SAFETY TECHNOLOGIES ADOPTION MODEL IN THE MALAYSIAN CONSTRUCTION INDUSTRY

YAP SZE CHEE

MASTER OF ENGINEERING SCIENCE

LEE KONG CHAIN OF FACULTY OF ENGINEERING AND SCIENCE

UNIVERSITI TUNKU ABDUL RAHMAN

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By

YAP SZE CHEE

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ABSTRACT

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Yap Sze Chee

The construction industry remains one of the most hazardous sectors, necessitating improved safety management through smart technologies. However, adoption remains limited, particularly in developing nations like Malaysia. This study examines the key enablers and inhibitors influencing smart technology adoption for occupational safety and health management. in the Malaysian construction industry. A tailored Likert-scale questionnaire was distributed to Grade 7 (G7) contractors, yielding 377 responses. Six major adoption drivers were found by factor analysis: organisational capability, cost-benefit perception, external environment influence, management commitment, technological acceptability and trustworthiness, and economic viability. Furthermore, facilitators and inhibitors were ranked by mean ranking analysis, which brought to light important obstacles such inconsistent standards, interoperability problems, and the requirement for staff training and managerial support. In order to evaluate the ways in which technological, organisational, economic, and environmental factors influence smart technology perceptions of ease of use (PEU), perceived usefulness (PU), and intention to use (IU), the study also used partial least squares structural equation modelling (PLS-SEM). The results show that PEU has little effect on adoption intentions, whereas PU strongly affects IU. This study offers a road map for removing obstacles and promoting technology-driven, sustainable safety management in Malaysian construction.

Keywords: Industrial safety, Technology, Building Construction, Technological change, Automation

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Approved by:

(Ir Ts Dr. Jeffrey Yap Boon Hui)

Date: 22th September 2025

Main Supervisor

Department of Surveying

Lee Kong Chain of Faculty of Engineering and Science

Universiti Tunku Abdul Rahman

(Ir Dr. Lee Wah Peng)

Date: 22th September 2025

Co-supervisor 1

Department of Surveying

Lee Kong Chain of Faculty of Engineering and Science

Universiti Tunku Abdul Rahman

(Ir Dr. Lew Yoke Lian)

Date: 22th September 2025

Co-supervisor 2

Department of Surveying

Lee Kong Chain of Faculty of Engineering and Science

Universiti Tunku Abdul Rahman

SUBMISSION SHEET

LEE KONG CHAIN OF FACULTY OF ENGINEERING AND SCIENCE

UNIVERSITI TUNKU ABDUL RAHMAN

Date: 22nd September

SUBMISSION OF FINAL YEAR PROJECT /DISSERTATION/THESIS

It is hereby certified that **Yap Sze Chee** (ID No: **2300342**) has completed this thesis entitled "**SAFETY TECHNOLOGIES ADOPTION MODEL IN THE MALAYSIAN CONSTRUCTION INDUSTRY"** under the supervision of **Ir Ts Dr. Jeffrey Yap Boon Hui** (Main Supervisor) from the Department of Surveying Lee Kong Chain of Faculty of Engineering and Science, **Ir Dr. Lee Wah Peng** (Co-Supervisor 1) from the Department of Surveying Lee Kong Chain of Faculty of Engineering and Science and **Ir Dr. Lew Yoke Lian** (Co-Supervisor 2) from the Department of Surveying Lee Kong Chain of Faculty of Engineering and Science.

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Yours truly,

Yap

(YAP SZE CHEE)

DECLARATION

I hereby declare that the dissertation is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UTAR or other institutions.

Name: Yap Sze Chee

Date: 22nd September 2025

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1.0 INTRODUCTION

1.1 Research Background

Smart technologies have emerged as transformative tools for improving occupational safety and health management. in the construction industry, Various studies have been conducted on smart technologies and health management. Yap et al., (2021) primarily examined the elements that encourage the use of safety management-related technologies. The findings indicate that wearable safety technology, robotics and automation, and Building Information Modelling (BIM) are the most successfully employed technologies. To anticipate construction hazards, enhance safety planning, and raise safety awareness, businesses in the construction sector support the development of cutting-edge technologies. Yap, Lam, et al., (2022) examined the challenges associated with implementing smart technology in safety and health management. Despite being viewed as useful instruments for occupational safety and health management, smart technologies are not as prevalent in the construction sector in most developing nations as they are in other industries.

Despite their benefits, several challenges has impeded the implementation of smart technologies in occupational safety and health management. For instance, Yap, Lam et al. (2022) identified barriers such as the high cost of investment, insufficient occupational safety and health regulations, weak safety culture, and lack of management commitment. Nnaji and Karakhan (2020) outlined the obstacles faced by contractors, including technical limitations and economic constraints. Arabshahi et al., (2021) examined the elements that influence the adoption of technology, as well as the efficacy of different types of sensing technology in construction safety. Six basic categories can be used to categorize the elements that influence the adoption of technology: cost efficiency, effectiveness, supplier characteristics and organizational culture, technical limitations, and user-friendliness. Although these studies have yielded insightful information, they largely concentrate on particular technologies or geographical settings, which limits their generalisability and ignores the larger ecosystem of technology integration.

Safety management has also investigated innovations like Virtual Design Construction (VDC), with studies like Shafiq and Afzal (2020) looking at how they help move traditional safety procedures into digital frameworks. However, despite the availability of cutting-edge solutions, safety management techniques have not changed much, therefore the use of such technology in Malaysia is still restricted. This emphasises the necessity for studies that investigate the fundamental causes of the obstacles to technology adoption and offer practical solutions.

Although earlier studies looked at the adoption of particular technologies, the majority of them do not include more comprehensive contextual factors in their analysis, which leaves a gap in our knowledge of how different organisational, technological, economic, and environmental factors interact to affect adoption decisions. Furthermore, current research frequently ignores the possible synergy between the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) paradigm in favour of concentrating on either one alone (Chen et al., 2019; Zhong et al., 2024). For instance, TOE looks at organisational and environmental aspects, whereas TAM stresses user PU and PEU. The capacity to address the complex nature of technology adoption in construction holistically is limited by the absence of an integrated approach.

By putting up an integrated TAM-TOE framework to investigate smart technology adoption for occupational safety and health management. in Malaysia's construction industry, this study fills these gaps. This integration is crucial because it enables a thorough examination of organisational and environmental factors in addition to individual user perspectives, leading to a more solid knowledge of adoption dynamics. Although earlier studies have used integrated frameworks for particular technologies, such as artificial intelligence (Na et al., 2022) or BIM (Qin et al., 2020), these studies ignore the interplay between several technologies and their overall influence on adoption. This study provides multidisciplinary insights that advance theoretical knowledge and useful solutions for improving safety management by concentrating on a larger ecosystem of smart technology.

1.2 Problem Statement

The construction sector in Malaysia is still very dispersed, inefficient, and sluggish to adapt new technology, which results in labour-intensive procedures, inefficiency, and inadequate safety management (Musarat et al., 2024). It is undeniable that various benefits can be generated from the implementation of advanced technologies in the construction industry. However, studies have shown that the adoption of smart technologies in the construction industry is unsatisfying (Klinc *et al.*, 2010). Klinc et al. (2010) further conclude the reasons for such low implementation of technologies adoption includes cultural obstacle and organizational culture, barriers in terms of technology such as lack of knowledge regarding the devices as well as ignorance towards the available technology devices.

Despite the existing technologies, their uptake is still restricted and primitive because of obstacles like a lack of industrial preparation, training, and direction in the Malaysian construction industry (Almatari et al. 2024). Nevertheless, to encourage construction enterprises to begin the transition towards construction 4.0, there is currently no comprehensive analysis of potential barriers for smart technologies adoption (Demirkesen and Tezel, 2022).

Recently, the use of several successful emerging technologies is favourably and strongly correlated with construction safety performance according to (Shafei *et al.*, 2024) model. In a different study, the systematic literature analysis on Industry 4.0 enabling technologies conducted by Forcina and Falcone, (2021) found that, in comparison to the traditional approach, technology transformation in construction safety management dramatically raised the competency level. Despite growing scholarly interest in the enormous potential of emerging technologies to improve H&S management, a poor adoption rate is noted because of high investment costs, construction workers' reluctance, unsupportive management, and technical difficulties (Yap et al., 2022a).

To address these gaps, this research attempts to rationalise the relationship between the factors influencing PEU and PU by using the PLS-SEM. PLS-SEM provides a higher level of exhaustive understanding compared to the first-generation multivariate analysis technique that is used in existing research. Factors gathered from literature review will be ranked and analysed to identify which enablers and inhibitors have the greatest influence before carrying out PLS-SEM Analysis to identify the precise causes hindering technology adoption. It is crucial to have a well-defined plan outlining the contributions of smart technologies, challenges as well as the why construction personnel adapt these technologies to be drawn.

1.3 Aim and Objectives

The study aims to investigate the uptake of emerging technologies for occupational health and safety management in the Malaysian construction industry.

The objectives of this study are:

1. To investigate the enablers and inhibitors of the adoption of smart technologies in the construction industry that contribute to occupational safety and health management.
2. To determine the underlying factors of the adoption of smart technologies in the construction industry that contribute to occupational safety and health management.
3. To develop a conceptual model based on the TAM-TOE framework for the adoption of smart technologies in the construction industry that contribute to

safety and health management.

1.4 Research Significance

The results of this study accelerate the construction industry's transition to a safer sector by promoting the broad adoption of cutting-edge technologies for safety and health management. Furthermore, the use of these new technologies might enhance the safety conditions on building sites, where accidents involving falls, electrocution, and collisions with objects are common. Because developing technologies can help safety managers in the development process by removing potential dangers on site or alerting workers to the threats they are exposed to in their everyday activities, this can lower the amount of work-related injuries and fatalities.

1.5 Research Outline

Chapter 1 summarised the research background of the study. It also covers the problem statement, the aims and objectives, and the outline of each chapter.

The information on safety and health management using developing technologies that was gathered from websites, journals, publications, and other publicly available sources was the main topic of Chapter 2. The occupational safety and health management. and types of developing technologies in construction industry were disclosed. Additionally, it demonstrated the theoretical underpinnings of the TOE-TAM framework.

The study's design and research technique were introduced in Chapter 3. Additionally, it explains questionnaire design, sampling techniques and sizes, as well as data collection methodologies. This chapter concludes with an overview of the data analysis techniques.

The study's results were thoroughly examined in Chapter 4 in order to evaluate the feasibility of integrating cutting-edge technologies for occupational safety and health management. in Malaysia's construction sector. Utilising statistical analysis, the information gathered from the survey was examined and contrasted with the pertinent literature study.

The study's conclusions and findings were wrapped up in Chapter 5. This chapter also pointed out shortcomings and offered suggestions for raising the calibre of related future study. Ultimately, the study's significance was determined to be its ability to accelerate the adoption of new technology for occupational safety and health management. in Malaysia's construction sector.

2.0 LITERATURE REVIEW

2.1 Systematic Literature Review

According to the Department of Statistics Malaysia Official Portal, (2022), the construction industry has accounted around 5-7% of the overall Gross Domestic Product (GDP) and has a significant contribution to the national GDP. With the dynamic improvement in diverse aspects of construction industry, health and safety in construction projects has become a prominent priority across the world (Furci and Sunindijo, 2020). Data collected reflecting the trends of fatal occupational injuries in the construction industry has reiterate the alarming issue of health and safety in the industry (Choi *et al.*, 2019). It is statistically proven that the most common accidents were 'falling from a higher level' and 'getting struck by objects or machinery', leading to high fatal occupational injury rates.

With the advent of modern technology, it is apparent that smart technologies are changing the traditional way of working in construction sector (Radley, 2019). Radley further elaborated that the use of drones has become more common in construction sites to improve survey data, improving efficiency and safety since some places on site are dangerous and hard-to-reach. Xu and Wang, (2020) emphasized that the conventional way of occupational safety and health management. such as risk assessment and analysis based on 2-dimentional drawing can no longer enhance occupational safety and health management due to the high complexity and dynamic of construction sector. The current BIM usage in Malaysia is 17%. However, it is 71% in the United States, 38% in the United Kingdom and 65% in Singapore (Bernama, 2019). The statistics have proven that the adoption of BIM in our country is relatively low.

Figure 2.1.1 shows the visualisation map for the relationship between all clusters and keywords extracted from core research by various scholars and their relationship by covering all the publications regarding occupational safety and health management in the construction industry with the implementation of technology. Table 2.1.1 shows the relevant keywords in these publications that are significant for this study. The bigger the nodes in the visualisation map, the larger the weightage of the keywords. The link strength will be higher for nodes that have shorter displacement. Clusters that are closer to each other have higher relevancy (Van Eck and Waltman, 2017).

A total of 5 clusters were identified. The keywords in Cluster 1 (red lines) are ‘accident prevention’, ‘construction safety’, ‘emerging technologies’, ‘environmental technology’, ‘internet of things’, ‘remote sensing’, ‘safety and health’, ‘safety technology’, ‘wearable sensors and technology’. Cluster 2 (green lines) includes ‘accidents’, ‘augmented reality’, ‘automation, BIM’, ‘computer aided design’, ‘digitalization’, ‘personal protective equipment’ and ‘virtual reality’. Cluster 3 (in blue) shows ‘artificial intelligence’, ‘deep learning’, ‘digital technologies’, ‘industry 4.0’, ‘machine learning’, ‘robotics’ and ‘technology adoption’. Cluster 4 (in yellow) consists of ‘information technology’, ‘occupational risks’, ‘project management’ and ‘safety engineering’. Cluster 5 (in purple) contains ‘occupational accident’, ‘occupational health and safety’, ‘safety management’, ‘technology’ and ‘technology adoption’.

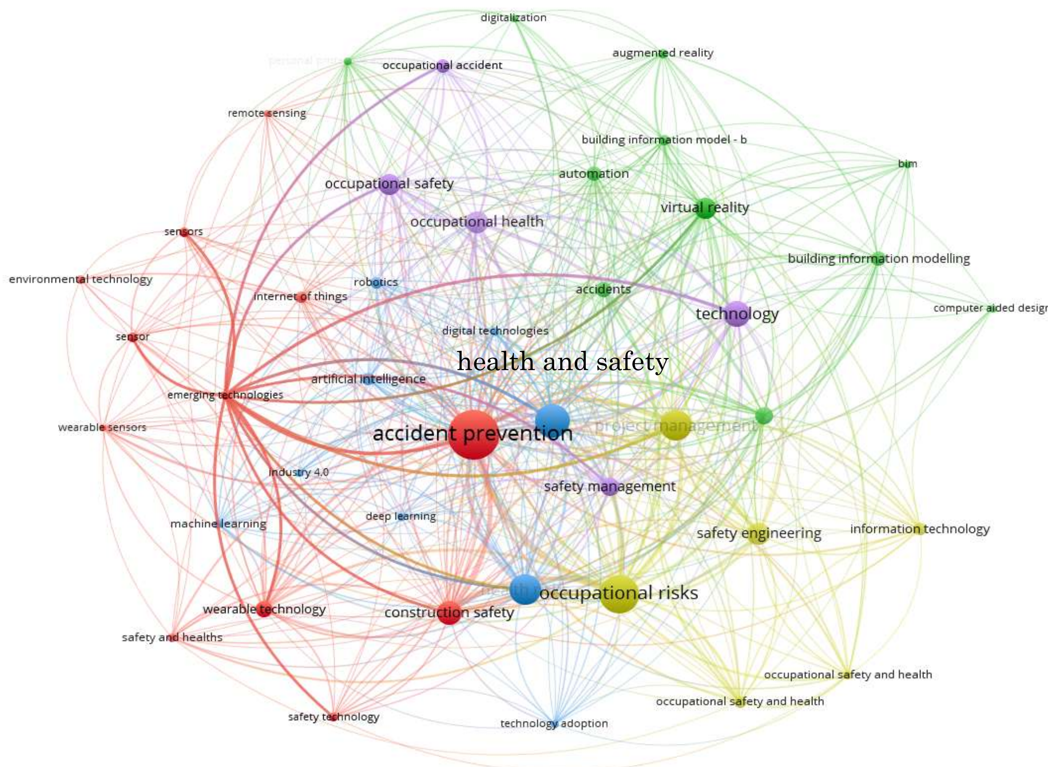

Figure 2.2.1: Visualisation Map of All Keyword

Table 1.1.1: Relevant Filtered Keywords

Keyword	Occurrences	Total Link Strength
Accident Prevention	120	1065
Occupational Risks	79	830
Project Management	54	250
Technology	42	356
Safety Engineering	36	291
BIM	39	276
Construction Safety	35	388
Safety Management	23	224
Automation	18	176

Artificial Intelligence	16	139
Information Technology	16	113
Occupational Accident	13	171
Robotics	13	119
Internet of Things	13	97
Augmented Reality	10	83
Machine Learning	9	97
Sensor	7	99
Wearable Sensors	6	79

According to Figure 2.1.1, there is a close relation between accident prevention, health and safety as well as project and safety management. This idea is further reiterated by Alkaissy et al., (2020), the failure in addressing project and safety management properly leads to inferior performance in perilous job site. The general overview in Figure 2.1.1 which shows the interconnectedness between all clusters reflects that safety management for accident prevention and health and safety in construction industry has a close link with technology adoption. The research by Akinlolu et al., (2020) has reinforced this relationship as technology is vital in project safety design and planning, visualisation and monitoring during construction projects.

