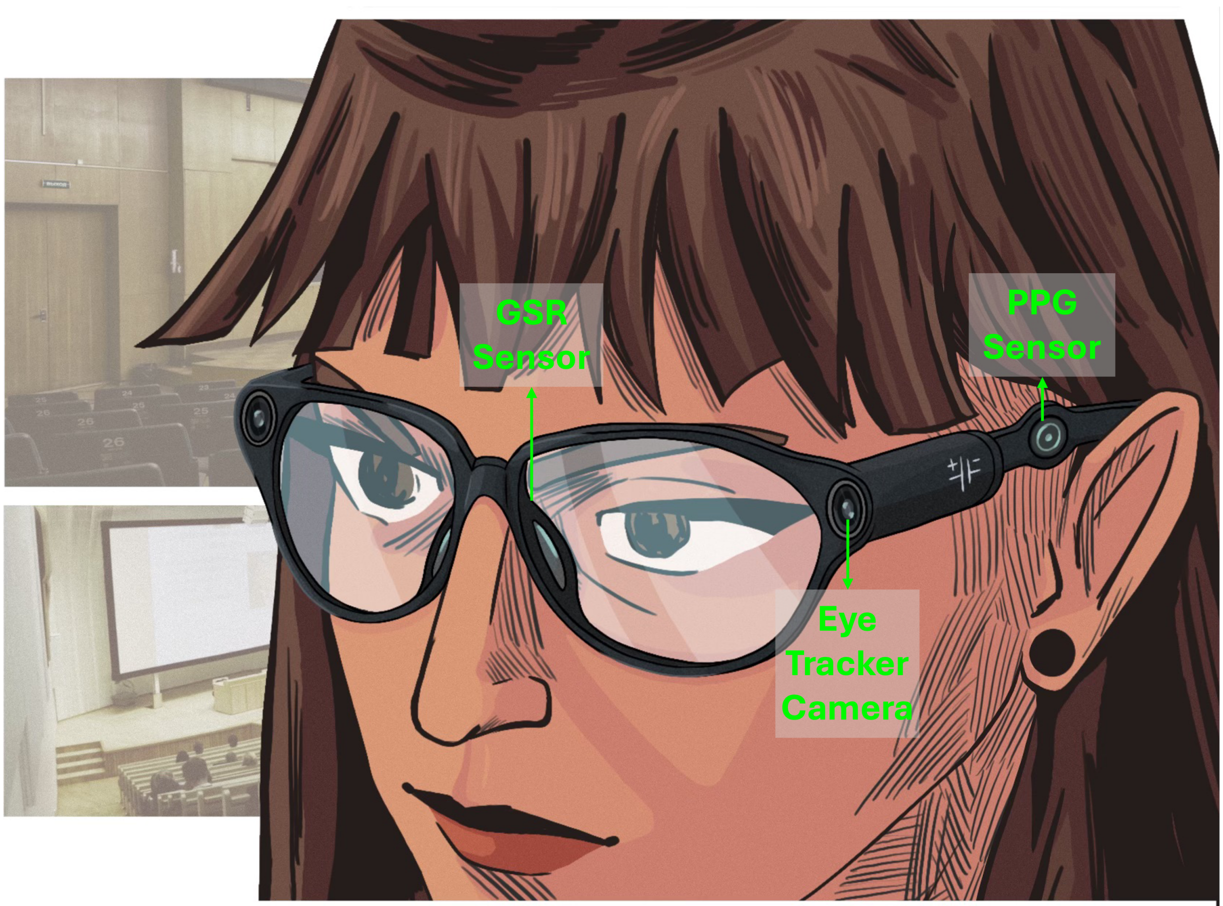

Figure 5.2: *Conceptual multisensory glasses with embedded eye-tracking, GSR, and PPG sensors*

5.8 Conclusion

This thesis has made significant contributions to the field of educational technology by demonstrating the value of a multisensory approach to monitoring attention and mind-wandering. The proposed design for a multisensory device that integrates GSR, PPG, and eye-tracking sensors offers a promising tool for enhancing learning experiences. By providing more accurate and comprehensive data on student engagement, this device has the potential to transform how education is delivered and experienced in the digital age.

The findings of this research hold interdisciplinary relevance beyond the immediate context of engineering education. The application of wearable technologies extends to fields such as psychology, healthcare, workplace training, and the creative arts. The ability to monitor cognitive and emotional states in real time opens up new avenues for research and practical implementation across these domains, further demonstrating the transformative potential of multisensory wearable devices.

By deepening our understanding of cognitive monitoring and learner engagement, this thesis contributes substantively to the field of educational technology while also establishing a foundation for future innovations in both educational and professional contexts. As wearable technologies continue to advance, their potential to enhance learning, performance, and creativity across diverse disciplines is expected to grow, offering novel approaches to improving human interaction within these environments.

