A Quantitative Study on the Performance of Construction Industry in IR 5.0 evolution: Using Conceptual Model Approach

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A project report submitted in partial fulfilment of the requirements for the award of Bachelor of Software Engineering (Honours)

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DECLARATION

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

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ABSTRACT

The construction industry currently faces limitations in knowledge and understanding of Industrial Revolution 5.0 (IR 5.0), which poses challenges to its adoption. This research project aims to investigate the performance of the construction industry in the context of IR 5.0 evolution. The objectives are: (i) to identify the variables that affect performance, (ii) to examine the relationship between readiness and intention toward performance, and (iii) to explore the impact of readiness and intention on performance. The study adopts a conceptual framework based on the Theory of Reasoned Action (TRA), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Theory of Organisational Readiness for Change (TORC). A quantitative approach was employed, where descriptive analysis was conducted using IBM SPSS, and Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied through SmartPLS to assess both the measurement and structural models. The findings indicate that readiness does not significantly influence the performance of the construction industry in IR 5.0, whereas intention demonstrates a significant relationship and positive impact on performance. In conclusion, the study emphasizes that intention plays a more critical role than readiness in enhancing construction industry performance in IR 5.0. These results contribute to theoretical understanding and provide practical insights for policymakers and construction players in fostering successful IR 5.0 adoption.

Keywords: Quantitative analysis, IR 5.0 Revolution, Performance, Construction Industry, Readiness and Intention

Subject Area: HA29-32 Theory and method of social science statistics

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LIST OF SYMBOLS / ABBREVIATIONS

$(1-\beta)$	Statistical power
Z	Z-score
Z_{α}	Critical value of significance threshold
Z_{β}	Critical value of statistical power
f^2	Effect size
β	Path coefficient
H_0	Null hypothesis
H_{2a}	Hypothesis 2a
H_{2b}	Hypothesis 2b
H_{3a}	Hypothesis 3a
H_{3b}	Hypothesis 3b
R^2	Coefficient of determination
Q^2 / $Q^2{}_{\_predict}$	Predictive relevance
α	Cronbach's Alpha
λ	Outer loading
n	Sample size
N	Population size
$(1-\alpha)$	Confidence level
k	Number of independent variables
R	Correlation coefficient
rho_{α}	Composite reliability
p	p-value
t	t-value

AI	Artificial Intelligent
IR	Industrial Revolution
IR 5.0	Industrial Revolution 5.0
IR 4.0	Industrial Revolution 4.0
IR 3.0	Industrial Revolution 3.0
IR 2.0	Industrial Revolution 2.0
IR 1.0	Industrial Revolution 1.0

IV_1	Independent variable 1
IV_2	Independent variable 2
DV	Dependence variable
SPSS	Statistical Package for the Social Sciences
IoT	Internet of Things
AR	Augmented Reality
SMEs	Small and Medium-sized businesses
Cobots	Collaborative Robots
KPI	Key Performance Indicator
KPIs	Key Performance Indicators
BSC	Balanced Scorecard
ERQM	European Foundation for Quality Management
BIM	Building Information Modelling
CBPP	Construction Best Practice Programme
CAPF	Contract Administration Performance Framework
TRA	Theory of Reasoned Action
UTAUT	Unified Theory of Acceptance and Use of Technology
ROI	Return On Investment
RQ	Research Question
ANOVA	Analysis of Variance
SAS	Statistical Analysis System
PLS	Partial least squares SEM Structural equation modelling
SEM	Structural Equation Modeling
PLS-SEM	Partial Least Squares Structural Equation Modeling
CB-SEM	Covariance-Based Structural Equation Modeling
CR	Composite reliability
AVE	Average Variance Extracted
VIF	Variance Inflation Factor
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CPS	Cyber-physical systems

IT	Information technology
HTMT	Heterotrait-Monotrait
LM	Linear Model
LM_RMSE	Linear Model Root Mean Squared Error
PLS-SEM MAE	Partial Least Squares Structural Equation Modeling Mean Absolute Error
PLS-SEM RMSE	Partial Least Squares Structural Equation Modeling Root Mean Squared Error

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CHAPTER 1

INTRODUCTION

1.1 General Introduction

There was a lot of new technology emerging in this generation. Technologies such as the humanoid robot half marathon, Deepseek, artificial intelligence, quantum computing became more well-known. The development of those modern technologies produced many advantages. For instance, it allowed construction industry to spend less time on repetitive tasks and more time on innovative and experimental tasks, which improved their overall performance. Aside from that, modern technology reduced the number of human accidents and increased the efficiency of human labour, contributing to better performance outcomes. It helped construction industry feel more secure in their work, especially in the construction industry. The IR 5.0 on the performance of the construction industry was covered in general in this study. This study also explored the conceptual model of performance within the construction industry. In addition, the quantitative analysis and methodology were presented to identify the construction industry that aims to transition to IR 5.0 for enhanced construction industry performance.

1.2 Overview of the Study

As the construction industry knew, industrial revolution continued to emerge over time. The industrial revolution that construction industry most familiar which was IR 4.0. However, following IR 4.0 that was a new Industrial revolution which was IR 5.0. In this study, the influence of IR 5.0 on construction industry’s performance was discussed insightfully. The conceptual model of the construction industry's performance was also explained insightfully in this study. In addition, the quantitative analysis and methodology were presented to identify the construction industry that aim to transition to IR 5.0. Some countries had already begun to adopt IR 5.0 such had China, Japan and Malaysia. In terms of technology advancement, according to (Andrew KP Leung, 2025) state China stood to gain significantly from the Fourth and Fifth

Industrial Revolutions, which were expected to fundamentally reshape the trajectory of the twenty-first century. According to Malaysian Investment Development Authority (2020) state Malaysia, a thriving country in Southeast Asia, had been steadily enhancing its technological and economic landscape to align with the global shift toward Industry 5.0.Moreover, according to Narvaez Rojas et al. (2021) state Society 5.0 was introduced in 2016 with the goal of establishing a "super-smart" society through the smooth integration of online and physical space to solve social problems and stimulated economic growth. As construction industry could observe, everything changed, yet the constant was the change itself remained inevitable. Because the adoption of IR 5.0 was challenging, some countries were still operating under IR 4.0 and had not yet made the transition. One example was Singapore, which had not moved forward to IR 5.0. According to WEDC (2022), Singapore had announced a plan called Manufacturing 2030, which focused on growing the manufacturing industry by 50%, indicating that the country was not yet ready to adopt IR 5.0. This hesitation also affected the construction industry, as it highlighted whether a country was prepared and intended to transition to IR 5.0. The performance of construction industry when applying IR 5.0 was influenced by their level of readiness and intention.

1.3 Importance of the Study

The analysis on the construction industry's performance in the context of IR 5.0 advancement was crucial. It provided construction industry a clearer picture of how the industry 5.0 revolution would affect construction industry performance. It provided insight construction industry of the reasons that the country was still in IR 4.0 and had not transitioned to IR 5.0. The obstacle prevented the construction industry from moving forward to the IR 5.0 revolution. The quantitative study provided insightful explanations of construction industry on their confidence in moving toward the IR 5.0 revolution. Construction industry could clearly grasp and acknowledge the advantages and disadvantages are that helped the country progress based on the quantitative analysis. The information increased construction industry confidence in the construction industry's performance potential during the IR 5.0 revolution. Without conducting research on how the construction industry was performing in the IR 5.0 evolution, construction industry could not determine whether the industry was prepared for IR 5.0 or not, nor could they determined the reasons behind some construction industry chose to forego the IR 5.0 revolution.