Table 2.1.1 shows the relevant and filtered keywords identified from the selected articles. The top three most researched smart technologies in the construction sector were BIM (39 occurrences), automation (18 occurrences) and AI (16 occurrences).

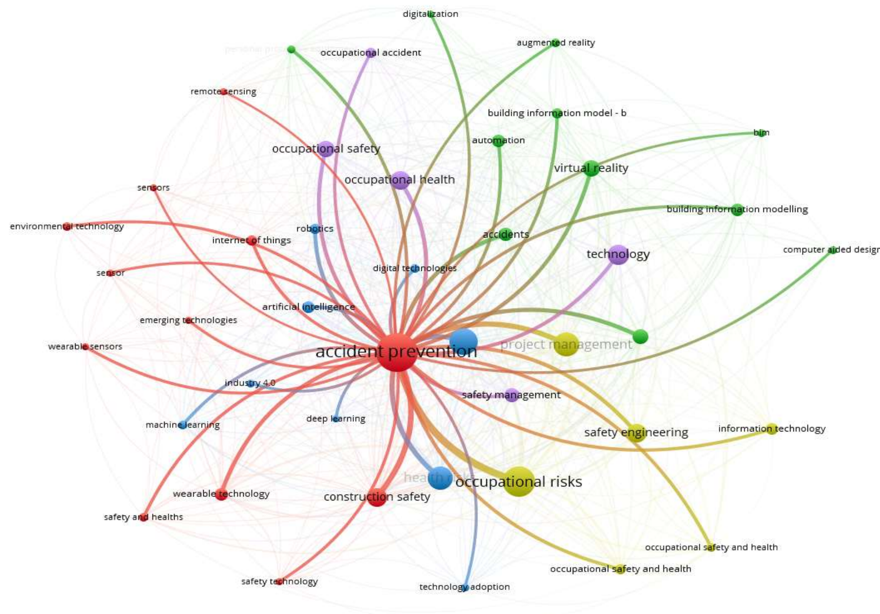

Figure 2.1.2: Keywords in Cluster 1 (Red)

Figure 2.1.2 focuses on the keywords in cluster 1 (red lines). 'Wearable sensors/technology', 'internet of things', and 'sensors' has a shorter displacement with regards to 'accident prevention'. Sensors or sensing technology are one of the smart technologies which includes radio frequency identification (RFID), light detection and ranging (LiDAR) or global positioning system (GPS). These sensing technologies can be to position the location of a person or object accurately and precisely which is vital in prevention for falling accidents on site (Kereri and Adamtey, 2019). These sensors can be incorporated into the personal protective equipment of construction site workers such as safety helmet and smart wristband to enhance occupational safety and health management (Martínez-Rojas *et al.*, 2021).

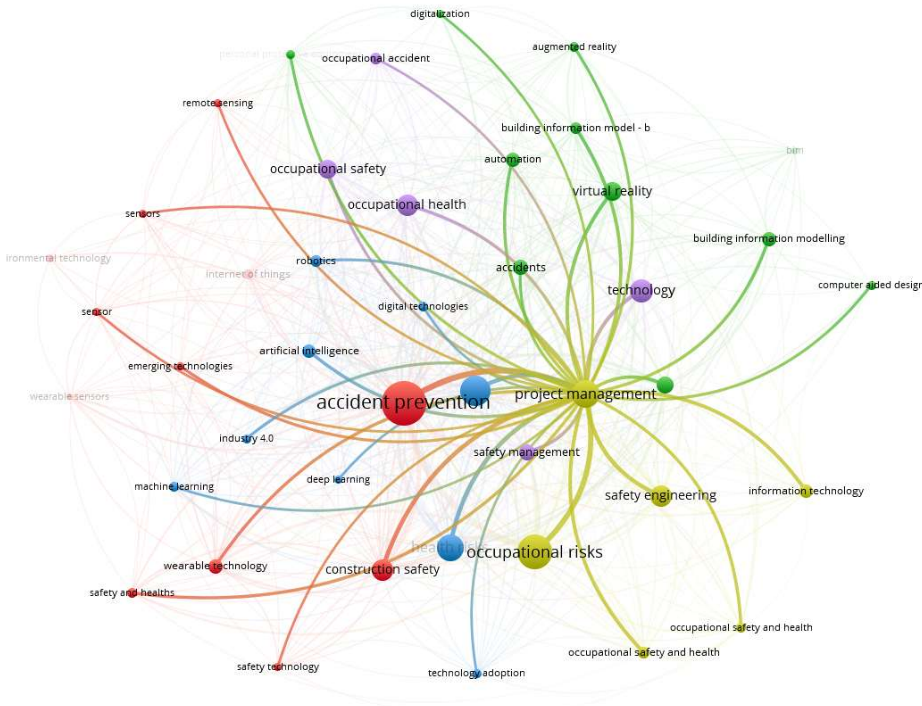

Figure 2.1.3: Keywords in Cluster 4 (Yellow)

Figure 2.1.3 focuses on the keyword in cluster 4 (yellow lines). The prominent links show that 'occupational risks' were often co-studied with 'project management', taking 'safety engineering' and 'informational technology' into consideration. The links in this cluster mainly shows that information technology is vital in occupational safety and health. It is essential for the application of big data technologies for the safety of construction that has become an alarming issue globally (Wang and Wang, 2021). Construction safety can be evaluated from two main perspectives, the project management perspective (accident causation, safety climate, risk assessment and perception, behavioural safety, hazard identification and management) as well as smart technologies (methods to implement innovative solution into construction projects) (Zhou *et al.*, 2013) .

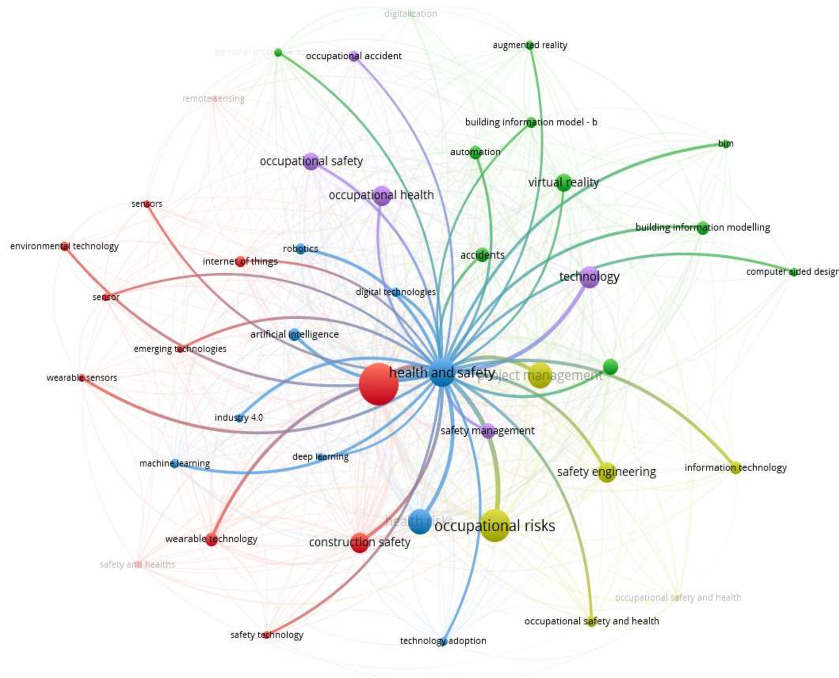

Figure 2.1.4: Keyword in Cluster 2, 3 and 5 (green, blue and purple)

Figure 2.1.4 focuses on the keyword in cluster 2, 3 and 5 (green, blue and purple respectively.) Cluster 2 shows a relationship between accident on site and implementation of VR, BIM and automation. Among these three smart technologies mentioned, BIM has the highest keyword occurrence, and it is undeniable that it is the most prominent smart technology implemented in our current practice within the construction industry. Data retrieved from various digital tools such as IoT sensors, drones and wearable devices can be used to BIM to attenuate occupational risks (Abioye *et al.*, 2021). According to Fargnoli and Lombardi, (2020), BIM contributes through dynamic visualisation, overlap and clashes detection, alternative design solutions for safety improvement to enhance the project occupational safety and health management.

Cluster 3 focuses on AI (such as virtual reality and augmented reality), deep learning, machine learning and robotics in health and safety perspective, with a close relation with cluster 5 on safety management. The extension field of AI such as machine learning, robotics and natural language processing are beneficial to tackle the safety issue in construction industry (Rao *et al.*, 2022).

2.2 Complementary Smart Technologies with Construction Industry in the context of Health and Safety

Construction hazards happen at various stages during construction activities. Huang et al., (2022 proposed six most common occupational hazards for construction workers: electrical injury, injury caused by falling objects, mechanical injury, foundation collapse injury, injury due to restricted space and injury caused by falling from higher places. occupational safety and health management is not merely identification of potential hazards at site before the commencement of work (Eiris *et al.*, 2018), it includes risk assessment and planning before and during construction (Zou *et al.*, 2007) as well as adequate training and education for construction site workers (Xie *et al.*, 2006). Integration of various smart technologies has become a trend to enhance the occupational safety and health management in the construction sector.

2.2.1 Smart technologies

1. **Building Information Model (BIM)**

   Implementation of BIM is extensively used throughout the entire cycle of building construction, from pre-construction (project definition) to post-construction (project inspection) stage (Torrecilla-García *et al.*, 2021). The accurate and predictive data collection from BIM and its 3D visualisation through digital twins stand out as a significant advancement in occupational safety and health management. The idea behind digital twinning is to create a digital clone of a physical thing and synchronise data from the physical twins to monitor, simulate and optimise the real object (Hou *et al.*, 2021). A digital twin enables virtual interaction whereas a BIM model provides visualisation (Zhang *et al.*, 2022). Zhang further elaborates that digital twin's conceptual underpinnings are digital representations, and BIM is the primary technology used to create these digital representations since it creates appropriate information models for the targeted components and gathers data specific to those components.

2. **Wearable technologies**

Wearable technologies are the incorporation of electronic technology or computers into garments and accessories that can be worn on then body (Sultan, 2015). In comparison with other smart technologies, it has the upper hand in terms of portability and cost in occupational safety and health management when performing high-risk construction works (Yap *et al.*, 2021). Wearable technologies can be integrated into personal protective equipment (PPE) such as smart safety boots (eg: SolePower), smart safety glasses (eg: XOEye) or integrated into personal accessories such as smart-watches or smart-bands (Nnaji *et al.*, 2021). Nnaji further reiterate that other than monitoring individuals' physiological and health conditions, wearable technologies can alert workers when they are close to energized electrical equipment, poisonous gas or fire.

3. **Unmanned Aerial Vehicle (UAV)**

UAV has become one of the most favourable technologies due to its inherent advantages such as accessibility, high efficiency to resolve certain difficulties in construction sector (Guan *et al.*, 2022). UAV can be integrated with various smart technologies such as sensing, monitoring system and even BIM for occupational safety and health management. A safety management model was introduced by Alizadehsalehi et al., (2020), where information acquired from UAV is incorporated into the BIM model. After the analysis and interpretation of data, adequate measurements will be taken to prevent accident on site. UAV can be integrated with other technologies such as photogrammetry and LIDAR system. UAV-based photogrammetry is used for image collection with cameras whereas UAV-based LIDAR system to measure ranges and distances on site (Guan *et al.*, 2022).

4. **Virtual Reality**

VR provides visualisation that uses 3D computerised depiction of reality in a synthetic environment using a VR headset (Yap *et al.*, 2021). Md Shamsudin and Abdul Majid, (2019) suggested that VR provides an excellent platform for educational purpose in occupational safety and health management in the construction industry. The boon of VR is further elaborated by Yap, Lee and Wang, (2021) as it is beneficial in safety education especially for the migrant workers or illiterate workers. By mimicking actual circumstances and giving workers a solid understanding of the reality in construction process, VR can stimulate participants' natural behavioural responses (Gao *et al.*, 2022).

5. **Augmented Reality**

Unlike VR, AR provides visualisation with a real-world setting. AR is offers an effective platform for supervision, training and planning in construction safety (Park and Kim, 2013). Placencio-Hidalgo et al., (2022) suggested that implementation of AR in construction training is effective in preventing injuries and disabilities that has become the alarming safety issue in construction industry. AR-based assessment is a highly effective evaluation technique that performs admirably throughout the construction safety training (Kyungki Kim *et al.*, 2019). AR can train employees without subjecting them to risks directly and reduce their fear of these risks.

6. **Robotics / Automation**

Robotics are used in construction to increase productivity and reduce the dancer of accidents on sties (Harinarain *et al.*, 2021). Japan was the first to invent on-site automated construction robots, which further on leads to the invention of bricklaying robots that mitigate occupational risks such as lower back pain or injuries (Gharbia *et al.*, 2020). Implementation of robotics and automation have been developed to better operate machinery (Aghimien *et al.*, 2022). Hence, the machine's operator can work safety away from the debris during demolition task. Robotics can be the substitution for human in inspection tasks due to its ability to manage numerical data and perform supervision in dangerous and cramped spaces that could provide threats to the workers (Yap *et al.*, 2021). The conventional procedure of traffic control flagging for construction works can be automated by automated flagger assistance devices (AFAD), allowing workers to manage the flag from a distance, obviating the risk of workers working near moving traffic (Karakhan *et al.*, 2019).

7. **Warning and Sensing Based Technology**

Sensing based technology in the context of location, vision and wireless sensor networks are used in construction occupational safety and health management (Zhang *et al.*, 2017). According to (Antwi-Afari *et al.*, 2019), some of the common sensing technology used in the construction industry are Radio Frequency Identification (RFID), Real Time Location System (RTLS), Bluetooth technology and Geographical Information Systems Geographical Information System (GIS or GPS).