Appendix A

Evaluation of Wearable Devices

During the PhD research, various commercial wearable devices with potential educational applications were evaluated. Although these devices were initially designed for health monitoring, their simplicity and lightweight design make them suitable for deployment in classroom settings for both students and teachers.

EEG Headset

The Ultracortex Mark IV headset from OpenBCI [176] was employed to capture brain activity data, as shown in Figure A.1. This open-source, 3D-printable EEG headset is designed for comfort, adjustability, and high signal quality. It supports acquiring EEG signals from up to 16 channels positioned at 35 potential locations on the scalp. The OpenBCI graphical user interface (GUI) enables real-time visualisation, recording, and streaming of EEG data, as illustrated in Figure A.2.

EEG Headband

Another example is the EEG Headband from OpenBCI that can be used to measure and record brain waves, as shown in Figure A.3. The EEG Headband allows prefrontal cortex measurements via three lead wires with flat EEG electrodes. Figure A.4 illustrates a sample of live-streamed brain data as it appears during collection.

EMG Sensors

Various hand-worn devices, such as Electromyography (EMG) sensors, were evaluated for their potential use in educational contexts, as illustrated in Figure A.5. These sensors are capable of capturing muscle activity by interfacing with an OpenBCI board connected to EMG/ECG disposable gel electrodes. For each targeted muscle group, two electrodes are used to record the signal, while a third electrode serves as a universal ground. The paired electrodes act as positive and negative terminals to detect potential differences across the muscle. Figure A.5 demonstrates how these components work together to stream muscle activity data.

Pulse Sensor

A pulse sensor developed by Arduino [177] and OpenBCI was evaluated for its potential educational applications. This plug-and-play heart-rate sensor connects to the Cyton board and can be placed on the fingertip or earlobe to measure heart rate and heart rate variability (HRV) using photoplethysmography (PPG).

Eye-Tracking Glasses

A review of suitable wearable eye-tracking glasses for educational settings was conducted. Lightweight glasses from the Pupil Core model were selected for further investigation, as shown in Figure A.7.

This wearable system includes a scene camera and an infrared-spectrum eye camera for dark pupil detection. Both cameras connect to a computer via high-speed USB. The video streams are processed using Pupil Capture software, which enables real-time pupil detection, gaze mapping, recording, and additional functionality.