The study also was crucial because the study provided insightful explanation the construction industry performance in moving forward IR 5.0 and the impacts of shift. It demonstrated how technologies influenced the construction industry and the extent to which these advancements impacted the industry's performance, readiness, and intention to transition. It represented a worst case if construction industry were unaware of the elements influencing the construction industry's transition to IR 5.0. Construction industries were not prepared to transition to IR 5.0 because they lacked awareness of their current circumstances, and it remained unclear whether the purpose was sufficiently strong to enable the construction industry to proceed. When construction industry was unaware, it was similar to boarding a flight without understanding the process or following the queue, unready and misinformed. This analogy reflected the reality for many constructions industry facing the shift to IR 5.0, where performance depended heavily on readiness and intention.

1.4 Problem Statement

According to A. Shaji George and A.s Hovan George (2020), IR 5.0 focused on human-centric, sustainable, and resilient methods, IR 4.0 emphasized more on automation and digitisation. IR 5.0 incorporated AI ethics, human-technology collaboration, environmental impact, and employee well-being. Due to its sluggish adoption of new technologies, the construction industry experienced a difficult time embracing IR 5.0. Transferring or even adopting the transition from IR 4.0 to IR 5.0 was not simple. Implementing IR 5.0 enabled the construction industry to adopt new issues and a different viewpoint. Despite this, in the context of IR 5.0, the specific factors that most strongly influenced construction performance remained unclear. According to Musarat et al. (2023) highlights that while IR 5.0 introduced advanced technologies, the construction industry or struggled with a shortage of technical skills, investment hesitancy, and cultural concerns regarding human-machine integration. These challenges contributed to the ambiguity surrounding the key factors influencing construction industry performance in the context of IR 5.0. Despite being identified in the literature as possible drivers of performance improvement, key characteristics including organisational readiness and intention to adopt new technologies were not thoroughly examined in the construction industry in light of IR 5.0 principles. According to Venkatesh (2003) and Weiner (2009) state the readiness and intention were the crucial factors that affected the performance of construction industry in adopting a new technology. Furthermore, there was no established conceptual model linking these variables in a manner that supported robust quantitative analysis. As a result, decision-makers lacked a reliable empirical foundation to improve readiness, encourage adoption, or evaluate construction performance effectively. This study aimed to address this research gap by identifying and structuring the key variables—readiness, intention, and performance, into a conceptual model tailored for quantitative assessment within the IR 5.0 context.

Furthermore, the construction industry was undergoing a substantial transition with the advent of IR 5.0, which necessitated striking a balance between the use of cutting-edge technology and human-centric principles. Despite the importance of readiness and intention in achieving successful integration, no empirical studies had specifically explored the relationship between these variables and performance in the context of IR 5.0. The majority of earlier research had concentrated on the broad digital change brought about by IR 4.0, ignoring the more intricate and comprehensive requirements introduced by IR 5.0. Because of this, it was still unknown how readiness, intention, and actual performance outcomes related to one another especially in the construction industry, where innovation adoption was typically slower and more dispersed. Construction companies and policymakers found it challenging to make well-informed decisions because of this information gap, which impeded both academic comprehension and practical application. Finding efficient solutions and guaranteeing the construction industry's smooth transition into the IR 5.0 era required examining the relationship between these independent variables (readiness and intention) and the dependent variable (performance).

Knowing the precise factors that influenced construction industry performance was more important than ever as the construction industry is faced growing pressure to enter the era of IR 5.0. It remained unknown how much readiness and intention affected performance, especially when it came to the particular requirements of IR 5.0, despite the fact that they were widely acknowledged as important aspects in digital transformation. In addition to prioritising technology innovation, according to A. Shaji George and A.s Hovan George (2020) state IR 5.0 also emphasised human well-being, collaboration, and sustainability, which further complicated performance evaluation and added to this uncertainty. According to (Naji et al., 2024) state there was not enough empirical evidence to establish a direct relationship between organisational preparation such as workforce readiness, digital infrastructure, or leadership support and outcomes like productivity, efficiency, or innovation. Similarly, according to Liu, Liu and Xu, (2023) state the influence of intention on performance had not been thoroughly measured. Intention represented the readiness or dedication of all parties involved to accept change. It became difficult for construction industry to manage their resources efficiently if they did not comprehend the importance or size of these issues. Whether more focus should have been on improving technical readiness or on fortifying leadership and change-oriented intention was still up for debate. For industry stakeholders, the uncertainty surrounding which variable had a greater influence on attaining high performance under IR 5.0 principles presented a serious obstacle. By examining how readiness and intention affected construction performance, this study aimed to close a critical knowledge gap. The findings helped decision-makers in the construction industry better understand which variables, readiness or intention, had a greater influence on improving performance under IR 5.0. This allowed them to allocate resources more strategically and enhance their overall competitiveness in an environment increasingly shaped by human-technology integration. Additionally, by clearly defining the existing problem statement, this study effectively outlined its aim and objectives, which centered on evaluating the specific factors influencing the performance of the construction industry during the transition to IR 5.0.

1.5 Aim & Objectives of the Study

As the construction industry transitioned into the IR 5.0 era, it became essential to understand how emerging technologies and human-centric principles influenced overall performance. Despite the potential of IR 5.0 to improve productivity, efficiency, and innovation, there remained a lack of clarity regarding which internal factors most significantly contributed to performance outcomes. This uncertainty made it challenging for construction industry to develop and implement targeted strategies for improvement. Therefore, the aim of the study was to investigate the performance of the construction industry in IR 5.0 evolution. The aim served the following specific objectives of the study:

Objective 1:
To determine the variables that affect the quantitative study on the performance of construction industry in IR 5.0 evolution.

Objective 2:
To investigate the construction industry relationship between the readiness and intention toward their performance in IR 5.0.

Objective 3:
To explore the impact of construction industry readiness and intention toward the performance in IR 5.0.

1.6 Research Questions

Based on the aim and objectives of the study, which focused on examining the performance of the construction industry during the IR 5.0 evolution, it was necessary to explore the variables that influenced this performance. The objectives guided the study toward identifying relevant variables and assessing their effects on how well construction industry adapted and responded to the evolving industrial landscape. By addressing these focus areas, the study sought to offer meaningful insights that could help construction industry enhance their performance under IR 5.0. To solve the objectives of the study, the following research questions were developed:

RQ_1:
What are the variables that affect the quantitative study on the performance of construction industry in IR 5.0 evolution?

RQ_{2a}:
What is the relationship between the readiness toward construction industry's performance in IR 5.0?

RQ_{2b}:
What is the relationship between the intention toward construction industry's performance in IR 5.0?

RQ_{3a}:
What is the impact of construction industry's readiness toward the performance in IR 5.0?

RQ_{3b}:
What is the impact of construction industry's intention toward the performance in IR 5.0?

1.7 Hypotheses

To measure the research questions in this study, the following hypotheses were developed to investigate the performance of the construction industry in IR 5.0 evolution:

H_1 – The readiness and intention are the factors affecting the quantitative study on the performance of construction industry in IR 5.0 evolution.

H_{2a} – There is a significant relationship between readiness toward construction industry's performance in IR 5.0.

H_{2b} – There is a significant relationship between intention toward construction industry's performance in IR 5.0.

H_{3a} – There is a significant impact of construction industry's readiness toward the performance in IR 5.0.

H_{3b} – There is a significant impact of construction industry's intention toward the performance in IR 5.0.