8. **Photogrammetry**

Photogrammetry us often integrated with light detection and ranging (LiDAR) technology to detect hazard on construction sites (Zhang *et al.*, 2017). The availability of camera systems, affordable price for software has contributed to the rise of popularity in photogrammetric methodologies (Fawcett *et al.*, 2019). Photogrammetry approach is often incorporated into BIM models through realistic 3D depiction of the design (Tang *et al.*, 2019a). Okpala, Nnaji and Karakhan, (2020) has proven the implementation of photogrammetry to be useful in occupational safety and health management of construction during the design, planning and construction execution state.

2.3 Occupational Safety and Health Management

Table 2.3.1: Note for Table 2.3.2

Abbreviation	Occupational Safety and Health Management.
HSM 1	Design for safety
HSM 2	General health monitoring
HSM 3	Hazard identification prevention
HSM 4	Risk perception, planning and assessment
HSM 5	Training and education
HSM 6	Supervision and inspection

HSM 1: Design for Safety

Design stage is crucial during pre-construction to ensure the safety of building as construction sites are complex (Côté and Beaulieu, 2019). Design for safety is one of the occupational safety and health management in construction that focuses on prevention of accidents through design, safety through design and safety by design (Farghaly *et al.*, 2022). According to Seo et al., (2021), virtual reality (VR) can be incorporated into occupational safety and health management to assist the role of designers. A case study by Hadikusumo and

Rowlinson, (2002) came up with a design-for-safety-process (DfSP) that incorporates VR into the design process. Construction professionals were able to use the DfSP to conduct a walkthrough of the virtual environment that is similar to their construction sites to detect potential hazards and adopt suitable alleviations to prevent occupational hazards.

HSM 2: General health monitoring

The physical environment affects how the human body reacts. According to Yang et al., (2017), the most common occupational injury on site (slip, trip and fall) can be observed by changes in worker's gain pattern, for instance, the footstep patterns. Wearable technologies can automatically detect and analyse physiological data such as heart and breathing rate, body posture to keep track of worker's weariness, bad posture to prevent injuries (Nnaji *et al.*, 2021). In the context of environmental sensing, poisonous gaseous, poor air quality, hazardous chemicals leak, unfavourable weather conditions can be incorporated into wearable technology to alert construction workers the potential hazards at sites (Awolusi *et al.*, 2019).

HSM 3: Hazard Identification and Prevention

Every construction project is different, making it impossible to detect all potential hazards. However, with the implementation of smart technologies, hazards identification and prevention can be made easier even before the project starts (Azhar, 2017). Kim et al., (2017) came up with a vision-assisted avoidance system with the integration of AR and wearable technologies that allowed workers to identify occupational hazards and prevent it. Unmanned Aerial

Vehicles (UAV) can be used for data collection to propose a hazard detection system (Shanti *et al.*, 2022). Images and videos taken by UAV serve as a huge contribution for the enlightenment of accident causation and provide solution to prevent it.

HSM 4: Risk Perception, Planning and Assessment

A case study by Choi et al., (2020) showcase the risk perception of operating forklifts. The experiment was assessed using a VR forklift simulation model for various tasks including moving forwards and backwards, loading and unloading as well as making turns. The study suggested various tasks of forklifts impact how much risk is perceived, and it is highly dependent on the complexity of the tasks. Hence, along with the implementation of VR in risk perception, adequate smart technologies such as sensing devices can be integrated into each task in construction projects to reduce the risks on site (Babalola *et al.*, 2023).

HSM 5: Training and Education

Due to numerous instances where knowledge has improved personality traits, work environments and organisational cultures, training and education are key components of occupational safety and health management (Babalola *et al.*, 2023). Knowledge, expertise and awareness workers have with safety place is vital to ensure their safety on jobsite (Hou *et al.*, 2021). The prevalence of accidents in construction sector due to lack of hands-on training and education can be mitigated by integration of VR-based technologies (Xu and Zheng, 2020). The traditional methods of safety training and education provided during tertiary studies was deemed to be ineffective since they are unable to accurately model real-life events on site (Le *et al.*, 2015).

HSM 6: Supervision and Inspection

Monitoring and inspection with the incorporation of smart technologies may ease some of the challenges that come with manual and conventional methods, which contributed to occupational safety and health management (Halder *et al.*, 2023a). Implementation of robotics or UAV offers a more secure and effective methods for carrying out building and infrastructure inspection (Afsari *et al.*, 2021). They increase the accessibility of human inspectors to dangerous locations like decks of bridge or high elevation above ground while shielding them from the related risks. According to Halder et al., (2023a), robots can be utilised not only for projects supervision, it can also monitor dangerous behaviour of construction workers.

Table 2.3.2: Previous Study on Smart Technologies

Complementary Smart Technologies	**Previous Research**								
	(Huang *et al.*, 2022)	(Yap *et al.*, 2021)	(Nnaji *et al.*, 2019)	(Yap *et al.*, 2022)	(Chen *et al.*, 2022)	(Dobrucali *et al.*, 2022)	(Chen and Chang-Richards, 2022)	(Shafiq and Afzal, 2020)	(Nnaji and Karakhan, 2020)
1. BIM									
HSM 1	√		√	√	√	√	√	√	√
HSM 2									
HSM 3	√	√	√	√	√	√		√	√
HSM 4		√	√	√				√	
HSM 5	√	√					√		
HSM 6					√				√
2. Wearables									
HSM 1	√								
HSM 2		√		√		√			
HSM 3		√		√		√			
HSM 4									
HSM 5									
HSM 6				√					
3. UAV									
HSM 1									
HSM 2									
HSM 3			√	√		√	√		√
HSM 4									
HSM 5									
HSM 6		√	√	√		√	√		
4. VR									
HSM 1	√								
HSM 2									
HSM 3	√	√	√	√				√	√

HSM 4	√	√		√		√			
HSM 5	√	√	√	√		√	√	√	
HSM 6		√				√	√		
5. AR									
HSM 1	√				√				
HSM 2									
HSM 3	√	√	√		√		√	√	√
HSM 4						√			
HSM 5	√	√				√	√	√	
HSM 6						√	√		
6. Robotics / Automation									
HSM 1									
HSM 2									
HSM 3		√	√	√	√	√	√	√	√
HSM 4						√			
HSM 5									
HSM 6								√	
7. Warning & Sensing Based Technology									
HSM 1	√	√			√				√
HSM 2		√			√				
HSM 3	√	√	√	√	√	√	√	√	
HSM 4									
HSM 5		√							
HSM 6		√		√	√		√	√	
8. Photogrammetry									
HSM 1									
HSM 2				√					
HSM 3		√		√		√			
HSM 4									
HSM 5									
HSM 6		√		√					

2.4 TOE-TAM Framework

The TOE framework is a well-known framework used to examine the factors that affect how a corporation adopts new technological innovations in the context of technology, organization, and environment(Bryan and Zuva, 2021). This framework shows how these factors affect attitudes towards using technologies, and how they affect the actual system used. ‘Technological’ context refers to the innovation that an organization is now utilizing as well as those that are in the market but have yet to be adopted. Organizational context relates to company size, structure, and human resources. The ‘environmental’ context refers to elements beyond the control of the organization, such as competition, business affiliates, and the industrial environment (Qin *et al.*, 2020a). Songer, Young and Davis, (2001) suggested that incorporating economic variables into the three dimensions mentioned above may contribute to the relevant study. Owing to the considerable risk involved in integrating technologies in construction, a high initial investment will have a direct impact on companies’ decisions (Aliu et al., 2025).

TAM examines PU and PEU to elaborate on why the industry is adopting new technology (Davis, 1989). A technology’s acceptance will increase if it enhances its effectiveness and efficiency while making it more convenient to use. The endpoint of TAM is readiness to use, which indicates the adoption of smart technologies and is influenced by adoption factors and challenges (Ajzen and Driver, 1991). Yap, Lee and Wang, (2021) suggested that the boon in smart technologies has a direct impact on the belief that such innovation will enhance the safety performance at construction sites. Therefore, a study of why organizations implement smart technology in the health and safety context would contribute to its PU.

The TOE framework considers various factors for the adoption of smart technologies, whereas the TAM allows the flexibility of examining external variables to study users' acceptance behavior. The integration of these two models would greatly contribute to the extensive study of the factors and challenges in the adoption of smart technologies in the context of occupational safety and health management. For instance, Gangwar et al., (2015) studied the cloud adoption mechanism in organizations using the combined model of TOE and TAM. Na et al., (2022) conducted research on the implementation of artificial intelligence-based technologies in construction organizations with these integrated models. Qin et al., (2020b) used the integrated TAM-TOE model to examine the factors influencing the adoption of BIM in the construction sector. Figure 2.4.1 shows the conceptual integration model of TOE and TAM.

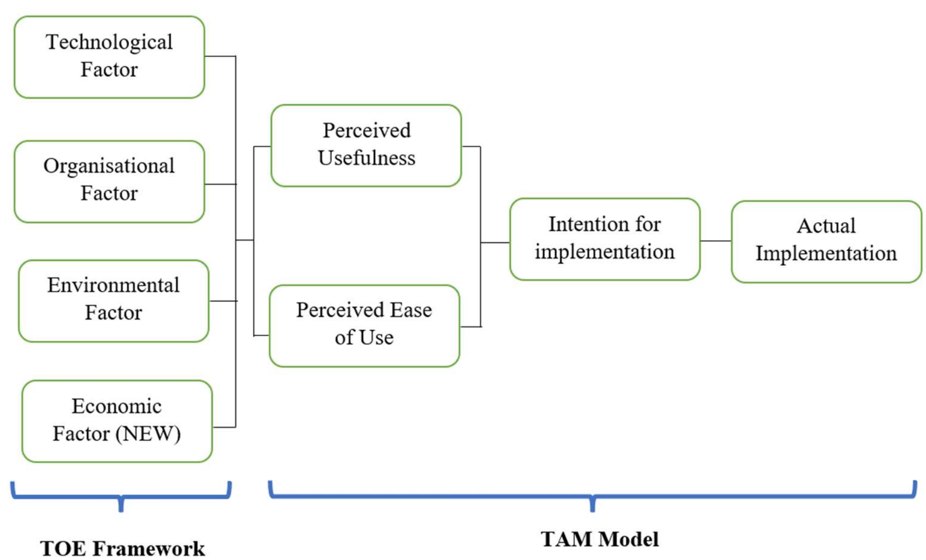

Figure 2.4.1: Integrated TOE-TAM Model

The TAM focuses on individual users' perceptions and attitudes towards technology, whereas TOE considers broader organizational and environmental factors that influence technology adoption. Integrating TAM and TOE provides a more exhaustive understanding of technology adoption in organizations by combining individual user perceptions with organizational and environmental factors. This approach helps technology adopters make informed decisions about technology adoption and improves the success of technology implementation to enhance occupational safety and health management.

Research on enablers of the adoption of technologies in the construction industry has been extensive, however, there is a lack of focus on the correlations between various enablers and is mostly limited to individual attitudes. In response, this study examines the enablers for the adoption of smart technologies in construction from a comprehensive perspective in terms of technological, organisational, environmental context and economical context. Additionally, the existing literature is lacking in a comprehensive assessment of the inhibitors preventing the implementation of emerging technologies in the construction sector. It is of utmost importance that a clear road map regarding the contributions of smart technologies for sustainable construction HSM is needed so that the construction sector can evolve and adapt to the use of emerging technologies to revolutionise the future of the construction safety landscape.
The list of enablers and inhibitors to utilising technologies for construction HSM as identified from the literature review is summarised in Tables 2.4.1 and 2.4.2 respectively.

Table 2.4.1: List of enablers identified from the literature review

Ref	Enablers
TF01	Compatibility
TF02	Relative advantage
TF03	Trialability
TF04	Observability
TF05	Perceived usefulness
TF06	Perceived ease of use
TF07	Technology optimism
OF01	Organisational scale
OF02	Organisational readiness
OF03	Absorptive capacity
OF04	Top management support
OF05	Managerial support
OF06	Human resources
EnF01	Market demand
EnF02	Competitive pressure
EnF03	Government support
EnF04	Trading partner readiness
EcF01	Cost of technology
EcF02	Return on investment
EcF03	High initial investment

Table 2.4.2: List of inhibitors identified from the literature review

Ref	Inhibitors
TC01	Steep learning curve
TC02	Technological limitations
TC03	Data protection and cybersecurity
TC04	Inconvenience of technology
TC05	Interoperability between technology
OC01	Lack of standardisation
OC02	Resistance to change
OC03	Lack of top management support
OC04	Insufficient human resource
EnC01	Poor government policies and incentives
EnC02	Nature of industry
EnC03	Lack of competitive pressure
EnC04	High technology illiteracy
EnC05	Prolonged exposure to virtual environment

Table 2.4.3: Previous Study on Implementation Challenges for Smart Technologies

Challenges	Previous Research										
	(Khalid *et al.*, 2021)	(Rui *et al.*, 2022)	(Prabhakaran *et al.*, 2022)	(Yap, Lam, *et al.*, 2022a)	(Kolaei *et al.*, 2022)	(Nnaji *et al.*, 2018)	(Nnaji and Karakhan, 2020)	(Bademosi and Issa, 2021a)	(Demirkesen and Tezel, 2022)	(Tabatabaee *et al.*, 2022)	(Khudzari *et al.*, 2021)
Technological Dimension											
1. Steep learning curve	√	√			√	√	√			√	√
2. Technological limitations			√	√	√	√		√		√	√
3. Data protection and cybersecurity			√	√			√	√	√	√	
4. Inconvenience caused by technological devices			√					√		√	
5. Interoperability			√		√		√			√	
Organisational Dimension											
1. Lack of standardisation				√			√		√	√	√
2. Resistance to change	√	√					√	√	√		
3. Lack of top management support	√			√		√					√
4. Insufficient human resources		√	√	√		√	√	√	√		
Environmental Dimension											

1. Poor government policies and incentives	√		√			√	√	√	√	√
2. Nature of industry			√	√			√	√		
3. Lack of competitive pressure	√									
4. High technology illiteracy							√		√	
5. Prolonged exposure to virtual environment		√		√						
Economic Dimension										
1. Low Return on Investment (ROI)	√	√	√		√	√	√	√		√
2. High initial investment	√	√	√		√	√	√	√		√

2.5 Hypotheses Development

Drawing from the Technology–Organisation–Environment (TOE) framework and the Technology Acceptance Model (TAM), this study develops a set of hypotheses to examine the enablers and inhibitors of smart technology adoption for health and safety management (HSM) in the Malaysian construction industry.

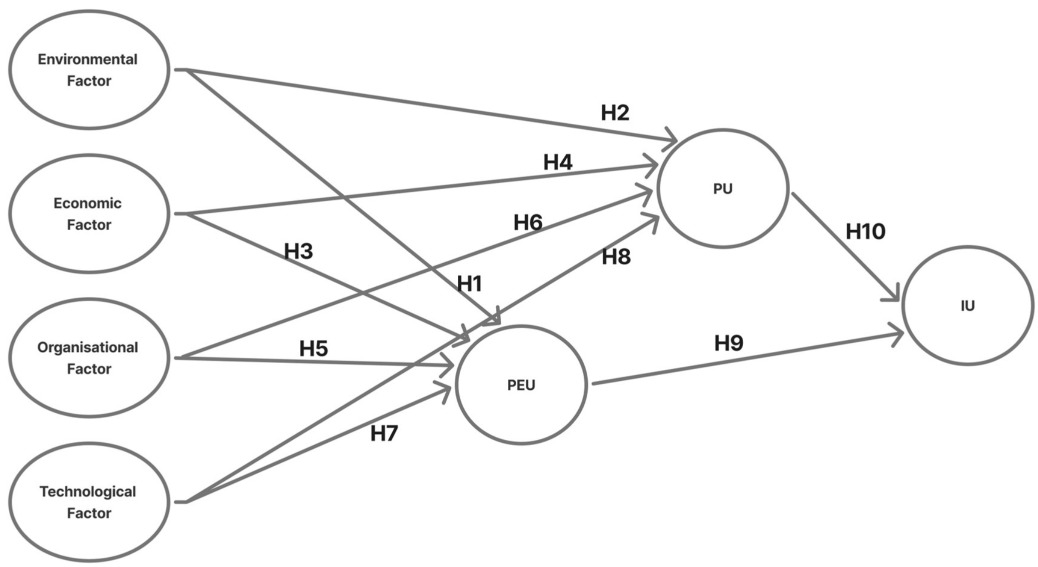

Figure 2.4.2 Hypotheses Development

H1: Environmental factors significantly influence PEU

H2: Environmental factors significantly influence PU

H3: Economic factors significantly influence PEU

H4: Economic factors significantly influence PU

H5: Organisational factors significantly influence PEU

H6: Organisational factors significantly influence PU

H7: Technological factors significantly influence PEU

H8: Technological factors significantly influence PU

H9: PEU significantly influences IU.