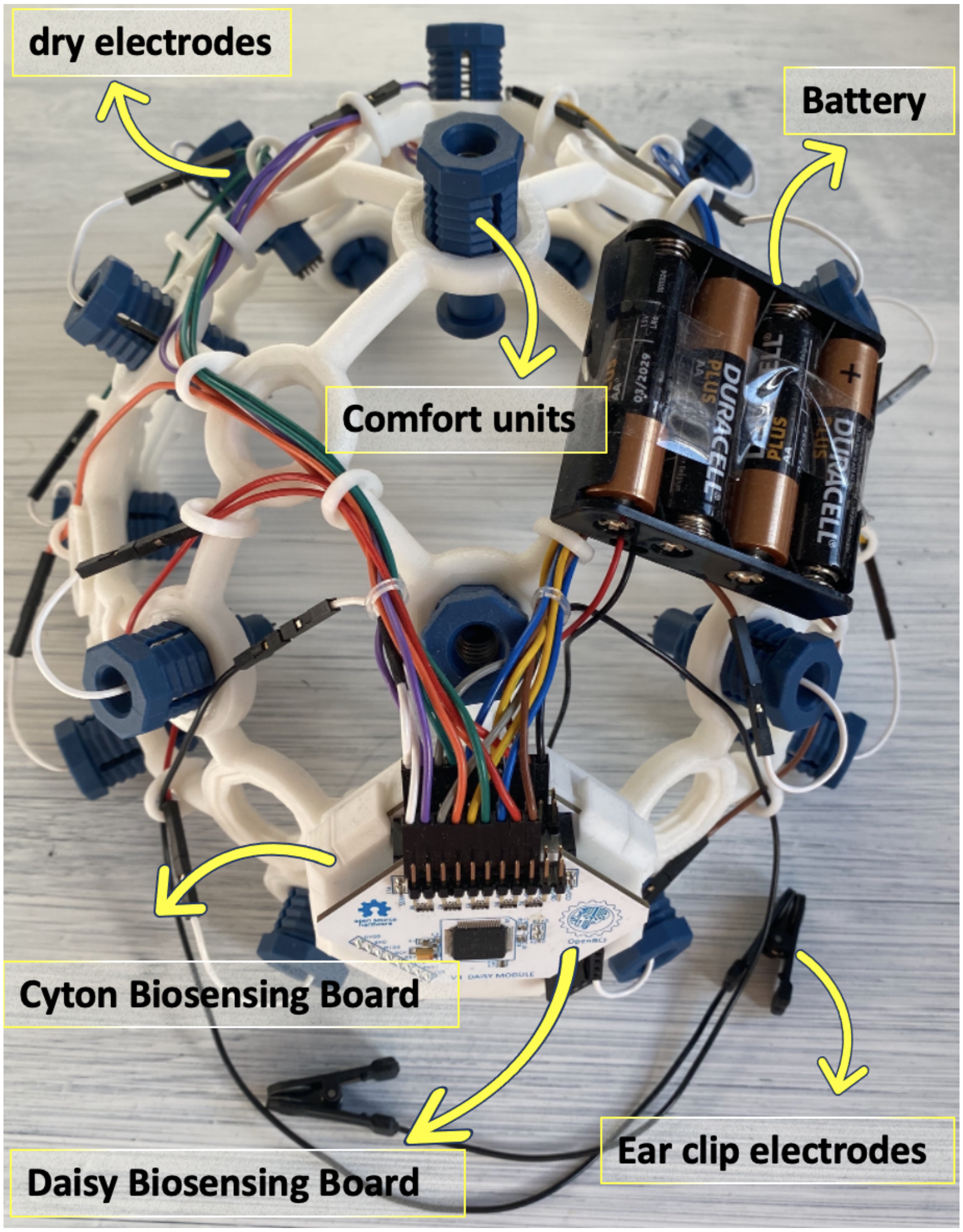

Figure A.1: *Ultracortex Mark IV EEG helmet*

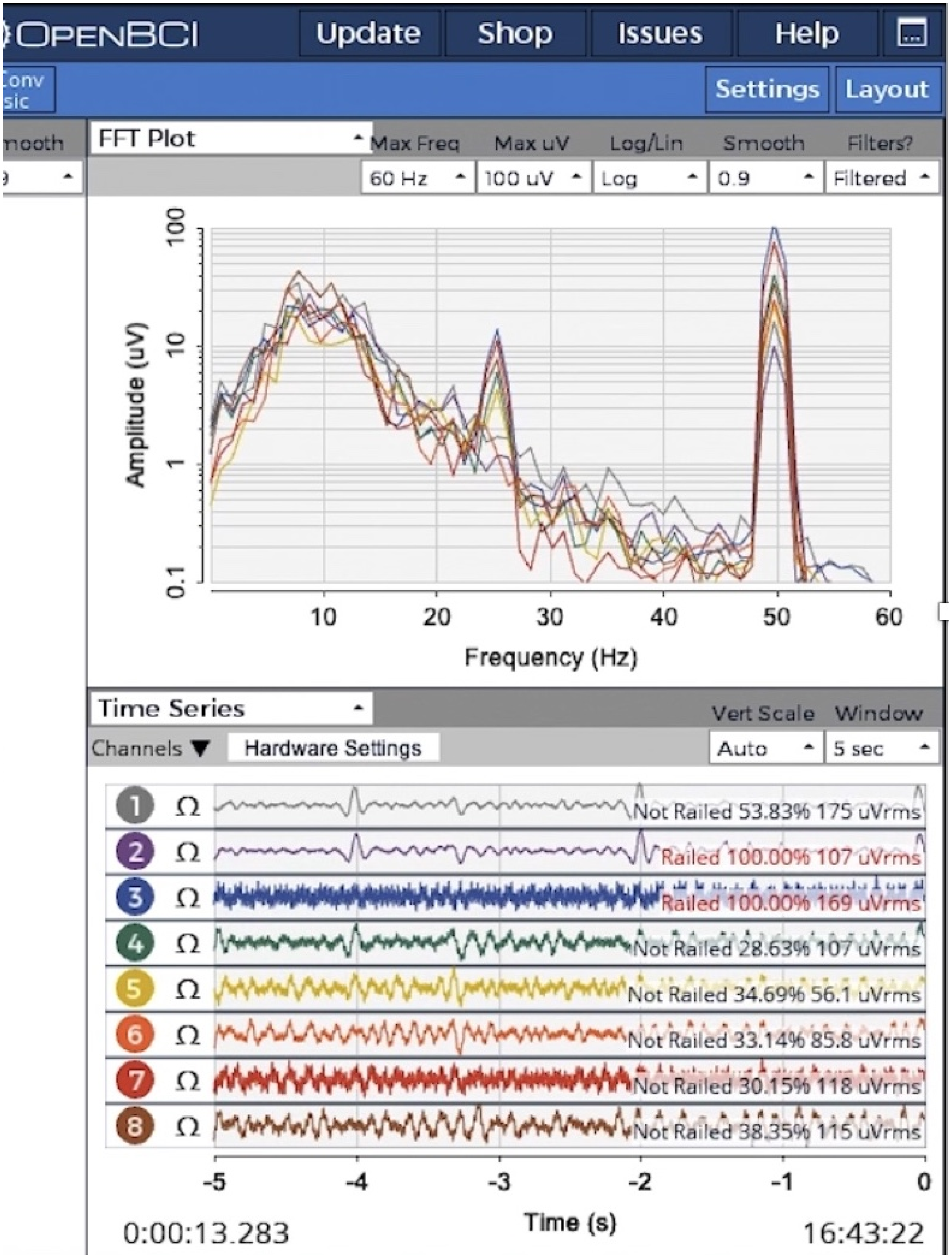

Figure A.2: *Ultracortex Mark IV