1.8 Scopes & Limitations of the Study

This study focused on a quantitative analysis of performance within the construction industry, with particular emphasis on how the variables readiness and intention affected overall industry performance. The scope was confined to key industry within the construction players, namely developers, consultants (including quantity surveyors and architects), main contractors, and subcontractors. These construction players were selected as they represent the core contributors to construction project execution and are directly involved in the industry's transition towards IR 5.0. The research aimed to develop a conceptual model that quantitatively linked readiness and intention with performance outcomes such as productivity, efficiency, and innovation. By focusing on these two independent variables, the study sought to provide a clearer understanding of the industry's preparedness and willingness to evolve in line with technological advancements.

However, the study also faced several limitations. It was restricted to the construction industry alone and did not consider other industry that may have been undergoing similar technological transformations. Furthermore, only the influence of readiness and intention was examined, excluding other possible determinants of performance such as government policy, funding availability, or organizational culture. The geographical scope and participant pool were also limited, which may have affected the generalizability of the results. As a result, the conclusions drawn might have been applicable only to the specific stakeholder groups and regions included in this research.

1.9 Contributions of the Study

In this study, an analytical and empirical contribution was disclosed to the academic field by statistically exploring the impact of readiness and intention on the performance of the construction industry during the evolution of IR5.0. By using a conceptual mode approach, this study filled a gap in the literature by providing an organised framework for comprehending the way digital readiness and human-centric innovation together affected organisational outcomes. According to Davis (1989) and Vial (2019) stated the results provided a strong basis for further study on IR 5.0 integration in historically manual businesses, supporting theoretical developments in technology acceptance models and performance management frameworks. This study advanced academic knowledge regarding why readiness and intention served as crucial drivers of digital transformation in sophisticated industries like construction, as IR 5.0 was still a developing field.

The study's contribution also examined useful and extremely actionable insights into how the construction industry could strategically be prepare for and adjust to the revolutionary change brought about by IR 5.0. By recognising readiness and intention as major determinants of performance, it allowed construction industry to focus on personnel training, digital literacy, and cultural adaptation to boost operational efficiency and creativity. According to Oesterreich and Teuteberg (2016) stated for business executives and legislators hoping to remain competitive in a time when automation, artificial intelligence, and human-machine collaboration were changing conventional workflows, these findings were essential. This study's findings can directly influence strategies for workforce development, organisational strategy, and technology adoption, making it an invaluable resource for decision-makers navigating the construction industry's future in the IR 5.0.

After that, the need for focused national initiatives that improved technology readiness in the construction industry was highlighted in this report, which made a clear and useful contribution to policy. Given that the results showed a strong correlation between organisational readiness and performance under IR 5.0, policymakers were encouraged to utilise this information to develop targeted regulations that promoted the development of digital skills, infrastructure financing, and incentives for technology adoption. According to Breque, De Nul and Petridis (2021), these regulations were necessary to guarantee that construction companies, particularly small and medium-sized businesses (SMEs), were suitably equipped to shift to a digitally connected and human-centered industry in accordance with IR 5.0 principles.

1.10 Impacts of the Study

By establishing a solid conceptual and quantitative framework for assessing the way IR 5.0 affected construction performance, this study enhanced scholarly research. It provided an empirical framework that enabled the study to methodically examine readiness and intention in the construction industry. According to Vial (2019), this supported further research on digital transformation, AI applications, IoT, and sustainability in the construction industry. This addition strengthened the groundwork for academic research and promoted the advancement of theories related to IR 5.0.

The study investigated at the way readiness and intention shaped performance, which offered construction industry important insights into the way they could prepare for the evolving demands of Industry 5.0. While the broad adoption of IR 5.0, including automation, robotics, and artificial intelligence, was still in its infancy, the results assisted construction industry in evaluating their present capacities and formulating strategic plans for the integration of humans and technology. According to Oesterreich and Teuteberg (2016), the creation of transformation roadmaps prioritized to process adaptation, sustainable innovation, and workforce upskilling was supported by this forward-looking viewpoint. Moreover, this study enabled construction industry to compare their performance with others using the conceptual modal, thereby driving industry-wide improvements through benchmarking and best practices.

Furthermore, this study helped bridge the research gap in the application of IR 5.0 concepts within the construction industry. As research on IR 5.0 was still limited for the current generation, this study contributed to enhancing and expanding academic knowledge the adoption of IR 5.0. According to Han and Bogus (2021) stated the lack of research on IR 5.0's integration into the construction industry emphasized the need for further empirical studies to examine its use and effects. In addition, this study provided a strong and valid conceptual framework for future academic researchers to conduct or refine in similar studies. This framework enabled future research to be carries out more efficiency and effectively. Moreover, this study improved the understanding of how construction organization behaviour and technology readiness influenced the performance of construction industry. Nevertheless, this study introduced several novel contributions to both academic research and industry practise.

1.11 Novelty of the Study

This study introduced a novel academic contribution by addressing the limited research on the application of Industrial Revolution 5.0 (IR 5.0) within the construction industry. While existing studies had primarily focused on digital adoption in the context of IR 4.0, this research shifted the focus to IR 5.0, emphasizing its human-centric and intelligent technology aspects. The study developed and validated a conceptual model that linked readiness and intention to the performance of the construction industry. Using a quantitative methodology, the study provided empirical evidence that strengthened theoretical understanding and filled a gap in the literature related to digital transformation frameworks, particularly under the lens of IR 5.0. This framework also served as a foundation for future academic research exploring organizational behaviour and technological integration in construction.

From an industry perspective, this study presented a new practical framework to help construction industry understand the relationship between readiness, intention, and performance as they prepared for the transition to IR 5.0. Unlike prior approaches that focused solely on technology implementation, this study highlighted the importance of organizational preparation, including strategic planning, workforce development, and cultural readiness. The findings enabled construction firms to assess their current capabilities, identify gaps, and make informed decisions about adopting IR 5.0 technologies such as artificial intelligence, robotics, and IoT. Moreover, the study encouraged the industry to develop tailored transformation roadmaps, aligning technological progress with human-centered innovation, safety, and long-term sustainability in the construction environment.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This study primarily conducted an in-depth investigation into the performance of the construction industry during the evolution of IR 5.0. The literature review first discussed the progression of various industrial revolutions, highlighting their differences, impacts, and the limitations that contributed to the emergence of newer stages of industrial development. To establish a clear understanding of IR 5.0, it was essential to first examine the historical context and evolution of the previous industrial revolutions, from IR 1.0 to IR 4.0, and how each phase transformed the construction industry.