H10: PU significantly influences IU.

3.0 RESEARCH METHODOLOGY

This chapter describes the methodological approach undertaken to achieve the research aim and objectives. It outlines the research framework, research design, sampling techniques, data collection process, and data analysis methods. The methodology is designed to ensure the reliability and validity of findings related to the enablers and inhibitors of smart technology adoption for occupational safety and health management in the Malaysian construction industry.

Figure 3.1 shows research framework from conceptual study, data collection, data analysis to data validation.

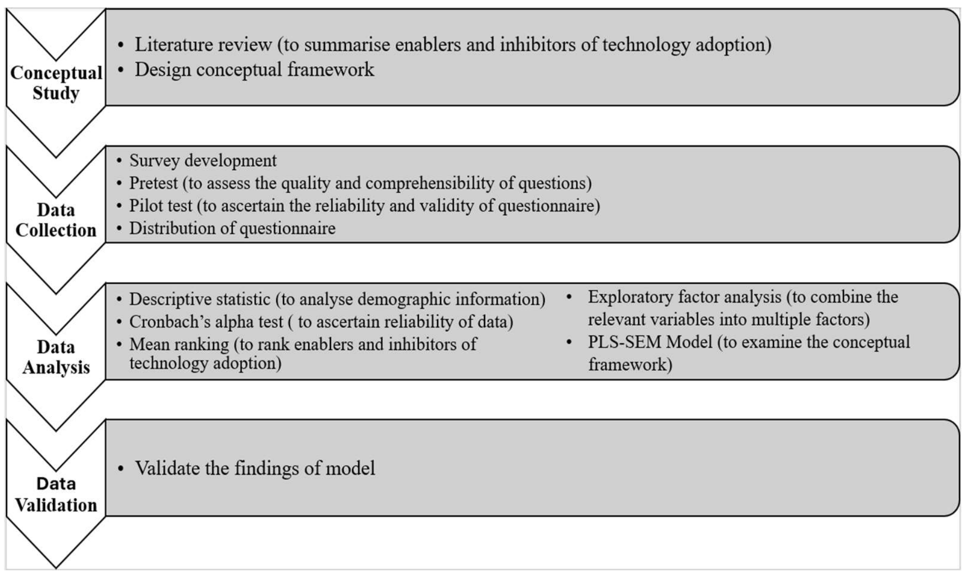

Figure 3.1 Research Framework

3.1 Questionnaire Design

At the time of release, cross-sectional studies were being undertaken to examine the adoption of smart technologies. This study used a questionnaire design to determine population characteristics to achieve the aims and objectives of this research. A validation using interviews with construction experts for the constructed model will be implemented to compensate for the shortcomings of the quantitative analysis method used in this research.

The questionnaire survey consists of Section A to gather demographic information of the respondents with a multi-choice response, including their position in the company, working experience in the construction industry, highest academic qualifications, types and sizes of project. Section B assessed the viewpoints of participants on their level of agreement on determinants that influence the implementation of smart technology from technological, organizational, environmental and economic dimension with a five-point Likert scale (with 1 – strongly disagree and 5 – strongly agree). Section C looked into their level of agreement on the impact of smart technologies on worker behaviour and health and safety culture with a five-point Likert scale (with 1 – strongly disagree and 5 – strongly agree). Section D includes their level of agreement on the following challenges of the integration of smart technologies with occupational safety and health management with a five-point Likert scale (with 1 – strongly disagree and 5 – strongly agree). The last section looked into their level of agreement on the intention and readiness of your company to embrace smart technologies for occupational safety and health management (with 1 – strongly disagree and 5 – strongly agree).

3.2 Sample Selection

The population size (n) and error margin determine the sample size (n) (Sevilla, 1984). For this research, Grade 7 contractors in Malaysia, which is the highest grade in the Construction Industry Development Board (CIDB), are targeted for the questionnaire because they are categorized as the highest grade in CIDB registration. Hence, they have no limitations in the tendering process in terms of project size, making them the best candidates in terms of survey collection, as they are most likely to be chosen for major projects. Grade 7 certification is a recognition of a contractor's talent and performance in a few crucial areas, such as financial stability, project management expertise, technical competency, and compliance with industry standards and laws. The Grade 7 contractors need to have at least five years of experience in the related field, which increases the credibility of the research(Muthusamy and Chew, 2020). Often sought after significant infrastructure projects both locally and globally, these contractors are regarded as elite players in the Malaysian construction sector.

This study used Slovin's algorithm to calculate the sampling size of Grade 7 contractors(Ananda Ismail *et al.*, 2022). The population size of grade 7 contractors is taken from the CIDB website and entered into this algorithm. The number of G7 contractors in Kuala Lumpur, Putrajaya, and Selangor was 1,675, 35, and 3,156, respectively, contributing to a total of 4866 G7 contractors. Because a 95% confidence level of data is required, a marginal error of 0.05 is applied. According to this equation, more than 370 individual respondents were included. Verbal and written consent of human participants has been obtained for the survey.

$$n = \frac{N}{(1+Ne^2)}$$

$$n = \frac{4866}{(1+4866\ x\ 0.05^2)} \approx 370$$

Where n = sample size, N = population size, e = marginal error

3.3 Sampling Technique

The obtained results were subjected to a quality check, along with any possible response biases, before data analysis was carried out. Malaysian construction experts were considered using convenience, snowball, and judgement sampling. Convenience sampling had no set guidelines and would stop data collection as soon as the desired number of responses was obtained, it was considered to be the most effective approach (Etikan, 2017). While judgmental sampling was used to get in touch with contractors who could offer the most knowledge on smart technology in the industry, the snowball strategy expedited the data collection process by connecting with the targeted participants through networking (Fellows and Liu, 2015).

3.3.1 Mean Ranking

Mean ranking is used to rank relevant variables in a study. Mean score ranking from 1-5 is applied in questionnaire with the 5 points Likert scale, ranging from one extreme to another. Higher mean scores indicate that the respondents see the variable with higher importance and vice versa. Standard deviation will be obtained if the variables have the same mean score. Using the 5 points Likert scale in questionnaire, this research has a cut-off point of mean score of 3. This means that any variables with a mean score exceeding 3 is a significant variable. Mean score that fell below 3.0 was regarded to be insignificant for the study. This method will be applied to the second objective of this study which is to determine the barriers for adoption of smart technologies. To test the reliability of the data collected through this research, Cronbach's Alpha will be used to measure the reliability of the data. The internal consistency of data will be measured for the data collected through questionnaire. Generally, when the alpha value is larger than 0.7, it indicates that the sets of data are correlated(Tavakol and Dennick, 2011).

3.3.2 Exploratory Factor Analysis

To ascertain the correlation patterns of a set of variables, exploratory factor analysis is employed as a multivariate statistical method and it is used widely as a data reduction technique by combining the relevant variables into multiple factors (Yap, Lam, *et al.*, 2022a). Hence, large data will be simplified into smaller sets of data that can be manged and understood easily. Factor analysis method will be applied to the first objective which is to examine the underlying structure caused by latent factors for the adoption of smart technologies.

3.3.3 PLS-SEM with Smart PLS

PLS-SEM is a statistical technique used to analyse the relationship between observed variables and underlying latent constructs. The implementation of technology in construction for occupational safety and health management involves a complex web of relationships between various factors such as organizational culture, technology adoption, environmental factors, and economic dimensions. It can model these complex relationships and test the hypothesized relationships between them (Hox and Bechger, 1998). As the topic of this research is multidimensional in nature, it is composed of multiple interrelated factors. PLS-SEM is a boon to measure and analyze these multidimensional constructs, which will be difficult to capture with simpler statistical methods. SEM can be used to test causal relationships between variables and identify the factors that are most important in predicting technology adoption and safety outcomes. Researchers can model and calculate the measurement error linked to each observed variable using the SEM(Lei and Wu, 2007). This improves the reliability and validity of the research. According toHair et al., (2017), PLS-SEM analysis is adopted based on the justification the goal is to determine 'driver' constructs and develop theories in exploratory research, the sample size is small or non-normally distributed and complex structural model with many constructs and indicators.

As a multivariate data analysis technique of the second generation, PLS-SEM empowers researchers to include latent variables that are indirectly assessed through indicator variables. This enables researchers to identify the key drivers in relevant research. Path models were constructed to visually display the hypotheses and relationships between the variables.

(i) Identification of the most significant factors associated with the implementation of smart technologies in each dimension, how they affect PEU, PU, and the intention to adopt. This provides insights into the relative importance and impact of these factors on the implementation of innovation in each dimension.

(ii) Assessment of causal relationships between the factors identified in each dimension and their impact on implementation outcomes. Smart-PLS analysis can provide insights into the complex interplay of factors across dimensions and help identify the most critical causal relationships that influence the implementation of innovation.

(iii) Quantification of the effects of the factors in each dimension on implementation outcomes. Smart-PLS provides numerical values to prioritize and rank factors based on their significance and impact on the implementation of technologies.

The conceptual framework was validated through the development of a hypothesized model and estimated using statistical techniques based on the PLS-SEM approach using SmartPLS 4. After validating the data using PLS-SEM, the measurement model assessment compromised the reliability test, and convergent and discriminant validity were carried out. The path coefficient and R2 value of the endogenous latent variable were displayed in the PLS-SEM model created. Based on the p-value from the statistical analysis, the model's hypotheses were further assessed to determine whether each was supported at the 98% confidence level.

PLS-SEM is a prediction-oriented approach to SEM since it concentrates on explaining variances instead of covariance (Ali *et al.*, 2018), which is suitable for research goals involving theory creation and prediction despite its shortcoming. It supports the goal of the study, which is to determine the main forces behind and obstacles to the adoption of smart technology by investigating the connections between variables affecting PU and PEU.

3.4 Data Collection

To ensure the credibility of the data, a pre-test with three seasoned industry practitioners and academic experts was conducted prior to the survey distribution. This ensured that the data were valid, pertinent, and easy for the respondents to understand. Before data collection, the questionnaires were reviewed and amended to consider all inputs from academic and industry experts. Following the collection of 30 samples, pilot testing was carried out if pre-testing investigations demonstrated the reliability of the data, with Cronbach's alpha values for the latent variable exceeding 0.80.

A total of 675 e-surveys were distributed to the targeted respondents via the LinkedIn platform and email, enabling quick responses and easy contact with the intended audience. Klang Valley, the core of Malaysia’s dominant economy, was the target area. After nearly four months, 376 completed questionnaires were collected, which was approximately 55.6 of the response rate. This surpasses the typical survey rate of 5-15% in studies related to construction (Wong and Soo, 2019). Subsequently, emails and messages were delivered during the process to encourage the participation of industry specialists. Ethics clearance was acquired from the University Tunku Abdul Rahman Scientific and Ethical Review Committee to conduct the survey under expedited review.

4.0 RESEARCH FINDINGS

4.1 Respondents' Background

Table 4.1 summarised the frequencies and percentage of respondents. The respondents of this study comprise mainly individuals holding managerial positions, with managers making up the largest group (43.9%), followed by executives (30.6%), senior managers (20.7%), and directors (4.8%). In terms of working experience, the majority have between 6 to 15 years of experience (61.2%), while 22.1% have 5 years or less, and only 3.7% possess more than 20 years of experience. Regarding academic qualifications, most respondents hold a Diploma/Certificate (41.0%) or a Bachelor's Degree (24.7%), while 23.7% completed high school and 10.6% obtained a postgraduate degree.

In terms of project involvement, a significant portion are engaged in private projects, particularly those valued between 100–500 million (40.4%), while 19.7% are involved in smaller private projects below 100 million, and 17.0% in projects above 500 million. For public projects, 11.4% are engaged in those worth 100–500 million, 7.7% in projects above 500 million, and 3.8% in smaller projects below 100 million.

As for categories of projects, the largest share of respondents are involved in commercial projects (43.9%), followed by residential projects (25.3%). Industrial (12.0%) and civil engineering projects (12.2%) make up moderate proportions, while 6.6% are involved in other types of projects.

Table 4.1: Demographic Background of Respondents

Demographic Information	Categories	Frequency (n)	Percentage (%)
Organisational position	Executive	115	30.6
	Manager	165	43.9
	Senior manager	78	20.7
	Director	18	4.8
Working experience	5 years or below	83	22.1
	6-10 years	114	30.3
	11-15 years	116	30.9
	16-20 years	49	13.0

	More than 20 years	14	3.7
Highest academic qualification	High school (secondary level)	89	23.7
	Diploma / Certificate	154	41.0
	Bachelor’s Degree	93	24.7
	Postgraduate Degree	40	10.6
Types and sizes of project	(Private) Less than 100M	74	19.7
	(Private) 100-500M	152	40.4
	(Private) More than 500M	64	17.0
	(Public) Less than 100M	14	3.8
	(Public) 100-500M	43	11.4
	(Public) More than 500M	29	7.7
Categories of project	Residential	95	25.3
	Commercial	165	43.9
	Industrial	45	12.0
	Civil engineering projects	46	12.2
	Others	25	6.6

4.2 Reliability of research instrument

The Cronbach’s alpha values for enablers and inhibitors surveyed where perceived effectiveness were 0.857 and 0.816 respectively as shown in Table 4.1.1 These values are greater than 0.8, indicating that they are highly reliable and have good internal consistency (Yap *et al.*, 2022).

Table 4.2.1 Cronbach’s Alpha Values

Variables surveyed	Cronbach’s alpha	Number of items
Enablers	0.878	20
Inhibitors	0.857	14

4.3 Mean Ranking

4.2.1 Ranking of Enablers

Table 4.2.1.1 shows the mean scores and standard deviation of the importance ratings for the top three enablers.

Table 4.3.1.1 Mean and Ranking of Enablers

Ref	Enablers	Mean	SD	Rank
EcF02	Return on investment	4.45	0.699	1
TF02	Relative advantage	4.40	0.766	2
EcF04	High initial investment	4.16	0.602	3

The industry places a strong emphasis on financial criteria when assessing new technology investments, as evidenced by the high mean rating for return on investment (ROI). The implementation of a new technology that offers measurable advantages could effectively counterbalance associated application costs. Nevertheless, capturing the costs and benefits of using new innovations before and after their application can be challenging, as there are significant intangible benefits that make calculating the ROI more complex (Cao *et al.*, 2015).

The second most important enabler is a relative advantage, or the perceived superiority of new technology over current practices. The benefits that the company receives from using smart technologies in HSM have a direct relationship with its relative advantage (Sabbah *et al.*, 2019). The heavy focus on relative advantage suggests that technologies with definite, observable advantages over existing methods are likely to be adopted by contractors.