Graphical User Interface (GUI)*

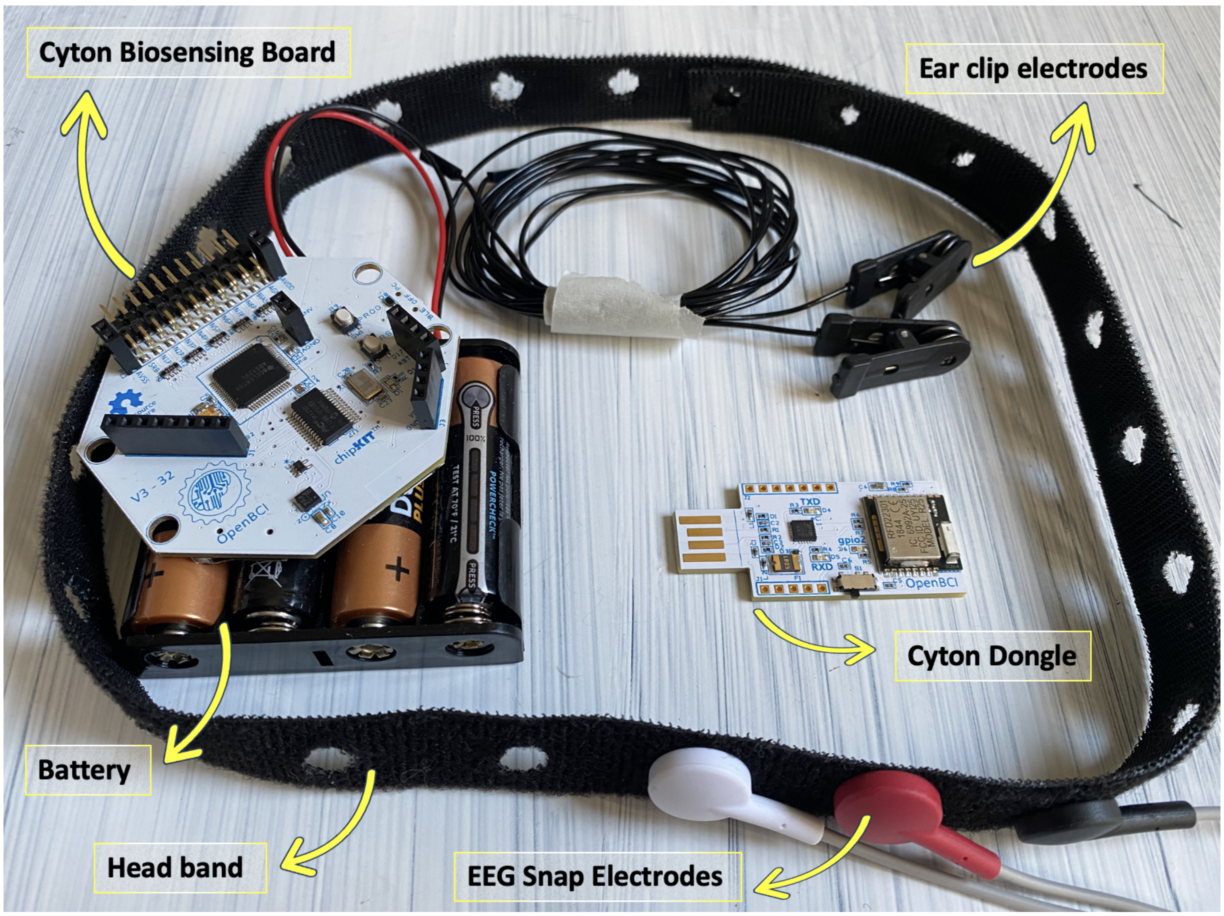

Figure A.3: *OpenBCI EEG headband*

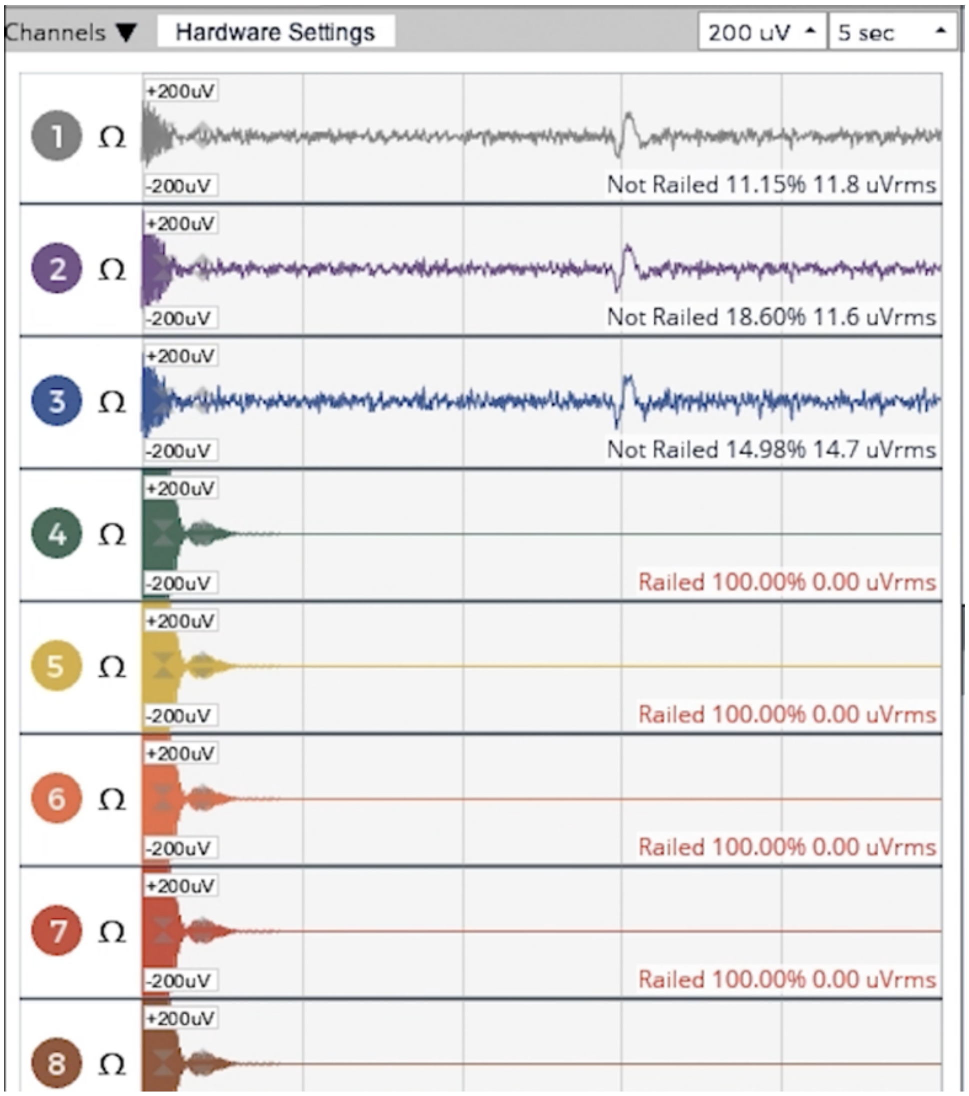