2.2 Introduction of Industrial Revolution

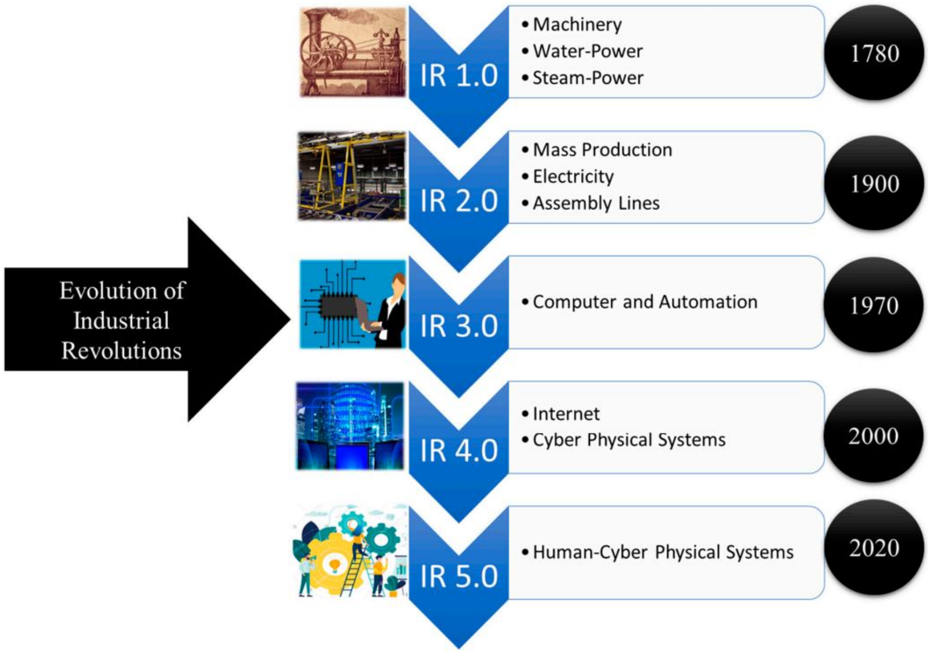


Figure 2.1: Industrial Revolution History (Source: Musarat et al., 2023).

According to Jennifer Abella et al. (2020), the Industrial Revolution described the period when human societies transitioned from hand production to machine-based manufacturing, signifying a shift from economies rooted in farming and handicrafts to those centered on industry and mechanical production. This transformation began in Britain during the 18th century and later disseminated across the globe. The term "Industrial Revolution" was used to describe Britain's economic development from 1760 to 1830. Furthermore, according to Jennifer Abella et al. (2020), while French authors had used the term earlier, it was English historian Arnold Toynbee (1852–1883) popularized it to explain this era of rapid industrial growth.

As show in Figure 2.1, each stage of IR brought new innovations that reshaped how industries operated, from early mechanization to the rise of digital and intelligent systems. These developments not only improved productivity and efficiency but also influenced global economic structures and labour dynamics. The early stages laid the foundation for modern industry, beginning with the transition to mechanized manufacturing.

2.2.1 Introduction of Industrial Revolution 1.0

The First Industrial Revolution (IR 1.0), which began in the late 18th century, marked a major shift from manual labor to machine-based production. According to Mokyr (1992) stated the enclosure movement forced small farmers to move to cities in search of work. Similarly, according to Cartwright and Tamorlan (2024), James Watt's steam engine as a breakthrough that transformed transportation and manufacturing processes. The occurrence of IR 1.0 had several effects on the community. IR 1.0 brought several benefits. According to Ashton and Hudson (1997), it increased production efficiency and supported economic growth. According to Neal (2024), added that new technologies created jobs and encouraged urbanization. However, not all effects were positive. According to Overton (1996) pointed out travel difficulties and weather risks, while Hobsbawm (1992) and Allen (2009) emphasized harsh working conditions, child labor, and environmental damage due to excessive coal use. These effects caused changes in the construction industry.

In terms of construction, IR 1.0 led to major changes in the construction industry. According to Landes (1969), mechanized tools and improved transport systems allowed for faster urban development and the construction of larger buildings, bridges, and railways. Moreover, according to Britannica (2023) stated the industry's use of new materials and equipment, and Mokyr (1992) stated that steam-powered tools reduced manual labor and enabled more complex structures. IR 1.0 implementation also presented several limitations that affected various industries, including construction. Nevertheless, IR 1.0 had its limitations. According to Landas (2003), the dependence on coal, lack of electricity, and outdated machinery restricted productivity and quality. Britannica (2023) also noted the absence of automation and poor working conditions. Therefore, the construction industry gradually transitioned to IR 2.0, which introduced electricity, assembly lines, and more efficient communication systems.

2.2.2 Introduction of Industrial Revolution 2.0

According to Landes (2003), the Second Industrial Revolution (IR 2.0) , which occurred in the late 19th and early 20th centuries, brought major changes through the introduction of electricity, advanced manufacturing techniques, and mass production. According to Mokyr (1990) and Britannica (2023), this revolution improved communication, transportation, and infrastructure, which in turn led to urbanization and strong economic growth. Next, according to Smil (2017), the shift from IR 1.0 to IR 2.0 was driven by the inefficiencies of steam power, such as high fuel usage and maintenance. According to Hughes (1983) stated innovations by Edison, Tesla, and Ford advanced electric systems, assembly lines, and industrial output. Furthermore, according to Landes (2003) stated IR 2.0 enabled large-scale production, reduced costs, and increased productivity, which enhanced living standards. The occurrence of IR 2.0 significantly impacted the community in various ways.

Moreover, according to Hobsbawm (1975) stated IR 2.0 brought electrification, stronger infrastructure, and more efficient transport systems. According to Mokyr (1998), assembly lines lowered labor costs, and according to Chandler (1990) stated railways, automobiles, and ships improved global connectivity. However, according to Ashton (1997) and Allen (2009) stated the revolution also caused poor working conditions, long hours, low wages, child labor, and environmental pollution. According to Taylor (2005) stated urbanization led to overcrowded housing, poor sanitation, and disease outbreaks. The effects of IR 2.0 caused the construction industry to adopt the changes it introduced. In addition, according to Misa (2013) stated IR 2.0 transformed the construction industry through electric tools, steel, and modern building methods and technologies like electric-powered equipment and prefabricated materials improved construction accuracy. According to Freeman & Louca (2001), steel and reinforced concrete allowed for stronger and taller structures, while prefabrication sped up construction processes. According to Edgerton (2006) stated these techniques made construction more cost-effective and productive.

According to Freeman & Louca (2001), improved transport helped deliver materials more efficiently, and according to Hughes (1983) stated telecommunication tools reduced project delays. Finally, despite its progress, IR 2.0 had limitations. According to Mokyr (1998) stated IR 2.0 reliance on mechanical systems without digital integration limited its flexibility. According to Piketty (2014), rising complexity in supply chains required smarter, automated solutions. These shortcomings led to the rise of IR 3.0, which focused on digital technologies, automation, and global connectivity.

2.2.3 Introduction of Industrial Revolution 3.0

According to Rifkin (2011), the Third Industrial Revolution (IR 3.0) introduced digital technology and automation that transformed communication and industrial processes. According to Schwab (2016), the rise of computers and information technology (IT) improved efficiency and reduced manual labour. According to Brynjolfsson and McAfee (2014), digital networks enabled globalization and business expansion. According to Gordon (2016) and Castells (1996), computing and the internet revolutionized sectors like healthcare, finance, and education through automation and remote access. According to Freeman & Louca (2001), the shift to the Third Industrial Revolution (IR 3.0) was driven by the need for automation, precision, and efficiency, as IR 2.0 still relied on manual processes. According to Gordon (2016), computers and automation improved quality control, reduced costs, and increased productivity. In addition, Brynjolfsson & McAfee (2014) stated that the rise of consumer electronics and telecommunications boosted demand for digital technologies and expanded global trade.

Moreover, according to Schwab (2016), IR 3.0 was powered by advancements in computers, telecommunications, and digital automation. According to Rifkin (2011), the invention of transistors and microprocessors led to electronic devices and global industrial integration. Similarly, Castells (1996) noted that robotics, AI, and data processing enabled smarter and more flexible production systems. According to Freeman & Louca (2001), IR 3.0 greatly enhanced productivity and cost efficiency. According to Brynjolfsson & McAfee (2014), automation helped businesses meet customer needs and expand globally. Furthermore, Schwab (2016) highlighted improvements in healthcare, education, and entertainment. However, IR 3.0 also had downsides. According to Gordon (2016), it led to job loss and high costs. Mokyr (1990) noted increased unemployment and technical issues, while Schwab (2016) pointed out digital inequality and environmental impacts. These effects caused changes in the construction industry.