Numerous studies have suggested the astronomical cost in terms of technology adoption in BIM (Davila Delgado *et al.*, 2019), robotics and automation (Bademosi and Issa, 2021b) and AR (Nassereddine *et al.*, 2022). The high cost of adopting smart technology indicates that further financial limitations and the absence of funding options like bank loans with long terms could be significant challenges to technology adoption (Yap, Lam, *et al.*, 2022b).

4.3.2 Ranking of Inhibitors

Table 4.3.2.1 shows the mean scores and standard deviation of the importance ratings for the top three inhibitors.

Table 4.3.2.1 Mean and Ranking of Inhibitors

Ref	Inhibitors	Mean	SD	Rank
TC01	Steep learning curve	4.41	0.838	1
OC02	Resistance to change	4.40	0.682	2
EnC04	High technology illiteracy	4.38	0.717	3

Steep learning curve received the highest mean ranking, indicating that it is perceived as the most significant inhibitor. Implementing smart technologies that necessitate substantial adjustments to ingrained habits and challenging learning curves has detrimental effects on users' perceived usefulness and perceived ease of use (Na *et al.*, 2022b). Consumers frequently need to pick up new skills and adjust to new systems when smart technologies are implemented, which can be difficult and time-consuming. It is evident from Jamal et al.'s research that the respondents are worried about the implementation of BIM since it is a relatively new technology which would impose a steep learning curve (Ahmad Jamal *et al.*, 2019).

Smart technology integration may cause workflow disruptions and necessitate that staff members adopt new procedures. Due to resistance to change in the direction of such adaption, organisations are unable to fully adopt and comprehend the benefits of digitalised construction (Demirkesen and Tezel, 2021). According to Akcay, the most prominent reason for the slow adoption of BIM is due to reluctance to learn innovation (Akcay, 2022).

Lawluvy et al. suggest that opposition to change (second highest mean ranking) and technology illiteracy are highly related as resistance arises from illiteracy (Lawluvy *et al.*, 2022). Some people may lack the knowledge and abilities needed to use smart technologies efficiently. People who are not tech-savvy could be intimidated by new technologies (Yap, Lam, *et al.*, 2022b). They might not have faith in their capacity to pick up new skills and adjust to strange devices and systems, resulting in them opting for traditional methods of working. Insufficient skilled personnel working in the construction industry leads to the lack of adoption of smart technologies in the construction industry (Prabhakaran *et al.*, 2022).

4.4 Correlation between enablers and inhibitors

Spearman correlation test examines whether two variables are correlated with one another or not. A perfect negative correlation is represented by a value of -1, no correlation is shown by a 0 and a perfect positive correlation by 1 (J and S, 2018). Given that, an increase in one variable causes an increase in the other and vice versa, two variables that show a tendency to move in the same direction are said to have a positive correlation. A detailed breakdown of the degree of correlations and their corresponding interpretations is given in Table 4.3.1. A close examination of Table 4.3.1 reveals that TF02 (Relative advantage) has the highest relation with inhibitors including TC05 (Interoperability), OC01(Lack of standardisation), OC02 (Resistance to change), OC03 (Lack of top management support) and EnC04 (High technology illiteracy). EcF02 (Return on investment) is highly related to TC01 (Steep learning curve) and OC02 (Resistance to change) as well.

Interoperability between various smart technologies makes it difficult for various technologies to work together and integrate seamlessly (sawal and Wankhede, 2025). Many smart technologies are used in various construction projects, including drones, Internet of Things (IoT) sensors, BIM and project management software (Silverio-Fernandez *et al.*, 2019). Every technology has its own set of operating systems, unique data formats, and possible communication protocols (Duarte-Vidal *et al.*, 2021). Tang et al. attest to the issue of seamless integration between on-site IoT sensors gathering real-time data and the BIM software used by architects (Tang *et al.*, 2019b). The disparity in data structures and file formats between these systems may make it more difficult to share and use information. The benefit of these technologies may be lessened if systems are unable to share or communicate data effectively, leading to operational inefficiencies and information silos. The deployment of smart device technologies may be hampered by the challenge of integrating new technologies with pre-existing equipment. Any object used in a construction project can be connected to a network of devices to collect data on the project, according to the concept of the IoT (Silverio-Fernandez *et al.*, 2019). We must take into account the interoperability of new and current devices to successfully transition from traditional construction to a new paradigm that takes the IoT into account.

Lack of standardization may impede the perceived benefits of smart technologies in promoting health and safety. The perceived benefits may be lessened if each technology adheres to different standards, as this can make it difficult to integrate them smoothly. Delgado et al. reiterate that the incompatibility of data standards hinders the adoption of BIM (Davila Delgado, Oyedele, Demian, *et al.*, 2020).

The main obstacles impeding the adoption of innovation are the lack of international standards and data-sharing protocols, lack of government support and policies, and financial limitations (Kumar *et al.*, 2021). Many construction companies continue to operate with long-standing legacy systems and procedures. The implementation of new standardized technologies frequently necessitates a significant shift in workflow and may encounter resistance because of the expenses and effort required to move away from these well-established systems (Muñoz-La Rivera *et al.*, 2021). It is evident from a study by Chan et al. that there is still a dearth in standardisation of BIM which hinders the adoption of this innovation (Chan *et al.*, 2019).

According to Bademosi and Issa, low technology literacy is the top barrier to the adoption of robotics and automation in the construction industry, which may show up as a resistance to learning new skills or a lack of comprehension (Bademosi and Issa, 2021b). Even if smart technologies have a lot to offer, they might go unrealized if the workforce lacks the knowledge or abilities to use them and reap their benefits. A lack of support from upper management can impede the relative advantage of smart technologies in the construction industry (Al Kurdi *et al.*, 2021). Lower-level employees may become reluctant or even actively resist the use of smart technologies for health and safety if senior management fails to adequately explain and endorse them. These developments are harder to put into practice without top-down support, which reduces their potential impact (Jere and Ngidi, 2020).

Smart technologies frequently have a learning curve. Workers require time to get used to and proficiently use these new tools. The adoption process may be hindered by the time and resources needed for training because of the temporary reduction in productivity that occurs during the learning phase. Despite significant return on investment from smart technologies, there may be a barrier due to the initial training costs, possible downtime, and learning curve (Ismail *et al.*, 2017). Putting aside the potential long-term benefits, companies may be discouraged from investing in these technologies if the learning curve is excessively steep when companies are uncertain about the return on investment in construction projects. Figure 4.3.1 shows the results of correlation between enablers and inhibitors.

Inhibitors \ Enablers	TF01	TF02	TF03	TF04	TF05	TF06	TF07	OF01	OF02	OF03	OF04	OF05	OF06	EnF01	EnF02	EnF03	EnF04	EcF01	EcF02	EcF03	Total significant correlations
TC01	0.287**	0.345**	-	0.135**	-	-	-	-0.331**	0.222**	-	-	-	0.257**	-	-	-	0.305**	-	0.449**	0.133**	9
TC02	0.142**	0.347**	-	-	0.118*	0.174**	0.247**	-0.136**	0.136**	0.134**	-	-	0.157**	-	-0.142**	-0.173**	-	-.0161**	0.280**	0.110*	14
TC03	0.148**	-0.188**	0.364**	0.372**	0.252**	0.346**	0.250**	0.333**	0.177**	-	0.150**	0.301**	0.192**	0.169**	0.292**	0.325**	-	0.240**	-.0180**	0.124*	18
TC04	0.157**	0.361**	-	0.118*	-	-	0.148**	-0.333**	-	-	-	-	-	0.134**	-0.131*	-	-	-	0.335**	0.229**	9
TC05	0.253**	0.428**	-	-	0.205**	0.134**	0.286**	-0.169**	0.228**	0.128*	-	-	0.148**	-	-0.120*	-	0.134**	-	0.356**	0.206**	13
OC01	0.233**	0.440**	-	-	0.233**	0.182**	0.303**	-0.136**	0.187**	0.187**	-	-	0.106*	-	0.138**	-	-	-	0.278**	0.134**	8
OC02	-	0.476**	-	-	-	-	-	-0.307**	0.132*	-	-	-	-	0.109*	0.185**	-0.167**	-	-	0.308**	0.180**	8
OC03	0.140**	0.423**	-	-	0.269**	0.243**	0.264**	-	0.176**	0.244**	-	0.172**	-	-	2.225**	-	-	-	0.254**	0.135**	11
OC04	0.244**	0.315**	-	-	0.241**	0.181**	0.313**	-	0.191**	0.196**	-	0.169**	0.240**	-	-	-	-	-	0.328**	0.160**	9
EnC01	0.367**	-	-	0.158**	0.159**	0.173**	0.190**	0.203**	-	0.155**	0.166**	0.282**	0.263**	-	0.164**	0.252**	0.234**	0.134**	-	0.145**	15
EnC02	0.191**	-	0.295**	0.194**	0.274**	0.318**	0.270**	-	0.141**	-	-	0.157**	0.212**	0.158**	-	0.186*	-	0.127*	-	0.152**	13
EnC03	0.198**	-	0.307**	0.266**	0.294**	0.284**	0.370**	0.120*	0.172**	-	-	0.240**	0.183**	0.141**	0.121*	0.163**	0.128*	0.151**	-	0.190**	16
EnC04	-	0.459**	-	-0.103*	0.118*	-	0.164**	-0.314**	-	-	-	-	-	-	-0.188**	-2.39**	-	-	0.331**	0.153**	9
EnC05	-	0.314**	-	-	-	-	0.194**	-	-	0.228**	-1.25*	-	-	-	-1.57**	-	-	-0.116*	0.141**	-	13
Total significant correlation	11	11	3	7	10	9	12	10	10	7	3	6	9	5	11	7	4	6	11	13	

Figure 4.3.1 Correlation Between Enablers and Inhibitors

4.5 Factor Analysis

Table 4.4.1 tabulates the results of factor analysis according to each group factor and they are reduced into six group factors which are technology acceptance and trustworthiness, management commitment, external environmental influence, cost-benefit perception, economic viability, and organisational capacity.

Table 4.5.1 Factor Loading and Percentage Variance

	Factor Loading	Eigenvalues	Percentage Variance	Cumulative Percentage of Variance
Factor 1: Technology Acceptance and Trustworthiness		6.243	31.217	31.217
TF05 Perceived Usefulness	0.647			
TF04 Observability	0.631			
TF06 Perceived Ease of Use	0.622			
TF07 Technology Optimism	0.598			.
TF03 Trialability	0.588			
TF01Compatibility	0.441			
Factor 2: Management Commitment		2.257	11.286	42.503
OF05 Managerial Support	0.680			
OF04 Top Management Support	0.676			
OF06 Human Resources	0.626			
Factor 3: External Environment Influence		1.682	8.411	50.914
EnF04 Trading Partner Readiness	0.726			
EnF02 Competitive Pressure	0.615			
EnF03 Government Support	0.560			
Factor 4: Cost-Benefit Perception		1.418	7.092	58.005
EcF02 Return on Investment	0.720			
TF02 Relative Advantage	0.651			
EcF04 High Initial Investment	0.415			
Factor 5: Economic Viability		1.143	5.713	63.718
EcF01 Cost of Technology	0.757			

EnF01 Market Demand	0.597			
Factor 6: Organisational Capacity		1.048	5.241	68.959
OF03 Absorptive Capacity	0.607			
OF01 Organisational Scale	0.554			
OF02 Organisational Readiness	0.409			

Factor 1: Technology Acceptance and Trustworthiness

Factor 1 accounted for 31.217% of the total variance explained which was the highest among all the factors. The degree to which smart technologies can enhance job performance and the level of enjoyment people derive from using them are the primary factors influencing people's intention to use them in the workplace (Hewavitharana *et al.*, 2021). Usefulness of new innovations, visibility of benefits, ease of use, trust in the potential of benefits, ability to trial and alignment with existing practices work together to affect how an individual decides which new technology to adopt. (Nnaji and Karakhan, 2020) employed factor analysis in a recent stufy to classify safety technology adoption predictors based on external, organisational and technological factors.

With a 25.63% total variance explained, technology predictors account for the largest portion of the variance. Reliability, the efficacy or technology, accessibility of technical support are the variables that contributes in the technology predictors. (MA Bhatti, 2022) further reiterates that the primary focus of integration of smart technologies in construction industry is employee's perceptions of these innovation. Abolfotouh et al., (2019) and Kim et al., 2019) provided more evidence towards this theory as personnels are more likely to embrace technology as part of the adoption of smart systems and to attain sustainable job performance if they believe these innovations are beneficial and practical.

The degree of acceptance and reliability that users assign to technology is determined by a combination of these factors. These variables are the subjective measures that take into account of technology’s functionality, end product’s quality, and consumer satisfaction (Silverio-Fernández *et al.*, 2021). When the experimental process of smart technology usage is positive, it contributes to a higher chance of adoption. Application of emerging technology by smart construction enterprises is contingent upon its expected value as an economic behaviour (Yang *et al.*, 2018). Thus, perceived usefulness isa direct influence on how valuable people believe it to be. To ensure that a new technology meets user needs and earns their trust and acceptance, it is important to recognize and address these factors collectively as they significantly impact on how successful a new technology is adopted and integrated into a particular environment.

Factor 2: Management Commitment

Factor 2 accounted for a total variance of 11.286 of the total variances explained. This factor grouping mainly looked into the three groups of personnel which includes mid-level managers who actively participate in decision-making and project management which provides support and encouragement from those in charge of daily operations; organization's leaders and higher-ranking executives' support which highlights how crucial technology has to be in line with the building company's overarching strategic vision and objectives; human resource support which is the abilities, education and general assistance employees offer. It is evident from Abbasnejad et al., (2021) research that highlights the importance of management's technological expertise, ability to lead and willingness to adapt in the process of technology diffusion of BIM in a construction firm. He emphasised on the supporting role by upper management in an organisation to enable and motivate staffs to adopt new technologies.

Regardless of the safety benefits provided by technologies, their full potential has not been realized as the challenges are associated with adoption within the organisation by executives and management (Yap *et al.*, 2022). Earlier research has pointed out that culture within an organisation begins at the leadership level, influencing employees to model their decision-making after the behaviour of top management (Yap and Chow, 2020). As a result, senior management must take the initiative and actively encourage safety initiatives at all levels. Organisations should fortify their organisational safety culture and make a commitment to introducing cutting-edge technology. A company that prioritizes technology will typically invest in areas that could encourage adoption or dedicate resources to purchasing new technology. The development of technologically proficient construction professionals can be extremely beneficial to the efficient application of new innovation. This emphasises how important it is for an organisation to allocate the resources required for developing new skills and improving the skill set of its current workforce.

Factor 3: External Environment Influence

The third factor accounted for 8.411 of the total variances explained, emphasising the significance of trading partner readiness, competitive pressure, and government support in technology diffusion in an organisation. These encompassing factors include all the outside factors and conditions that affect how technology is adopted in the construction sector. Trade partner readiness indicates how ready and willing other parties in the construction sector are to accept and use new technologies, including suppliers, customers, and partners. Recent research from (Ruangkanjanases *et al.*, 2022) emphasize that the preparedness of both organisational partners is crucial to optimise the technology in use. To support the readiness of blockchain integration in construction industry, it is imperative to encourage the partners to get ready for the integration and develop the relevant stakeholder understanding (Wang *et al.*, 2010).

The competitive pressure refers to the impact of rival companies in the industry pushing for the adoption of technology to obtain a competitive advantage, as well as the influence of market competition (Cruz-Jesus *et al.*, 2019). Government, being the top of the hierarchy in occupational health and safety department denotes the part played by laws, subsidies and other initiatives that ease the use of technology in the building industry (Yap *et al.*, 2022). The top-down strategy that is currently being used to promote adoption emphasizes the critical role that government plays in spreading adoption. As Davila Delgado et al., 2019) suggested, public infrastructure spending has a significant influence on the uptake of new technology. It is evident from (Enshassi *et al.*, 2016) that the Singaporean government has spearheaded the adoption of BIM in Asia and mandated its use in numerous public projects. Through the amalgamation of these three factors into a unified category, this research investigate the ways in which these exogenous factors jointly mold and impact the technological terrain of the construction sector.