Figure A.4: *OpenBCI EEG headband data collection*

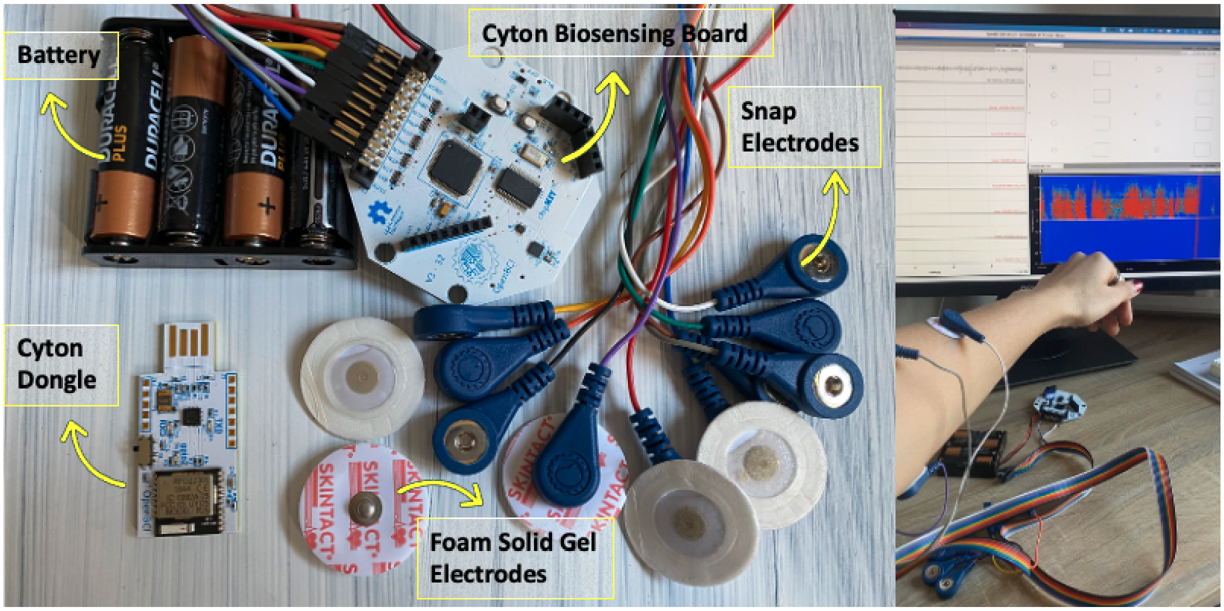

Figure A.5: *Components of OpenBCI EMG sensors used to record and measure muscle signals*