In the construction industry, according to Schwab (2016), IR 3.0 introduced automation and data-driven systems. Rifkin (2011) emphasized the use of Building Information Modelling (BIM) , drones, and IoT in improving coordination and sustainability. Yet, Gordon (2016) argued that limitations such as lack of intelligent automation remain. The shift from machines to smart systems began after IR 3.0. Finally, according to Mokyr (1990), IR 4.0 brought cyber-physical systems, AI, and IoT to enable smarter production. According to Rifkin (2011), the complexity of supply chains and the push for sustainability are driving this shift. As a result, IR 4.0 focuses on energy efficiency, eco-friendly solutions, and intelligent automation.

2.2.4 Introduction of Industrial Revolution 4.0

IR 4.0, also known as the Fourth Industrial Revolution, was recognized by construction industry at the next stage following IR 3.0. Before IR 4.0, IR 3.0 introduced technologies such as computers, microprocessors, programmable logic controllers, telecommunications, the internet, and networking. IR 4.0 evolved from IR 3.0 by integrating more advanced technologies, including the Internet of Things (IoT), artificial intelligence (AI), big data, and cloud computing. In this study, IR 4.0 was considered a direct evolution of IR 3.0, representing a shift toward more intelligent, connected, and autonomous systems. These technologies helped machines and factories work more faster, increase efficient, make better decisions and reduce human effort. The emergence of IR 4.0 was not without cause; several key factors contribute to the development. There are several important aspects that contributed to the development of IR 4.0. According to Schwab (2016) states these included the increasing demand for automation, the need for smart manufacturing, advancements in AI and machine learning, and the rise of cyber-physical systems (CPS). The beginning of IR 4.0 does not come with non-reason it is some reason cause the industrial revolution to be occur.

2.2.4.1 Factors Driving the Emergence of Industrial Revolution 4.0

IR 4.0 emerged due to rapid technological growth, rising efficiency demands, customization needs, and evolving digital consumer behaviour. Technological advancement was a key driver. According to Attar et al. (2022), innovations such as AI, IoT, robotics, and 5G improved automation, enhanced data utilization, and enabled instant communication, thereby helping construction industry work more efficiently. AI also played a vital role in reducing delays and minimizing errors. According to Kuzmanko and Vrbová (2025) stated AI handled decision-making and predictive tasks more accurately than humans. Efficiency demands also propelled industries forward, as heavy reliance on manpower increased operational costs. IR 4.0 addressed these costs through automation and real-time analytics. Customisation was another reason for the shift. According to Powell and Yang (2023), customers now expected tailored solutions. Construction industry actively search online for tools that match their needs and were willing to invest in personalised technologies.

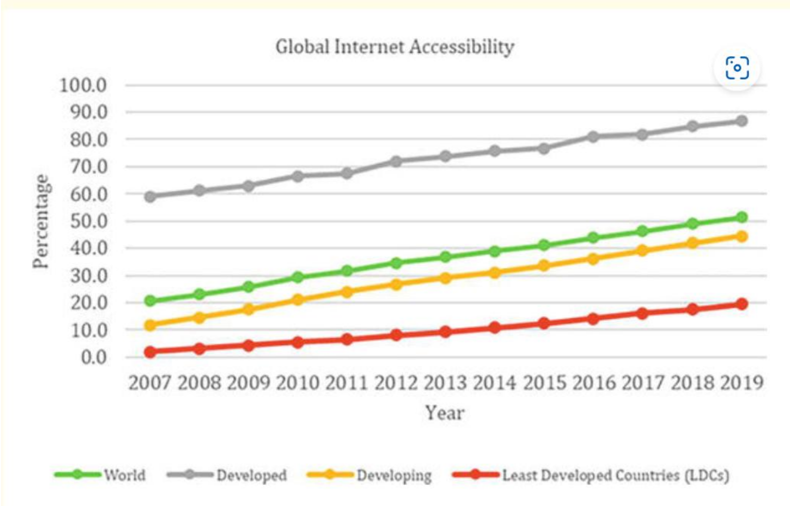


Figure 2.2: Global Internet Usage from 2007 – 2019 (Source: Ajayi, Bagula and Maluleke, 2023).

Based on Figure 2.2, global internet usage rose steadily from 2007 to 2019, showing how essential the internet became for construction industry to access information and tools efficiently. The growing demand for customised products further drove the adoption of IR 4.0 technologies. According to Powell and Yang (2023), digital tools like product configurators and digital twin software supported customisation without significant cost increases. The shift in consumer behaviour also played a key role. According to Zhou et al. (2023) stated the rise of online shopping and digital platforms pushes industries to adopt smart technologies such as AI, IoT, and automation to meet expectations for speed and personalisation. According to Smith (2023) noted companies like Amazon and Alibaba use AI analytics to manage inventory and automate operations. Construction industry began applying similar tools to enhance project tracking and client satisfaction. These changes in technology, customisation needs, and digital behaviour continued to shape IR 4.0 adoption in the construction industry.

IR 4.0 emerged from the convergence of advanced technologies, economic demands, sustainability goals, workforce shifts, and digital infrastructure growth. According to Kagermann et al. (2013) state IR 4.0

integrated AI, IoT, cloud computing, big data, and cyber-physical systems, enhancing efficiency, predictive maintenance, and smart manufacturing. According to Ghobakhloo (2018), automation included data-driven decision-making, increasing productivity and supply chain agility. According to Zhou et al. (2023), smart factories self-adjusted in real time, improving quality while reducing costs. Sustainability also droves this shift. According to Stick and Seliger (2016), AI helped manage resources and cut emissions using technologies like smart grids and energy-efficient systems. According to Kumar et al. (2020), automation reshaped workforce demands, requiring construction industry to gain digital skills, supported by upskilling efforts from governments and institutions. According to Xu et al. (2018), real-time connectivity through 5G, cloud, and edge computing enabled global integration and smart system adoption. In summary, IR 4.0 transformed the construction industry into a smart, data-driven environment. According to Williams et al. (2024), it changed how construction industry operated, made decisions, and remained competitive in a global market.

IR 4.0 brought major benefits to the construction industry by improving efficiency, reducing costs, and enhancing quality through technologies like automation, AI, IoT, and big data. According to Kagerman et al. (2013), smart manufacturing and real-time analytics helped construction industry cut waste and focus on higher-value tasks. According to Ghobakhloo (2018) stated robotics and predictive maintenance lowered downtime and operating costs by detecting issues early. Instant access to digital information also supported better decisions. According to Xu et al. (2018) stated cloud systems and CPS enabled real-time monitoring, improving transparency and resource use. According to Stock and Seliger (2016) stated IR 4.0 gave construction industry a competitive edge by boosting productivity and innovation. According to Zhou et al. (2023), tools like AI inspections and 3D printing allowed customisation and reduced defects. Beyond construction sites, IR 4.0 improved living standards through smart cities and sustainability. According to Kumar et al. (2020) state smart tech cut waste, enhanced healthcare, and reduced physical strain on workers. Despite these benefits, IR 4.0 also brought challenges that construction industry had to manage.