Factor 4: Cost-Benefit Perception

The fourth factor accounted for 7.092 of the total variances explained, emphasising the significance of aspect related to investment and beneficial technological attributes. (Alaloul *et al.*, 2020) research suggests that the unpredictability of investment returns hinders the implementation of innovation in the industry. The fundamental tenet of investment perspective is that there is not any concrete proof that implementing robotics will result in lower asset delivery costs (Davila Delgado *et al.*, 2019). This lack of evidence is a major barrier in the construction industry, which is a low-profit and high-risk sector. More precisely, no comprehensive cost-benefit analysis of robotics adoption has been published in the literature, unlike studies on sustainability for instance (Pan *et al.*, 2018). The possibility of lowering labour and injury costs associated with smart technology adoption is commonly recognized. Studies on potential time saving have calculated that up to 50% of the time needed can be saved by employing robots for certain construction tasks which enhance health and safety perspective (Perkins and Skitmore, 2015). Nevertheless, these studies concentrate only on specific tasks while ignoring the financial and time implication of extra training and safety regulations. These factors further emphasize the importance of diffusion of smart technology from the investment point of view.

It is essential to note that when a new technology offers more benefits than existing ones, an organisation is more likely to adopt it (Perkins and Skitmore, 2015). Through the integration of these three variables into one factor group, scholars can investigate how companies view the financial consequences of implementing technology in the building industry. This consolidated factor offers insights into the overall economic factors influencing technology adoption in the construction industry by enabling a more focused examination of the interplay between the perceived benefits, expected returns, and initial investment challenges. The impact of comparative advantage or relative advantage on users' perceptions of the utility of building technologies is demonstrated empirically by (Wang *et al.*, 2019). Relative advantage has also been proposed as an antecedent of technology adoption in other literature (Al-Rahmi *et al.*, 2019) which established its significance in technology diffusion in the industry.

Factor 5: Economic Viability

Cost of technology and market demand contributes to the fifth factor with a total variance of 5.713. (Adaloudis and Bonnin Roca, 2021) suggests that in the ensuing decades, it is projected that the labour shortage will get worse. Cost of Technology includes the out-of-pocket costs for purchasing, putting into practise, and keeping up the technical solutions used in the building operations (Chen *et al.*, 2023) which is a substantial influence in adoption of technology. Numerous studies have suggested the astronomical cost in terms of technology adoption in BIM (Davila Delgado *et al.*, 2019), robotics and automation (Bademosi and Issa, 2021b) and AR ((Nassereddine *et al.*, 2022). The high cost of adopting smart technology indicates that further financial limitations and the absence of funding options like bank loans with long terms could be a significant obstacle to technology adoption (Ebekozien and Samsurijan, 2022).

It is believed that the labour shortage would drive technology into the industry rather than the technology driving out workers. It is an indisputable fact that market demand affects technological adoption greatly. It is important to note that cost is an important predictor in technology adoption. The examination of the economic factors and external pressures that organisations consider before adopting new technologies can be facilitated by this consolidated component, which offers a narrow focus. Nevertheless, the theories towards market demand regarding innovation are contradictory. (Davila Delgado, Oyedele, Beach, *et al.*, 2020) suggests that construction companies lacks understanding of the dynamics of immersive technology hardware and software market, making it challenging to compare decides and get advice regarding procurement plans. These challenges are mostly caused by the inexperience of AR and VR markets as well as a dearth of professional guidance. In the engineering and construction sectors, immersive technology is not well-regarded as the perception towards them are primarily for entertainment purposes and having little application in intricate engineering tasks. This idea, however, ignores the enormous potential advantages that engineering-grade AR and VR technologies can have for the AEC (Architecture, Engineering and Construction) industries. Adoption efforts are hampered by the notion that AR and VR technologies are solely for entertainment because there is not enough time for testing. Despite the conflicting opinion in terms of market demand for technologies, it is an indisputable fact that it is one of the predictors in technology diffusion in the industry.

Factor 6: Organisational Capacity

The last factor accounts for 5.241 of the total variances explained, with absorptive capacity, organisational scale and organisational readiness in consideration. Findings by Safie et al., (2025) imply that even businesses with access to cutting-edge technology are unlikely to succeed in integrating if there are insufficient policies, skills, and resources available. Technologies have a wide range of safety advantages, but their uses in building projects have not yet reached their full potential. The challenges of adoption at the organisational level may be a major contributing factor (Yap *et al.*, 2022). The ability of an organisation to identify, absorb, and use new ideas and technological knowledge is determined by each personnel's educational background and expertise in related fields (Limaj & Bernreturn der, 2019) which affects the diffusion and application of smart technology. Further attest that higher education levels and more innovative activities among staff members were positively correlated with high absorptive capacity, which is beneficial to adoption of innovation (Schmidt, 2009).

Organisational Scale indicates the size and reach of the organisation by taking into account variables including the size of the workforce, the scope of projects, and the organization's overall ability to adopt and maintain technological advancements. (Cruz-Jesus *et al.*, 2019) asserts that firm size is a predictor of technology adoption within the organisational context. Zhang et al.,

(2019) study has proven that as an organisation grows, it can offer more resources such as training programs related to innovation. Large organisational structures tend to be more flexible and diversified, which is more conducive to the establishment and growth of small informal organisations. It was further proven in the study that large organisations are more motivated to make promotional decisions than small and medium-sized organisations, which affects their keenness to adapt to the changes brought about using technology in construction processes. This unified factor group shows the ways in which an organization's internal competencies, scale, and general preparedness all work together to impact its capacity to integrate and utilise technology in the construction sector. This combined factor offers a more thorough understanding of the organisational elements that support effective technology adoption.

4.6 PLS-SEM with SmartPLS

4.5.1 Structural Equation Modelling - Measurement Model

1. Common Method Bias

The Variance Inflation Factor (VIF) values of the inner model were used to evaluate the common method bias. Because every VIF result in the current study was less than 3.33, as shown in Table 4.2.6.1, the model was free of common method bias (Kock, 2015).

2. Reliability and Validity

Composite Reliability (CR) was used to measure the reliability of the variables. Internal consistency reliability was the first requirement in a measurement model to be looked at. Composite reliability (CR), which takes into account different outer loadings of the indicators, was used in this investigation. CR values are separated into tolerable (0.60–0.70), satisfactory (0.70–0.90), and unfavourable (>0.95) (Hair *et al.*, 2017). Hence, factor loadings below 0.600 were excluded to maintain a strong measurement model. Table 4.5.1.1 displays the findings for validity and reliability as well as the factor loadings for the remaining items.

Subsequently, Table 4.5.1.1 assessed the Convergent Validity (CV) which provided an explanation for the association between the indicators under the same construct. Factor loadings (FL) and average variance extracted (AVE) were considered in order to evaluate the validity of a reflective measurement model. CV is supported by the fact that all CRs were greater than the suggested threshold of 0.700, and that the Average Variance Extracted (AVE) was higher than 0.500 (Hair *et al.*, 2017).

The amount of a specific concept that can be separated from other latent variables is known as Discriminant Validity (DV) (Rehman Khan and Yu, 2021). Fornell-Larcker was traditionally recommended for Discriminant Validity (DV), although it was criticized for having low sensitivity (Cepeda Carrión *et al.*, 2016). Despite the conceptual differences between these notions, it may not always be easy to identify them empirically in different research settings. To evaluate DV in this case, cross-loadings and the heterotrait-monotrait (HTMT) criterion, which prioritized sensitivity and specificity, were applied. According to the results in Table 4.5.1.2, each item loaded the most with its parent construct. Table 4.5.1.3 demonstrates that the HTMT values fall below the 0.85 criterion and the constructs differ from one another empirically.

Table 4.6.1.1: VIF, Item Loadings, Reliability and Validity

	VIF	Loadings	Composite reliability (rho_c)	Average variance extracted (AVE)
Environmental factor			0.775	0.537
EnF01	1.172	0.650		
EnF02	1.170	0.689		
EnF03	1.346	0.845		
Economical factor			0.839	0.638
EcoF01	1.231	0.674		
EcoF02	1.604	0.835		
EcoF04	1.631	0.873		
Organisational factor			0.870	0.629
OF02	1.279	0.647		
OF04	1.649	0.793		
OF05	2.067	0.865		
OF06	2.071	0.850		
Technological factor			0.809	0.586
TF01	1.113	0.725		
TF03	1.573	0.733		
TF04	1.641	0.833		

Table 4.6.1.2: Cross Loading

	E1	EnF	EcoF	OF	PEU	PU	TF
E1	1	0.109	0.054	0.317	0.207	0.276	0.172
EnF01	-0.142	0.65	0.439	0.222	0.212	0.225	0.422
EnF02	0.361	0.689	0.199	0.391	0.265	0.221	0.076
EnF04	0.014	0.845	0.317	0.268	0.318	0.279	0.254
EcoF01	-0.025	0.366	0.635	0.258	0.156	0.209	0.34
EcoF02	-0.077	0.308	0.837	0.425	0.268	0.207	0.428
EcoF03	0.037	0.31	0.853	0.441	0.308	0.259	0.506
OF02	0.235	0.307	0.421	0.647	0.322	0.252	0.395
OF04	0.196	0.308	0.356	0.793	0.345	0.377	0.29
OF05	0.248	0.318	0.404	0.865	0.435	0.433	0.435
OF06	0.332	0.336	0.456	0.85	0.399	0.372	0.361
PEU	0.207	0.366	0.304	0.472	1	0.655	0.558
PU	0.276	0.331	0.283	0.454	0.655	1	0.565
TF01	0.358	0.297	0.425	0.417	0.459	0.493	0.725
TF03	-0.031	0.214	0.376	0.239	0.298	0.319	0.733

TF04	0.009	0.237	0.405	0.387	0.483	0.449	0.833

Table 4.6.1.3: HTMT

	E1	EnF	EcoF	OF	PEU	PU	TF
E1							
EnF	0.315						
EcoF	0.165	0.692					
OF	0.357	0.606	0.676				
PEU	0.207	0.483	0.334	0.531			
PU	0.276	0.441	0.324	0.507	0.655		
TF	0.214	0.619	0.725	0.624	0.667	0.678	

4.6.2 Structural Equation Modelling - Structural Model

Table 4.5.2.1 shows all the VIF values for this study are below 5.00, which indicates that it has no collinearity issue (Becker et al., 2015). A high correlation between the constructs is inappropriate according to the PLS-SEM theory, claim Hair et al. (2017).

The R2 measures and the path coefficient between the latent variables were then evaluated to verify the model's quality. While the route coefficient showed the links between the latent variables, R2 measures showed how much of the variance in an endogenous variable was explained by the exogenous constructs (Durdyev *et al.*, 2018).

The explanatory power of the model is indicated by R^2, which shows the variance explained in each of the endogenous constructs (Shmueli and Koppius, 2010). The results in Figure 4.5.3.1 show that all the R^2 results for PU is 0.394 and PEU 0.4 respectively, indicating that that 39.4% and 40% of the variance in them have been explained by factors of technology adoption, which shows that the model explanatory power is substantial (Cohen, 1988). The R^2 for E1 is 0.077, denoting that 7% of the variance in E1 can be explained by PU and PEU, which is satisfactory. Since the model is less sophisticated, the R2 values obtained are low. Since it greatly depends on the model complexity, where more exogenous variables raise the R2 value of the endogenous variables, the PLS-SEM theory states that there is no set acceptable value for R2 (Durdyev *et al.*, 2018; Tenenhaus *et al.*, 2005; Yuan, 2012).

Table 4.6.2.1: VIF Inner Model

	E1	EnF	EcoF	OF	PEU	PU	TF
E1							
EnF					1.298	1.298	
EcoF					1.677	1.677	
OF					1.521	1.521	
PEU	1.753						
PU	1.753						
TF					1.504	1.504	

4.6.3 Direct hypotheses results

The measurement model demonstrated reasonable validity and reliability of the gathered data. Using 5,000 resamples, bootstrapping was used to evaluate the hypotheses. It is discovered that bootstrap, a computer-intensive resampling strategy is better than alternative approaches which frequently assume things that aren't true, like that the indirect impact has a normal distribution (Alfons *et al.*, 2022). The bootstrap is usable in a greater range of scenarios since it makes fewer assumptions, particularly in cases when analytical formulations for the standard errors are unavailable. As a result, the bootstrap offers general methods for consistently creating indirect effect confidence intervals (MacKinnon *et al.*, 2007; Preacher and Hayes, 2004). The p-value was used to conduct the hypothesis tests, and a p-value less than 0.05 meant that the hypothesis was supported with 95% confidence. Table 4.5.3.1 displays the results of tfhe SEM of the bootstrapping procedure. It is important to note that the key findings of the hypotheses show that PEU does not have a considerable effect on intention of adoption whereas PU have a considerable effect on intention of adoption.

Table 4.6.3.1 Results of Structural Model

Hypothesis	Beta Coefficient	Standard deviation	T statistics	P values	Decision
H_1. EnF -> PEU	0.160	0.056	2.838	0.005	supported
H_2. EnF -> PU	0.130	0.045	2.880	0.004	supported
H_3. EcoF -> PEU	-0.107	0.055	1.937	0.053	supported
H_4. EcoF -> PU	-0.148	0.050	2.958	0.003	supported
H_5. OF -> PEU	0.256	0.061	4.188	0.000	supported
H_6. OF -> PU	0.250	0.056	4.455	0.000	supported
H_7. TF -> PEU	0.444	0.052	8.480	0.000	supported
H_8. TF -> PU	0.486	0.055	8.759	0.000	supported
H_9. PEU -> E1	0.045	0.070	0.651	0.515	Not supported
H_{10}. PU -> E1	0.246	0.070	3.520	0.000	supported

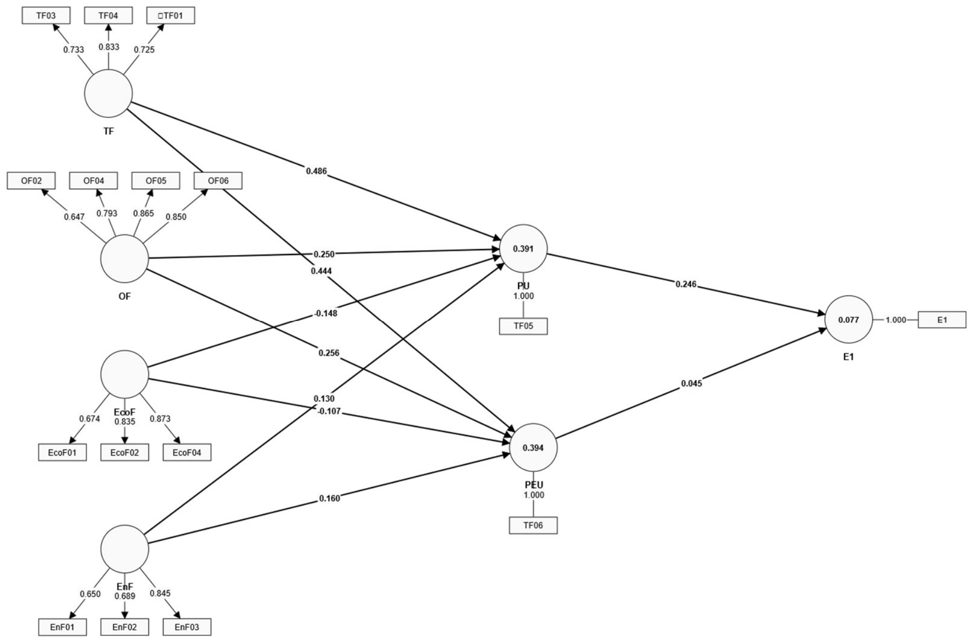

Figure 4.6.3.1 Structural model with path coefficients and R^2 value

H_1. Environmental factors have a significant positive influence on the PEU.