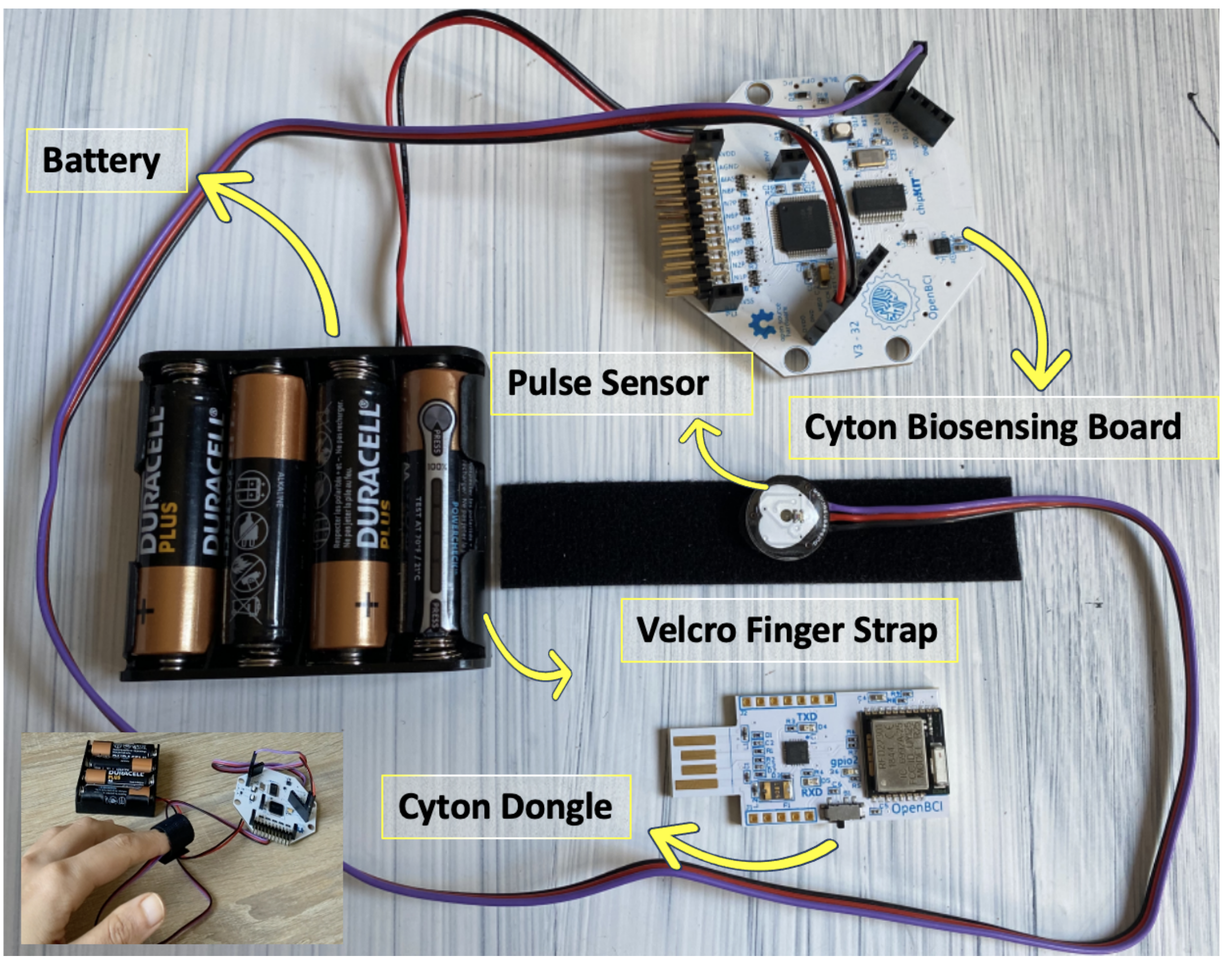

Figure A.6: *Components of Arduino pulse sensor*

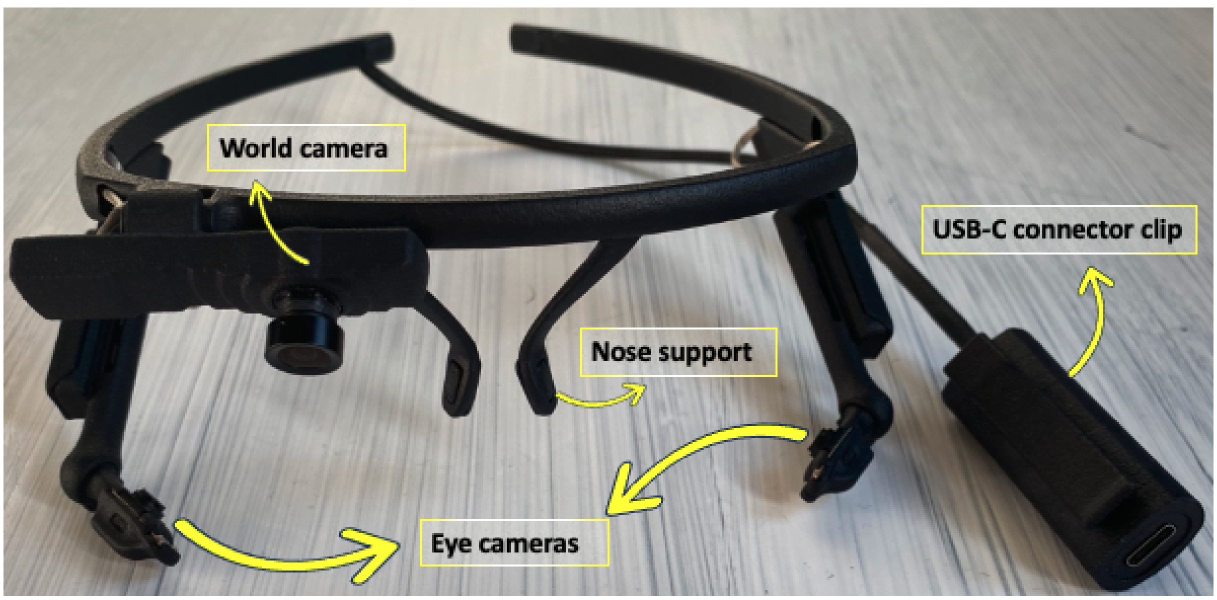

Figure A.7: *Pupil Core eye-tracking glasses*

Appendix B

Ethics and Evaluation Instruments

The following documents were included as part of the experimental procedures and evaluation instruments:

Dr. Julie R. Williamson
Senior Lecturer

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Tel.: +44 141 330 3718
Julie.Williamson@glasgow.ac.uk

Glasgow, May 10 2023

Ethical approval for:

Application Number: 300220154

Project Title: Exploring the Elusive Mind: A Multimodal Wearable Sensor Solution for Measuring Mind Wandering in University Students

Lead Researcher: Dr Rami Ghannam

This is to confirm that the College of Science and Engineering Ethics Committee has reviewed the above application and **approved** it. Please keep this letter for your records. Also please download and read the Collated Comments associated with your proposal. This document contains all the reviews of your application and can be found below the approval letter on the Research Ethics System. These reviews may contain useful suggestions and observations about your research protocol for improving it. Good luck with your research.

Sincerely,

Dr Julie R. Williamson
Ethics Officer
College of Science and Engineering
University of Glasgow

Pre-experiment

Instructions:
Please try your best to answer the questions below. These questions relate to the video you are about to watch. Select only one answer for each question.

---

1) Why do researchers conduct large-scale international comparison studies in education?
○ A. Cross-cultural data highlights differences between educational systems and informs future policies
○ B. Countries can see how their students perform compared to others
○ C. International data helps understand psychological mechanisms of learning and achievement
○ D. The data helps shape educational reform efforts
○ E. All of the above

---

2) What is the attitude-achievement paradox in international educational research?