While IR 4.0 offered many advantages to the construction industry through technologies like automation, AI, IoT, and big data, it also presented challenges that affected construction industry differently. According to Chui et al. (2017), SMEs often struggled with high implementation costs due to limited budgets. According to Brynjolfsson and McAfee (2014) stated the need for ongoing upgrades, maintenance, and staff training added to the financial burden, reducing competitiveness for smaller firms. Another concern was the high failure rate of IR 4.0 initiatives. According to the World Economic Forum (2020), nearly 70% of projects failed due to unclear goals, weak planning, and poor execution. According to MachineMetrics (2020), internal conflict, lack of coordination, and competing stakeholder agendas also slowed decision-making and hindered progress. Cybersecurity was another major issue. According to Deloitte (2016), increased connectivity exposed construction systems to cyberattacks that can lead to data breaches and financial losses. According to Schumacher et al. (2020) stated the use of cloud computing, AI, and IoT made construction industry more vulnerable to ransomware and data theft. According to Tupa, Simota and Steiner (2017), insider threats and weak security practices further highlighted the need for strong cybersecurity frameworks. These challenges showed that while IR 4.0 brought progress, it also created significant impacts for the construction industry.

2.2.4.2 Impacts of Industrial Revolution 4.0 on the Construction Industry

According to Oesterreich and Teuteberg (2016), IR 4.0 impacted the construction industry by introducing technologies such as BIM, automation, robotics, and IoT, which helped construction industry improve productivity, reduce costs, and enhance safety by minimising human error and accidents. According to Sawhney, Riley and Irizarry (2020) state the use of digital twins and real-time data allowed for better planning, monitoring, and risk management, helping construction industry anticipate issues, reduce waste, and improve project quality. However, according to Zhou, Irizarry and Li (2021) stated the construction industry needed to address challenges like cybersecurity threats, data management, and high implementation costs, as increased connectivity raised the risk of cyberattacks and required strong systems to handle large volumes of data effectively.

2.2.4.3 Adoption of Industrial Revolution 4.0 in Construction Industry

The construction industry steadily adopted IR 4.0 by integrating automation, artificial intelligence, and smart construction techniques. According to Perera, Nanayakkara and Senaratne (2020), technologies like drones, 3D printing, and prefabrication improved accuracy, reduced labour costs, and minimised material waste, helping construction industry complete projects more safely and efficiently. Drone-based inspections also reduced risks by limiting the need for workers in hazardous areas. According to Bilal et al. (2016) stated digital project management tools and cloud platforms enhanced stakeholder communication through real-time data sharing, reducing delays and improving decision-making. However, according to Zhou, Irizarry and Li (2021), SMEs faced challenges such as high implementation costs and a lack of skilled workers, making it harder for them to adopt IR 4.0 effectively. This highlighted the need for government and industry support through funding and training. While IR 4.0 offered major benefits, its limitations also pushed the construction industry toward IR 5.0.

2.2.4.4 Limitations of Industrial Revolution 4.0 Driving the Shift to Industrial Revolution 5.0

According to Breque, De Nul & Petridis (2021), construction was among the industries that had adopted IR 4.0 slowly, necessitating additional technology developments and accelerating the shift to IR 5.0. In contrast to IR 4.0, which emphasised automation and digitisation, IR 5.0 emphasised human-machine collaboration by integrating human intelligence with smart systems. A human-centric approach was given priority in this new phase, where technology was intended to augment rather than replace workers' abilities. IR 5.0 aimed to establish a more flexible and effective workplace that struck a balance between automation and individualised decision-making by fusing robotics, artificial intelligence, and human intuition.

According to Nahavandi (2019), innovation and efficiency were restricted by the incomplete implementation of IR 4.0, underscoring the need for even more sophisticated solutions including improved cybersecurity and artificial intelligence-driven decision-making. The challenges of digital transformation, such as high expenses, cybersecurity flaws, and workforce adaption, are difficult for many firms to handle. Industries suffered from slower growth, decreased competitiveness, and inefficiencies that impeded long-term advancement if IR 4.0 was not widely adopted. Businesses needed to make investments in safe, scalable digital infrastructure and promote an innovative, learning-oriented culture in order to overcome these obstacles.

The transition to IR 5.0 became unavoidable as companies and industry worked towards intelligent and sustainable automation to fill the gaps left by IR 4.0. By combining eco-friendly production techniques, human-centered artificial intelligence, and renewable energy sources, this shift not only increased efficiency but also supported moral and sustainable industrial practices. To ensure that industry remained robust and competitive in the changing global market, governments and business leaders had to work together to establish regulations, funding, and educational initiatives that promoted this transformation.

2.2.5 Introduction of Industrial Revolution 5.0

According to Prysmian Group (2024), the main difference between IR 4.0 and IR 5.0 was their major focus. IR 4.0 placed a strong emphasis on automation and data-driven decision-making, leveraging robotics, AI, and the IoT to increase production and efficiency. IR 5.0, on the other hand, aimed to combine human intelligence with these technical developments to create a cooperative setting where construction industry and robots cooperated. By placing a high priority on sustainability, human-centred solutions, and ethical issues, this strategy ensured that advancements in technology were consistent with environmental stewardship and societal values. While IR 4.0 focused on automating processes to maximise production, IR 5.0 addressed operational effectiveness as well as broader societal challenges by attempting to strike a balance between technological innovation, worker welfare, and environmental responsibility.

According to Breque, De Nul & Petidis (2021), building on the principles of IR 4.0, IR 5.0 was the next phase of industrial transformation that emphasises human-intelligent machine collaboration. IR 5.0 sought to establish a human-centered, resilient, and sustainable industry that incorporated cutting-edge technologies while giving ethical and environmental considerations top priority, in contrast to IR 4.0, which concentrated on automation and digitalisation. This change ensured that industries addressed social and ecological issues in addition to efficiency, creating a more responsible and balanced industrial ecology.

IR 5.0 improved worker well-being and productivity by utilising AI-driven decision assistance, human-robot collaboration, and sustainable practices. By enabling workers to collaborate with intelligent systems, this shifts empowered workers and promoted innovation, creativity, and customised manufacturing. Furthermore, IR 5.0 encouraged the creation of circular economy plans and energy-efficient technology, which lessened the environmental effect and industrial waste. Adopting human-centric digitalisation as industry developed ensured that technology continued to advance rather than impede progress, paving the way for a future in which humans and robots coexisted together. There were some of the reasons that caused the IR 5.0 occur.

2.2.5.1 Reasons for the Emergence of Industrial Revolution 5.0

IR 5.0 emerged as a result of IR 4.0's flaws, particularly in areas like worker displacement, cybersecurity concerns, and the need for sustainable production. According to Nahavandi (2019), although automation and AI were successfully deployed by IR 4.0, they raised ethical issues with relation to labour reduction, data privacy hazards, and machine-driven decision-making. There were concerns about job losses and the devaluation of human skills because of many industries being overly reliant on AI and robotic automation. According to Breque, De Nul and Petridis (2021), although IR 4.0 improved productivity, it also leads to social and environmental inequalities, which necessitated a change to a more sustainable, human-centered industrial strategy necessary. This led to the urgent need for a new paradigm that struck a balance between human welfare, ethical responsibility, and technological developments.

IR 5.0 combined human intelligence, creativity, and problem-solving skills with smart technologies to create a more ethical and inclusive industrial revolution. This ensured that construction industry were empowered with improved tools rather than being replaced. According to Xu, David, and Kim (2018) stated by encouraging energy-efficient production, green manufacturing techniques, and responsible resource management, IR 5.0 addressed sustainability issues. According to Stock, Obenaus, Slaymaker, and Seliger (2018), industries were increasingly required to implement sustainable business models and circular economy strategies that promoted social and environmental well-being. This industrial evolution ensured that technological advancements were in line with long-term economic stability, workforce well-being, and society demands by emphasising human-centric digitalisation.