H_2. Environmental factors have a significant positive influence on the PU.

Figure 6 shows the structural model with path coefficients and R^2 . EnF → PEU (0.160, $p < 0.05$) and EnF → PU (0.130, $p < 0.05$) indicated that market trends, competitive pressures, and the government can positively influence PEU and PU. These pathways imply that regulations like mandatory use of technology in construction industry could encourage technology adoption. In construction safety, technology adoption is often non-voluntary – mandated by regulations or company policy Perera et al., (2025). The government, at the top of the hierarchy in the occupational health and safety department, denotes the part played by laws, subsidies, and other initiatives that ease the use of technology in the building industry (Yap *et al.*, 2022). The top-down strategy currently being used to promote adoption emphasizes the critical role that the government plays in spreading adoption. As Davila Delgado et al., (2019) suggested, public infrastructure spending significantly influences the uptake of new technologies. This is akin to the findings of Qin et al., (2020a) as strengthening the culture of technological implementation will bring in the standardization of technolog.

H_3. Economic factors have a substantial negative influence on the PEU.
H_4. Economic factors have a substantial negative influence on the PU.
The accessibility and affordability of smart technology solutions are affected by economic issues, which have a substantial impact on PEU and PU. The cost of technology includes the out-of-pocket costs for purchasing, putting into practice, and maintaining the technical solutions used in building operations, (Chen *et al.*, 2023) which has a substantial influence on technology adoption. Numerous studies have suggested astronomical costs in terms of technology adoption in BIM(Davila Delgado *et al.*, 2019), robotics, automation, (Bademosi and Issa, 2021b) and AR (Nassereddine et al., 2022). The initial high cost of adopting smart technology indicates that further financial limitations and the absence of funding options, such as bank loans in the long term, could be significant obstacles to technology adoption(Ebekozien and Samsurijan, 2022), especially small-medium enterprises with constrained financial means.

Alaloul et al., (2020) research suggests that the unpredictability of investment returns hinders innovation implementation in the industry. When smart technologies yield significant benefits in terms of increased efficiency, safety, and cost-effectiveness, stakeholders are more inclined to view them favorably. The fundamental tenet of the investment perspective is that there is no concrete proof that implementing robotics results in lower asset delivery costs(Davila Delgado *et al.*, 2019). This lack of evidence is a major barrier in the construction industry, which is a low-profit, high-risk sector. More precisely, no comprehensive cost-benefit analysis of robotics adoption has been published in the literature, unlike studies on sustainability (Pan *et al.*, 2018).

H_5. Organisational factors positively affect the PEU considerably.
H_6. Organisational factors positively affect the PU considerably.

Organizational factors, such as the readiness of the company, top management support, managerial support, and human resources play a crucial role in shaping PEU and PU. The ability of an organization to identify, absorb, and use new ideas and technological knowledge is determined by each personnel's educational background and expertise in related fields, (Limaj & Bernreturn der, 2019) which affect the diffusion and application of smart technology. Furthermore, higher education levels and more innovative activities among staff members were positively correlated with high absorptive capacity, which is beneficial to the adoption of innovation(Schmidt, 2009). This finding has conflict with (Wong *et al.*, 2023), as the earlier research concentrated on BIM technology, which presents particular adoption obstacles like high learning curves and interoperability problems. On the other hand, smart technologies have a wider variety of tools, some of which might be easier to use and more advantageous right away, which increases the impact of organisational support on perceptions.

The organizational scale indicates the size and reach of the organization by considering factors including the size of the workforce, the scope of projects, and the organization's overall ability to adopt and maintain technological advancements. Cruz-Jesus et al., (2019) asserts that firm size is a predictor of technology adoption within an organizational context. Zhang et al., (2019) studies have proven that as an organization grows in size, it can offer more resources such as training programs related to innovation. Zhong et al., (2025) studies demonstrate that younger and newer businesses placed a higher importance on technical training more than older and established companies. It was further proven in the study that large organizations are more motivated to make promotional decisions than small and medium-sized organizations, which affects their ability to adapt to the changes brought about by the use of technology in construction processes. This unified factor group shows how an organization's internal competencies, scale, and general preparedness work together to impact its capacity to integrate and utilize technology in the construction sector. This combined factor offers a more thorough understanding of the organizational elements that support effective technology adoption.

H_7. Technological factors have a positive significant effect on PEU.
H_8. Technological factors have a positive significant effect on PU.

Technology compatibility, trialability, and observability had positive and significant impacts on PEU and PU, which is akin to the findings of Wong et al., (2023). The degree to which smart technologies can enhance job performance and the level of enjoyment people derive from using them are the primary factors influencing their intention to use them in the workplace(Hewavitharana *et al.*, 2021). According to research by Chiu et al., (2017), Compatibility is one of the most important factors in technology adoption. The usefulness of new innovations, visibility of benefits, trust in the potential of benefits, and the ability to trial and align with existing practices work together to affect how an individual decides which new technology to adopt. This is in line with the findings of Qin et al., (2020a) as ccompanies must have mature technical conditions before they can implement new technology, which calls for standardisation of services in addition to hardware and software infrastructure. An organisation should therefore think about deploying new technology if it is beneficial, compatible with its current technology, straightforward to use and simple to test before the implementation (Okanlawon *et al.*, 2025).

H_9. PEU does not have a considerable effect on intention of adoption.
H_{10}. PU have a considerable effect on intention of adoption.

The outcomes refute the impact of PEU on adoption intention, which is further supported by (Gutierrez-Aguilar *et al.*, 2022). This indicates that respondents did not value simplicity of use because digital adoption is frequently required. Under the direction of the government and organizations, the majority of respondents acquiesced to the necessary digital technologies passively, hardly ever taking the ease of use of the technology into account when making this decision(Qiu *et al.*, 2023). Therefore, adoption intention was not directly affected by PEU; rather, it was affected by PU and this is in line with the study of (Wong *et al.*, 2023). The positive and considerable effects of PU on adoption intention are consistent with (Okoro *et al.*, 2023) people deciding whether to adopt or reject a new system, depending on whether they think it will help to enhance their work.

4.7 Validation of Model

To validate the outcome of the model, a total of six construction practitioners were invited to share their insights. Judgemental sampling was employed to connect with contractors that could provide the most industry knowledge with more than 20 years of experience in the construction industry on smart technology. Hence, majority of the experts (83%) agree with the ranking of the variables and supports the application of model in real construction practice.

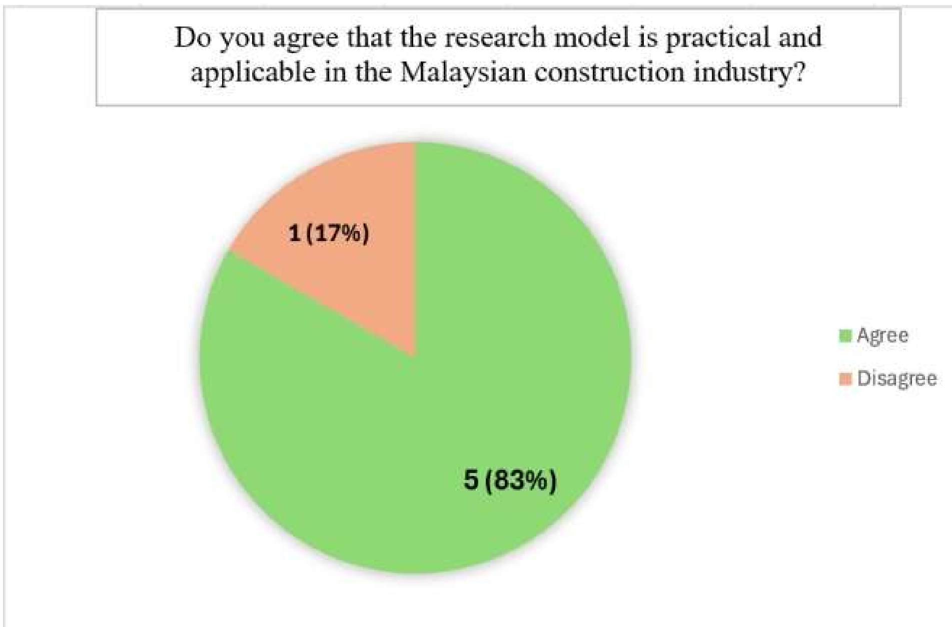

Figure 4.7 Validation of Model

Agreement of the Five Experts

According to the experts, the model is well-structured and takes into account the key elements influencing the adoption of smart technology in the building sector. Environmental, economic, organisational, and technical aspects have all been recognised for their practical significance. This study was further supported by Thirumal et al., (2024) which identified the main hurdles of technological adoption as nature of building section and regulatory, investment, stakeholder, standardisation. In line with these findings, Xue et al., (2025) demonstrates that adoption is not determined by any single factor, but rather by a combination of interdependent conditions.

The Disagreeing Expert's Divergence

The disagreement draws attention to a possible improvement, specifically in the model's incorporation of sociocultural variables which impacted the practicality. Although it wasn't initially incorporated, this feedback can be utilised to improve the model and make sure it includes all the factors affecting adoption in Malaysia in the future studies.

Hence, the model's applicability is well supported by the feedback received overall, while it is suggested that behavioural and cultural factors be added. Future iterations or expanding the study to incorporate qualitative insights about workforce acceptability and adaptability can address this.

5.0 Conclusion

5.1 Safety Technology Adoption Model

Comprehensive methods of implementation planning can be guided by understanding the interrelationships between variables like enablers and inhibitors, ensuring that investments in smart technologies result in the intended gains in sustainable HSM. Construction organisations should invest in technology literacy and skills development and perform a cost-benefit analysis to prioritize investments in emerging technologies while acknowledging the potential challenges associated with the steep learning curve and resistance to change. Deliberate steps must be taken to standardise technologies, improve technology literacy, and win over senior management. The potential advantages of smart technologies might not materialise if these important inhibitors are not removed, which would result in inefficiencies in operations and a lack of innovation in the industry.

Exploratory factor analysis of the integration of smart technologies in Malaysia's construction industry reveals six key factors that are influencing the use of these technologies, ranked in order of importance. The results can be utilised to develop models for predictive analysis with the goal of enhancing technology adoption decision-making, hence reducing the discrepancy between theory and practice. Owing to the ever-changing nature of technology adoption in construction sector, a fresh study enables an updated analysis that considers the latest advancements and trends. In addition, with the result of six factor groupings provided in this research, it provide higher accuracy in identifying the underlying characteristics that motivate technology adoption, enabling a more accurate depiction of the various elements at work. Therefore, the findings are guaranteed to stay applicable and useful for the present stakeholders.

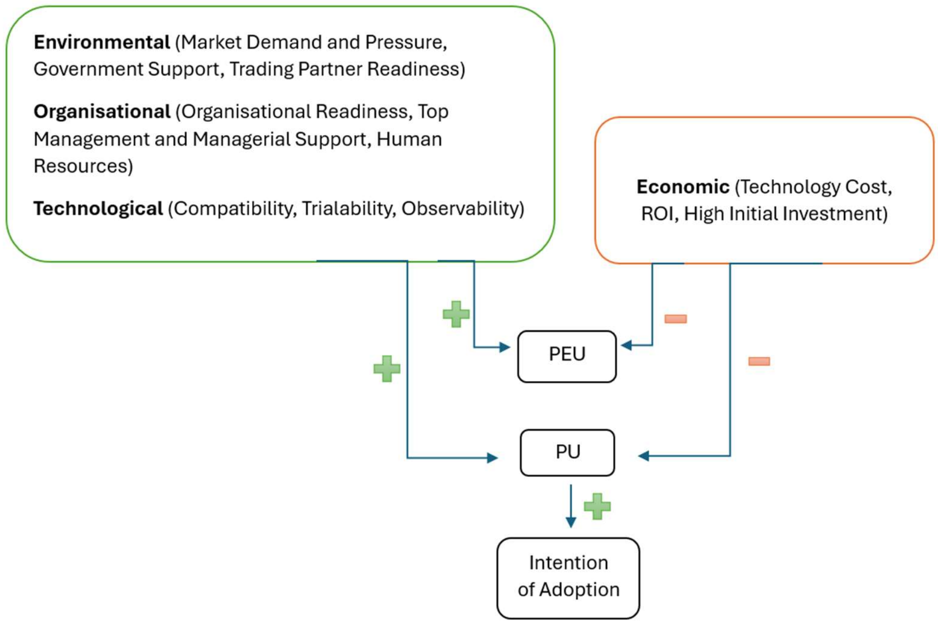

Figure 5.1: Finalised Model

The results of the PLS-SEM in Figure 5.1 provide insight into the intricate interactions of technological, organizational, economic, and environmental elements. The findings demonstrate that environmental factors have a significantly positive impact on both the PEU and PU of smart technologies. However, economic issues have a significantly negative impact on both PEU and PU, highlighting the difficulties associated with cost considerations and budgetary limitations when implementing smart technology. Organizational elements, on the other hand, stand out as crucial facilitators, having a considerable positive impact on both PEU and PU. This highlights the vital role that top management and managerial support, human resources, and organizational readiness play in developing positive attitudes towards technology adoption. Furthermore, PEU and PU show a significant positive effect from technical elements, suggesting that technological characteristics and improvements are important for improving perceptions of usability and utility.

It is interesting to note that although PEU has little bearing on adoption intentions, PU shows a strong positive influence, underscoring the critical role that perceived utility plays in determining adoption intentions for smart technologies. This study is aligned with Nortey et al., (2025) that shows that PEU and PU positively affected acceptance of technology, with PU having the stronger effect. Overall, these findings offer insightful information to Malaysian stakeholders in the construction industry, highlighting the need for strategic interventions to improve organizational support, address economic obstacles, and take advantage of technological developments to encourage the widespread adoption of smart technologies for occupational safety and health management.

5.2 Accomplishment on Research Objectives

Objective 1: To investigate the enablers and inhibitors of the adoption of smart technologies in the construction industry that contribute to occupational safety and health management.

- The mean ranking analysis revealed that return on investment and relative advantage were the strongest enablers, while steep learning curve and resistance to change were the most significant inhibitors.
- Correlation analysis further showed that enablers such as ROI and relative advantage are closely linked with inhibitors like resistance to change, interoperability issues, and technology illiteracy, highlighting the interplay between drivers and barriers.

Objective 2: To determine the underlying factors of the adoption of smart technologies in the construction industry that contribute to occupational safety and health management.

- Factor analysis reduced the determinants into six underlying groups: technology acceptance and trustworthiness, management commitment, external environmental influence, cost-benefit perception, economic viability, and organisational capacity.
- These factors emphasise that both technological perceptions (usefulness, ease of use, trust) and organisational readiness (management support, human resources) are crucial for successful adoption.

Objective 3: To develop a conceptual model based on the TAM-TOE framework for the adoption of smart technologies in the construction industry that contribute to safety and health management.

- The PLS-SEM results confirmed the suitability of the integrated TAM-TOE framework.
- Technological factors significantly influenced both perceived usefulness (PU) and perceived ease of use (PEU), while organisational and environmental factors also played supportive roles.
- Importantly, PU was found to significantly affect the intention of adoption, whereas PEU did not — reflecting that in construction, usefulness (e.g., safety improvements, efficiency) outweighs ease of use.