○ A. Students with poor attitudes in class perform poorly in school but succeed in life
○ B. Confident students tend to study less and perform poorly on tests
○ C. Countries with the most confident students perform worse than less confident countries
○ D. Students who do better in math tend to like it less

---

3) Which of the following is true about existing large-scale international comparison data?
○ A. It includes achievement data in all subjects taken by elementary students
○ B. It includes math and science achievement plus student attitudes
○ C. Politicians support these surveys to motivate student improvement
○ D. It is a long survey including student, parent, and teacher input

---

4) Which of the following is the most significant predictor of student achievement in international data?
○ A. Class size
○ B. Academic self-concept
○ C. Test anxiety
○ D. Self-esteem

---

5) Which of the following is NOT true about Germany's reaction to PISA results?

○ A. Germany undertook extensive educational reforms
○ B. Germany introduced national standards for teaching
○ C. Germany aimed to improve results for all students, not just the top performers
○ D. Germany stopped participating in PISA due to complex issues
○ E. None of the above (all are true)

Post-experiment

Instructions:
Please select only one answer to each of the 18 questions below.

---

1) Which of the following is NOT a reason why we conduct large-scale international comparisons?

○ A. To compare the educational systems of different countries
○ B. To help us understand the psychological mechanisms underlying learning
○ C. To understand the ways individual children change over time in their academic achievement in different countries
○ D. To better understand what is associated with good performance and use this knowledge to improve education

---

2) Researchers from Qatar argue that they perform poorly on TIMSS tests only because their mathematics curriculum is so different from that of Western countries. If the Qatar researchers are correct, which of the following should be true?