2.2.5.2 Evolution and Emergence of Industrial Revolution 5.0

The demand for a more human-centric industrial paradigm, together with ongoing developments in robotics, AI, data analytics, and smart manufacturing, led to the formation of IR 5.0. IR 4.0 placed a lot of emphasis on efficiency and automation, but it did not adequately address sustainability, ethical issues, or human involvement. According to Xu, David & Kim (2018) stated governments, academics, and businesses began looking for ways to combine automation and human expertise as industry recognised these gaps, ensuring a balance between technology and workforce empowerment. This shift paved the way for AI-assisted decision-making systems and collaborative robots (cobots), which complemented rather than replaced human capabilities. This reflected how intention to integrate technology while retaining human control could influence construction industry's performance. These developments promoted innovation and skill development by enabling construction industry to work on higher-value, more strategic, and creative projects.

Moreover, IR 5.0 was significantly shaped by the growing demand for sustainability and corporate social responsibility. According to Breque, De Nul, and Petridis (2021), IR 5.0 prioritised environmental consciousness, energy efficiency, and ethical manufacturing, in contrast to IR 4.0, which focused primarily on efficiency and digital transformation. This shift encouraged the construction industry to adopt low-carbon manufacturing strategies, circular economy principles, and green technologies. By utilising AI-driven optimisation, businesses were able to reduce waste, enhance energy efficiency, lower carbon emissions, and contributing to more environmentally sustainable production practices.

Apart from sustainability, IR 5.0 was also influenced by the emergence of cyber-physical-human systems. According to Javiad et al (2022), these technologies enabled real-time human-machine and digital system collaboration, thus supporting intelligent, efficient, and adaptable production techniques. Construction industry interacted with machines more naturally thanks to digital twins, augmented reality (AR), and sophisticated sensors, which improved output and operational accuracy. AI-powered decision support systems further assisted human operators in making data-driven, well-informed decisions, which improves risk management, efficiency, and reduces errors.

Furthermore, IR 5.0 fostered the workforce welfare and broader societal benefits by ensuring that technological developments aligned with human value and labour rights. According to Stock, Obenaus, Slaymaker & Seliger (2018), organisations placed strong emphasis on human-robot collaboration, reskilling initiatives, and inclusive workplace models to develop a workforce that is more resilient and adaptive. Within the construction industry, this shift reflected the need for construction industry to demonstrate both readiness and intention to adopt IR 5.0. In addition to increasing productivity, this human-centered approach also helped construction industry create safer workplaces, reduce stress at work, and improve job satisfaction factors that enhanced overall performance. Therefore, IR 5.0 represented a transformation towards an industrial era that respected both human dignity and technological progress, ensuring that industries advanced in a sustainable and socially responsible manner. This shift supported the construction industry's objective of achieving high performance through the balanced integration of technological innovation and workforce well-being. Moreover, although IR 1.0 through IR 4.0 offered numerous benefits, IR 5.0 provided unique advantages to society, particularly when construction organisations were intentionally aligned and prepared to adapt to this evolving industrial paradigm.

2.2.5.3 Advantages of Industrial Revolution 5.0

According to Breque, De Nul & Petridis (2021), emphasising human-machine collaboration was one of IR 5.0's main benefits, as it increased industrial operations' productivity, flexibility, and customisation. In contrast to IR 4.0, which focused largely on efficiency and automation, IR 5.0 ensured that human workers continued to play a key role in technological advancements, thereby enabling more intelligent, creative, and adaptable production systems. This shift allowed industries to transition from mass production to mass customisation, where products were tailored to precisely match the needs of customers without sacrificing effectiveness. AI-assisted decision-making systems and cobots augmented human capabilities, resulting in increased accuracy, quicker production cycles, and lower operating expenses. This shift towards human-centric strategies required both intention and readiness from construction industry to adopt such systems, which directly impact their performance in terms of productivity, efficiency, and adaptability.

According to Javaid et al. (2022), in addition to increasing employee engagement, IR 5.0 promoted sustainability by supporting resource-efficient manufacturing, renewable energy sources, and environmentally friendly production methods. Industries significantly reduced waste, energy use, and carbon emissions by applying AI-driven optimisation, circular economy models, and low-carbon production techniques. For construction organisations, demonstrating readiness to implement such sustainable practices, together with the intention to embrace green technologies, directly influenced their overall performance, thereby contributing to a more sustainable and efficient sector. This commitment to sustainable industrial operations aligned with global initiatives aimed at responsible manufacturing and climate neutrality. Additionally, companies that adopted ethical supply chains and green technology benefited from enjoy cost savings, enhanced corporate reputation, and higher regulatory compliance.

Furthermore, according to Stock, Obenaus, Slaymaker & Seliger (2018), by enhanced flexible and intelligent manufacturing processes, IR 5.0 improved economic competitiveness and corporate resilience. Businesses react quickly to changes in the market, supply chain disruptions, and customer needs by implementing AI-driven supply chain management, predictive maintenance, and real-time data analytics. These developments made industries more flexible and future-proof in a constantly shifting global economy by assisting companies in decreasing downtime, allocating resources optimally, and enhancing overall operational efficiency. In the construction industry, organisations that exhibited the right readiness and intention to adopt these AI-driven systems and flexible production techniques saw significant improvements in operational efficiency and resilience, which directly influenced performance outcomes.

2.2.5.4 Challenges of Industrial Revolution 5.0

IR 5.0 had many advantages, but it also had some limitations that have prevented it from being widely adopted. According to Nahavandi (2019), the high implementation costs of integrating human-centric AI systems, upgrading current infrastructures, and implementing sophisticated robotics and smart manufacturing technologies were some of the main challenges. SMEs found it difficult to retrain staff, acquire new technology, and stay competitive as a result of these financial obstacles. The overall influence of IR 5.0 on international industries was limited if many constructions industry were unable to make the switch without adequate government backing, financial incentives, or cost-effective adoption tactics. In the construction industry, this challenge directly impacted the performance of construction industry as SMEs struggled to adopt advanced technologies due to financial and operational constraints, which hindered their readiness and intention to innovate.

A highly specialised workforce was also required by IR 5.0, which called for ongoing training, upskilling initiatives, and multidisciplinary knowledge of robotics, AI, data analytics, and cyber-physical systems. However, according to Javaid et al. (2022), constructions industry were unable to adjust to new positions or effectively use emerging technology due to skills gaps caused by the rapid rate of technological improvements. This issue exacerbated inequality and resulted in workforce displacement if it was not resolved by extensive educational reforms, corporate training programs, and public-private cooperation, all of which ran counter to IR 5.0's objective of human-centric industrialisation. In the construction industry, these skill gaps limited the intention and readiness of construction industry to embrace the technological advances of IR 5.0, thus hindering overall performance improvements.

According to Xu, David & Kim (2018), the ethical and security concerns around intelligent automation, human-machine collaboration, and AI-driven decision-making were also significant issues. Industries became more susceptible to algorithmic biases, data breaches, and cyberattacks as they depended more on AI, data-sharing networks, and cyber-physical systems. Strict laws, strong cybersecurity measures, and open AI governance were necessary to ensure the moral and safe application of AI and robotics in order to stop prejudice, data misuse, and labour exploitation. For construction industry in the industry, these ethical and security concerns directly influenced their adoption of AI and automation, as they needed to demonstrate readiness to address these issues before implementing new technologies that could have impacted workforce trust and performance. Furthermore, according to Breque, De Nul & Petridis (2021), privacy problems were raised by the possibility of AI-driven surveillance and over-automation, which was why it was crucial to set up explicit ethical standards and labour laws that prioritised human rights and decent working conditions. In the construction industry, balancing technological progress with human-centric values ensured that performance gains did not come at the cost of workforce well-being and rights.