5.3 Theoretical Implications

By demonstrating the contextual dependencies within the Technology Acceptance Model (TAM), this study contributes to the theoretical discussion on technology adoption. Although PU and PEU are both traditionally emphasised by TAM as important factors, this study shows that outside factors like industry standards, organisational culture, and legal requirements can tip the scales in favour of PU when it comes to adoption decisions. By taking into consideration industry-specific limitations and incentives that propel technology integration, this realisation improves on current adoption models.

By combining organisational, technological, environmental, and economic factors, the study also emphasises the need for a multifaceted approach to technology adoption. This study emphasises the social and systemic character of technology spread in construction, in contrast to conventional models that see adoption decisions as largely individual choices. The study offers a more comprehensive understanding of adoption behaviours by incorporating these external variables into the TAM framework, especially in sectors where safety and compliance are vital.

The ability of the six major adoption factors to be used for predictive modelling represents another theoretical contribution. These elements work as building blocks that can be added to upcoming decision-support tools, enhancing researchers' and decision-makers' capacity to predict adoption patterns. This study lays the groundwork for future investigations that incorporate new technological developments and changes in industry goals, as the dynamic nature of construction technology adoption demands ongoing theoretical improvement.

5.4 Practical Implications

Practically speaking, the results indicate that rather than viewing technology adoption as a simple operational improvement, construction companies and politicians should view it as a strategic endeavour. Given PU's powerful influence, decision-makers ought to give top priority to proving quantifiable gains in productivity, adherence, and ROI in order to win over stakeholders. This calls for a change in training approaches that prioritise success stories and real-world applications over merely technical competence.

For adoption to be widely accepted, financial obstacles must also be removed. Although cost is a barrier, businesses can lessen their financial worries by using lease models, phased deployment plans, or joint ventures with technology providers to split costs and gains. Organisations could also look into financial options and regulatory incentives that promote digital transformation in the building industry.

Establishing an innovative culture within organisations is another crucial component. Strong leadership commitment, organised change management programs, and unambiguous communication of the long-term advantages of smart technologies are necessary to overcome resistance to change, which is frequently a significant barrier. Cross-sector partnerships, industry-wide best practices, and standardisation initiatives can all help to improve overall technological preparedness and lessen adoption hesitation.

In the end, using the knowledge gained from this study helps construction companies create a more focused and knowledgeable strategy for implementing smart technology. A more seamless transition to a technologically sophisticated and safety-conscious industry can be ensured by stakeholders by addressing both systemic issues and organisational dynamics.

5.5 Recommendations and Limitations

To surmount the inhibitors for implementation of technology in construction industry, this paper suggests augmenting interoperability via industry-wide guidelines, advocating for technological literacy via comprehensive instruction, gaining upper management backing by showcasing enduring advantages and alleviating the learning curve through intuitive technologies and ongoing training initiatives. The adoption and standardisation of smart technology in the building industry can also be greatly aided by government policies and incentives. By putting these methods into practice, smart technologies can be used more effectively, increasing the industry's competitiveness in the global market. The direction and degree of correlations between variables can be determined using Spearman's correlation test, however, it has several drawbacks. Since it relies on monotonic relationships, Spearman's test could miss non-linear correlations. Additionally, it is susceptible to the impact of outliers and sample size. Future studies may use additional statistical methods, including multiple regression and factor analysis, to supplement Spearman's test to overcome these constraints. This allows for a more nuanced interpretation of the data and the validation of the conclusions. Moreover, construction practitioners are urged to increase organisational capability, win over management, demonstrate cost-effectiveness, assure economic viability, and foster a culture of trust in new technology. By taking care of these issues, construction companies can more successfully utilise smart technology to boost industrial innovation and enhance occupational safety and health management procedures. However, this study's focus is limited to the construction industry in Malaysia. Future studies could extend its reach to include comparison with other countries, allowing for the development of more broadly applicable findings.

By addressing these problems, construction firms can leverage smart technologies to advance industrial innovation and improve protocols for occupational safety and health management. Future studies could examine in-depth case studies of construction companies that have included smart technologies for managing health and safety. Through an examination of these companies' experiences, researchers can pinpoint critical success factors, lessons learned, and best practices that other organizations looking to implement similar technology can use. In-depth case studies can be conducted to analyze how the construction industry's embrace of smart technology has affected the health and safety results. To measure the advantages of technology adoption and guide future investment decisions, researchers can evaluate the changes in accident rates, injury severity, and overall safety performance before and after the introduction of smart technologies.

The sample size of the current study may be restricted, and the diversity of the Malaysian construction industry may not be adequately represented. Future research should include larger and more varied sample sizes to improve the generalizability of the results. In addition, with a focus on target respondents from contractors in the Malaysian industry, this exploratory quantitative study is a cross-sectional study conducted in 2024. Subsequent investigations may employ qualitative research techniques, including focus groups and interviews, to gain a deeper and more comprehensive understanding of smart technology adoption. Besides, to address the concern regarding validation of experts, sociocultural variables which impacted the practicality of study could be included in the future research.

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7.0 Appendices

Appendix A: Survey Questionnaire

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SAFETY TECHNOLOGIES ADOPTION MODEL IN THE MALAYSIAN CONSTRUCTION INDUSTRY

Dear Sir/ Madam,
My name is Yap Sze Chee, a postgraduate student undertaking Master of Engineering Science from Lee Kong Chian Faculty of Engineering & Science (LKC FES) at University Tunku Abdul Rahman (UTAR). I am currently conducting a survey for my study entitled "SAFETY TECHNOLOGIES ADOPTION MODEL IN THE MALAYSIAN CONSTRUCTION INDUSTRY". This survey aims to develop a framework regarding the use of smart technology-based construction health and safety (H&S) management for construction projects.
It would be highly appreciated if you could spend about 10 - 15 minutes to complete this survey form. I'm here to assure you that all the information collected will be kept private and confidential, which will be strictly used for academic research purposes only. Your opinion and information provided in this survey will significantly contribute to the study and industry. Shall you have any inquiries about this survey, kindly contact me for further details.
Thank you.
Name: Yap Sze Chee
Contact number: 011-39352813
Email: szechee1998@gmail.com

Section A: Respondents' Demographic Information

A1. Position in the company (*please select only one)*:

- Executive
- Manager
- Senior Manager
- Director (top management)

A2. Working experience in the construction industry *(please select only one)*:

- 5 years or below
- 6 - 10 years
- 11 – 15 years
- 16 – 20 years
- More than 20 years

A3. Highest academic qualification *(please select only one)*:

- High school (secondary level)
- Diploma / Certificate
- Bachelor’s degree
- Postgraduate degree (Master, PhD)

A4. Types and Sizes of Project

<u>For Private project (value of project)</u>

- Less than 100M
- Approximately 100M-500M
- More than 500M

<u>For Public project (value of project)</u>

- Less than 100M
- Approximately 100M-500M
- More than 500M

A5. Categories of project

- Residential

- o Commercial
- o Industrial
- o Civil engineering projects
- o Others: ____________

Section B: Determinants of the implementation of smart technologies

Kindly state your level of agreement on the following determinants that influence the implementation of smart technologies.

*Technological Dimension

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
TF01 Compatibility (align with business's ideas, values and needs)	1	2	3	4	5
TF02 Relative Advantage	1	2	3	4	5
TF03 Trialability (ease of trying out technologies)	1	2	3	4	5
TF04 Observability (ability to identify the outcomes of technologies)	1	2	3	4	5
TF05 Perceived Usefulness	1	2	3	4	5
TF06 Perceived Ease of Use	1	2	3	4	5
TF07 Technology Optimism (trust and confidence towards technology)	1	2	3	4	5

*Organisational Dimension

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
OF01 Organisational Scale	1	2	3	4	5
OF02 Organisational Readiness	1	2	3	4	5
OF03 Absorptive Capacity	1	2	3	4	5
OF04 Top Management Support	1	2	3	4	5
OF05 Managerial Support	1	2	3	4	5
OF06 Human Resources	1	2	3	4	5

*Environmental Dimension

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
EnF01 Market Demand	1	2	3	4	5
EnF02 Competitive Pressure	1	2	3	4	5
EnF03 Government Support	1	2	3	4	5
EnF04 Trading Partner Readiness	1	2	3	4	5

*Economic Dimension

Factors	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
EcF01 Cost of Technology	1	2	3	4	5
EcF02 Return on Investment	1	2	3	4	5

*Economic Dimension

Factors	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
EcC01 Low ROI	1	2	3	4	5
EcC02 High Initial Investment	1	2	3	4	5

Section C: Impact of technology implementation on worker behaviour and occupational safety and health management

Kindly state your level of agreement on the following impact of smart technologies on worker behaviour and health and safety culture.

C1. The implementation of smart technologies positively influences worker behaviour towards health and safety.

Strongly disagree 1 2 3 4 5 Strongly agree

C2. Smart technologies promote a safety-conscious work environment and improve health and safety culture.

Strongly disagree 1 2 3 4 5 Strongly agree

C3. The use of smart technologies enhances worker engagement and participation in health and safety initiatives.

Strongly disagree 1 2 3 4 5 Strongly agree

C4. Smart technologies foster a sense of accountability and responsibility for health and safety among workers.

Strongly disagree 1 2 3 4 5 Strongly agree

C5. The implementation of smart technologies helps in creating a positive health and safety climate in the construction industry.

Strongly disagree 1 2 3 4 5 Strongly agree

Please rate the following smart technologies that have the highest potential in realizing the relevant occupational safety and health management.

HSM1: Enhance occupational safety and health management during the design stage

Scale Technologies	Least Beneficial				Most Beneficial
BIM	1	2	3	4	5
Wearable Technologies	1	2	3	4	5
UAV (drones)	1	2	3	4	5
VR (Virtual Reality)	1	2	3	4	5
AR (Augmented Reality)	1	2	3	4	5
Robotics / Automation	1	2	3	4	5
Warning & Sensors (RFID, GPS, GIS)	1	2	3	4	5
Photogrammetry	1	2	3	4	5

HSM2: Enhance health monitoring

Scale Technologies	Least Beneficial				Most Beneficial
BIM	1	2	3	4	5
Wearable Technologies	1	2	3	4	5
UAV (drones)	1	2	3	4	5
VR (Virtual Reality)	1	2	3	4	5
AR (Augmented Reality)	1	2	3	4	5
Robotics / Automation	1	2	3	4	5
Warning & Sensors (RFID, GPS, GIS)	1	2	3	4	5

Photogrammetry	1	2	3	4	5

HSM3: Hazard Identification

Scale Technologies	Least Beneficial				Most Beneficial
BIM	1	2	3	4	5
Wearable Technologies	1	2	3	4	5
UAV (drones)	1	2	3	4	5
VR (Virtual Reality)	1	2	3	4	5
AR (Augmented Reality)	1	2	3	4	5
Robotics / Automation	1	2	3	4	5
Warning & Sensors (RFID, GPS, GIS)	1	2	3	4	5
Photogrammetry	1	2	3	4	5

HSM4: Risk Perception, Planning, Assessment

Scale Technologies	Least Beneficial				Most Beneficial
BIM	1	2	3	4	5
Wearable Technologies	1	2	3	4	5
UAV (drones)	1	2	3	4	5
VR (Virtual Reality)	1	2	3	4	5
AR (Augmented Reality)	1	2	3	4	5
Robotics / Automation	1	2	3	4	5
Warning & Sensors (RFID, GPS, GIS)	1	2	3	4	5
Photogrammetry	1	2	3	4	5

HSM5: Training and Education

Scale Technologies	Least Beneficial				Most Beneficial
BIM	1	2	3	4	5
Wearable Technologies	1	2	3	4	5
UAV (drones)	1	2	3	4	5
VR (Virtual Reality)	1	2	3	4	5
AR (Augmented Reality)	1	2	3	4	5
Robotics / Automation	1	2	3	4	5
Warning & Sensors (RFID, GPS, GIS)	1	2	3	4	5
Photogrammetry	1	2	3	4	5

HSM6: Enhance Supervision and Inspection

Scale Technologies	Least Beneficial				Most Beneficial

BIM	1	2	3	4	5
Wearable Technologies	1	2	3	4	5
UAV (drones)	1	2	3	4	5
VR (Virtual Reality)	1	2	3	4	5
AR (Augmented Reality)	1	2	3	4	5
Robotics / Automation	1	2	3	4	5
Warning & Sensors (RFID, GPS, GIS)	1	2	3	4	5
Photogrammetry	1	2	3	4	5

Section D: Challenges of integration of smart technologies with occupational safety and health management system.

Kindly state your level of agreement on the following challenges of the integration of smart technologies with occupational safety and health management

*Technological Dimension

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
TC01 Steep Learning Curve	1	2	3	4	5
TC02 Technological Limitations	1	2	3	4	5
TC03 Data Protection and Cybersecurity	1	2	3	4	5
TC04 Inconvenience of Technology	1	2	3	4	5
TC05 Interoperability between technologies	1	2	3	4	5

*Organisational Dimension

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
OC01 Lack of Standardisation	1	2	3	4	5
OC02 Resistance to Change	1	2	3	4	5
OC03 Lack of Top Management Support	1	2	3	4	5
OC04 Insufficient Human Resource	1	2	3	4	5

*Environmental Dimension

Factors	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
EnC01 Poor Government Policies and Incentives	1	2	3	4	5
EnC02 Nature of Industry	1	2	3	4	5
EnC03 Lack of Competitive Pressure	1	2	3	4	5
EnC04 High Technology Illiteracy	1	2	3	4	5
EnC05 Prolonged Exposure to Virtual Environment	1	2	3	4	5

Section E: Intention and readiness to embrace smart technologies for occupational safety and health management

Kindly state your level of agreement on the intention and readiness of your company to embrace smart technologies for occupational safety and health management.

E1. I have the intention to use smart technologies in the construction industry.

Strongly disagree 1 2 3 4 5 Strongly agree

E2. I think that there will be a good return on investment for the company if I invest in smart technologies for construction projects.

Strongly disagree 1 2 3 4 5 Strongly agree

E3. I am interested to use smart technologies for occupational safety and health management in my construction projects.

Strongly disagree 1 2 3 4 5 Strongly agree

E4. Kindly rate the willingness to adopt the smart technologies stated below for occupational safety and health management in my construction projects.

	Least willing to use				Most willing to use
ST1 BIM	1	2	3	4	5
ST2 Wearable Technology	1	2	3	4	5
ST3 UAV (drones)	1	2	3	4	5

ST4 VR	1	2	3	4	5
ST5 AR	1	2	3	4	5
ST6 Robotics / Automation	1	2	3	4	5
ST7 Warning & Sensors (RFID, GPS, GIS)	1	2	3	4	5
ST8 Photogrammetry	1	2	3	4	5

Section F: Perceived effectiveness of smart technologies in construction industry for occupational safety and health management

Kindly state your level of agreement on the effectiveness of smart technologies in the construction industry for occupational safety and health management.

	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
C1. Smart technologies enhance hazard identification and risk assessment processes.	1	2	3	4	5
C2. Smart technologies improve incident reporting and investigation.	1	2	3	4	5
C3. Smart technologies facilitate real-time monitoring and alerts for potential health and safety hazards.	1	2	3	4	5
C4. Smart technologies enhance communication and coordination among workers to improve health and safety.	1	2	3	4	5
C5. Smart technologies contribute to a reduction in accidents and injuries on construction sites.	1	2	3	4	5
C6. Smart technologies improve the overall health and safety culture in the construction industry.	1	2	3	4	5
C7. Smart technologies boost health and safety awareness	1	2	3	4	5
C8. Smart technologies improve health and safety training	1	2	3	4	5
C9. Smart technologies will bring long-term benefits to the company.	1	2	3	4	5