○ A. Students from Qatar should improve their TIMSS performance on the next wave of data collection
○ B. Students from Qatar should decline in TIMSS performance on the next wave of data collection
○ C. Students from Qatar should perform similarly on TIMSS and PISA
○ D. Students from Qatar should perform better on PISA than TIMSS
○ E. None of the above

---

3) Which of the following is true about PISA?

○ A. It assesses the mathematics and science achievement of 4th and 8th grade students
○ B. It provides information about the curriculum and effectiveness of various educational systems in teaching that curriculum
○ C. It was developed in order to help researchers determine the psychological processes associated with learning
○ D. It measures students’ ability to use knowledge from schooling to solve real-life problems

---

4) Which of the following is true about TIMSS?

○ A. It was developed to describe and explain differences in academic achievement
○ B. It is administered every four years
○ C. It is curriculum-based (questions cover what is taught in school)
○ D. All of the above

---

5) How are attitude variables (e.g., enjoyment of math, confidence in math) and math achievement related to each other when comparing countries?
○ A. Countries that report lower attitude ratings have higher math achievement
○ B. Countries that report higher attitude ratings have higher math achievement
○ C. Attitude variables are unrelated to math achievement when comparing countries
○ D. Both A and B have been found numerous times, depending on the year, grade level, and collecting organization (PISA or TIMSS)

---

6) Which factors are associated with higher academic achievement within a single country?
○ A. Enjoyment of subject
○ B. Greater classroom socioeconomic diversity
○ C. High academic self-concept
○ D. A and C only
○ E. All of the above

---

7) Which of the following is NOT a potential explanation of the attitude-achievement paradox?
○ A. Issues with translating questionnaires to different languages
○ B. Sampling differences across countries
○ C. East Asian students' tendency to select moderate rather than extreme responses
○ D. Higher pressure in East Asian countries affecting enjoyment

---

8) Which explanation of the attitude-achievement paradox might no longer apply if students were asked open-ended questions?
○ A. Translation error
○ B. Modesty bias
○ C. Academic pressure
○ D. A and B only
○ E. All of the above

---

9) If "academic pressure" is the main cause of the paradox, which would be true?
○ A. Students in high-pressure U.S. schools should feel more confident in math
○ B. Students in high-pressure U.S. schools should feel less confident in math
○ C. There would be no difference in math confidence
○ D. It is impossible to tell

---

10) Which is TRUE about PISA 2000 data on Germany?
○ A. Performance tied to socioeconomic status
○ B. Performance tied to immigration background

○ C. Performance tied to class size
○ D. A and B only
○ E. All of the above

---

11) What would Germany’s education system be like if they had not participated in PISA?
○ A. They would address class size issues
○ B. They would retain a 3-track school system
○ C. National standards would be introduced
○ D. None of the above

---

12) In Germany, which school types match each academic focus?
○ A. Hauptschule (high), Gymnasium (low), Realschule (vocational)
○ B. Gymnasium (high), Hauptschule (low), Realschule (vocational)
○ C. Hauptschule (high), Realschule (low), Gymnasium (vocational)
○ D. Realschule (high), Hauptschule (low), Gymnasium (vocational)

---

13) What limitations of Germany’s school system were revealed by PISA?
○ A. Large class sizes
○ B. Low funding
○ C. Low university attendance
○ D. All of the above

---

14) What was Germany’s reaction to the PISA findings?
○ A. They improved immigrant student performance
○ B. They addressed all shortcomings
○ C. They couldn’t agree on reforms
○ D. They used PISA as a reform guide

---

15) What potentially harmful change followed PISA in Germany?
○ A. Teachers followed national standards
○ B. Focus shifted to test performance
○ C. Focus shifted to structural learning factors
○ D. Both B and C
○ E. All of the above

---

16) How did Germany’s PISA performance change over time?
○ A. Performance improved; SES gap unchanged

○ B. Performance same; SES gap reduced
○ C. Performance improved; SES gap reduced
○ D. Performance same; SES gap unchanged

---

17) If Germany kept the same curriculum until grade 12, what change should occur?
○ A. SES would have less impact on achievement
○ B. SES would have more impact on achievement
○ C. Achievement would be less tied to school funding
○ D. Achievement would be more tied to school funding

---

18) Based on Germany's PISA experience, what should the U.S. do with international data?
○ A. Publicize global comparisons
○ B. Adapt policies based on each wave
○ C. Study culturally unique practices and integrate them
○ D. Send teachers abroad to observe best practices
○ E. All of the above

Overall engagement rating

Please indicate your level of agreement with the following statements by selecting only one option for each.

---

1) The material covered in the lesson was very interesting:
○ A. Strongly agree
○ B. Agree
○ C. Undecided
○ D. Disagree
○ E. Strongly disagree

---

2) My attention was fully focused on the video:
○ A. Strongly agree
○ B. Agree
○ C. Undecided
○ D. Disagree
○ E. Strongly disagree

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