The construction industry was impacted by the benefits and disadvantages of IR 5.0, as construction industry navigated these challenges in their pursuit of more efficient, sustainable, and human-centered practices.

2.2.5.5 Impacts of Industrial Revolution 5.0 on the Construction Industry

The construction industry was significantly impacted by IR 5.0, as it introduced new levels of efficiency, safety, and sustainability. According to Perera, Nanayakkara & Senaratne (2020), by integrating intelligent robots, AI-driven decision-making, and human expertise, construction industry was able to enhance project management, improve workplace safety, and reduce environmental waste. This technological shift enabled the creation of more resilient and adaptable structures while maintaining human oversight in critical decision-making processes, ensuring both efficiency and ethical considerations were met. For construction firms, adopting these advancements enhanced their readiness and intention to optimize their operations, ensuring higher performance while adhering to ethical standards.

2.2.5.6 Adoption of Industrial Revolution 5.0 in Construction

By combining collaborative robots, human-centric AI, and digital transformation techniques, the construction industry embraced IR 5.0 with the goal of augmenting rather than replacing worker capabilities. The use of cobots and AI-assisted design tools to automate labour-intensive and repetitive processes was one of the major developments. According to Yitmen, Almusaed, and Alizadehsalehi (2024), this enhanced productivity and safety on building sites by freeing up human workers to focus on intricate decision-making, innovation, and project management. According to IAARC (2024), multi-agent robotic systems, for instance, were used to minimize errors and reduce manual labour in precision-based construction, site monitoring, and real-time data collection.

Furthermore, IR 5.0 in the construction industry placed a strong emphasis on sustainability, as construction industry increasingly used smart materials, environmentally friendly designs, and energy-efficient building methods. In order to ease the housing scarcity and lessen the environmental impact of construction, according to Kaszyńska, Skibicki and Hoffmann (2020) state 3D printing concrete became popular as a cutting-edge technique for creating structures more quickly and with less waste. In line with international sustainability targets, AI-driven energy management systems further optimized resource use, water conservation, and carbon footprint reduction.

The construction industry moved towards a more robust, sustainable, and effective model by incorporating these cutting-edge technologies, which ensured that technical developments enhanced human skill rather than replace it. However, according to Brkovic et al. (2023), to guarantee that these technologies were used in a realistic and scalable way, IR 5.0 deployment required ongoing workforce training, regulatory backing, and financial investments. This highlighted the necessity of IR 5.0 in the construction industry.

2.2.5.7 Key Drivers Behind the Adoption of Industrial Revolution 5.0

As the construction industry looked to strike a balance between technological innovation and environmental and human concerns, the shift to IR 5.0 was crucial. By applying IR 5.0 principles, construction industry improved workforce well-being, enhanced operational efficiency, and reduced their carbon footprint, making the construction industry more sustainable and socially responsible (Xu, David & Kim, 2018). Moreover, as global markets demanded more ethical and eco-friendly production methods, adopting IR 5.0 ensured that construction industry remained competitive and aligned with emerging regulatory frameworks.

Similarly, by ensuring that technology supported construction workers rather than replacing them, Breque, De Nul, and Petridis (2021) contended that IR 5.0 promoted a more socially conscious industrial model. According to Nahavandi (2019), implementing IR 5.0 enabled construction industry to stay competitive and adhere to changing rules as global markets placed a rising demand for ethical and environmentally sustainable construction practices. This change positioned construction industry to satisfy stakeholders' and customers' expectations while addressing societal and environmental issues.

The adoption of IR 5.0 in the construction industry played a crucial role in improving performance by fostering a more efficient, adaptable, and sustainable work environment. By emphasizing human-centric approaches, IR 5.0 enhanced the capabilities of construction industry, ultimately leading to increased performance. This shift not only strengthened the operational capacity of the construction industry but also aligned with the evolving demands for higher performance, making it an essential focus for insightful understanding how readiness and intention impacted overall construction industry performance.

2.3 Construction Performance

With its substantial contributions to employment and infrastructure expansion, the construction industry was considered vital to economic growth. The performance of the construction industry was examined in the next section. According to Okar et al. (2016), the definition of "performance" was explained by several study. It referred to any action or sequence of actions that produced a result or had an impact on the environment. On the other hand, according to Okar et al. (2016), "performance" relates to how well a person or machine performed, as well as how successfully an activity or job had been completed. In this study, it was observed that the performance could be employed as an adjective in addition to its use as a nouns and verbs.

Furthermore, in the following study, the term performance was referred to as the performance in the construction industry. According to Ahmad, H. & Mohamed, F (2020), performance was not only an action; it could also be seen as a result. The term “performance” was used generally and connoted a certain calibre of work. The reason "performance" was a middle word was that, unlike "success," which meant "good result," "failure" simply meant "bad result," and construction industry might have used it as a measure or adjectival word to describe the action. In this study, different area was needed to view the performance in the construction industry. According to Ahmad, H. & Mohamed, F (1999), the owner's strategic decision-making process and the effects of those decisions on the supply chain, design procedures, and product performance were reflected in the overall performance of a project.

Following that, the term "performance" was crucial for study to utilise when assessing the construction industry. This was because it made it easier for consumers to comprehend and observed how the building operated. As the study previously mentioned, the construction industry, or perhaps the nation as a whole, began implementing IR 5.0. However, the study was still unsure of how well it was performing. Therefore, it was essential for construction industry to conduct performance review to determine whether the construction industry was successful. These reviewed examined worker's progress, the status of projects , and how worker effort affected the project's efficiency. Project managers used performance appraisals to identify workers who are struggled with their tasks, particularly in adapting to new technologies introduced by IR 5.0 according to

Virtual Construction Assistants (2024). Additionally, performance reviews allowed construction industry to determine whether a company or employee was suited to their position and to evaluate overall efficiency. They also provided an opportunity to assess team dynamics and identify what worked and what did not by gathering feedback from individual team members (Virtual Construction Assistants, 2024). Although performance was important to the construction industry, the review process had impacts.

Regular performance evaluations brought several benefits. Firstly, they encourage responsibility, as construction industry understood their performance would be assessed objectively. This motivated construction industry to strive for excellence and take their responsibility seriously. Performance evaluations also offered rewards and recognition such as bonuses or promotions, for outstanding performance. By identifying both strengths and training needs, performance reviews laid the foundation for ongoing improvement. Additionally, by identifying areas of skill and areas in need of additional training, performance evaluations set the groundwork for ongoing improvement. To construction industry, performance serves as valuable data that highlighted opportunities, weaknesses, and areas for improvements. These assessments supported continuous growth by offering structured feedback aligned with company goals. (WorkRamp, 2023). When planning for IR 5.0, construction industry used evaluations to compare outcomes with IR 4.0, monitoring efficiency, project duration, and technology adoption. Performance assessments also ensured safety compliance by evaluating adherence to safety procedures, thereby reducing risks and meeting industry standards. Other than that, the construction industry’s performance enabled the companies to determine whether employee was suitable and able to apply the new technology safety or not. Moreover, regular reviews provided a competitive edge. Companies that prioritised performance evaluation maintained high standards, reduced errors, and boosted productivity. Recognition of employee contributions enhanced motivation and loyalty, while professionalism strengthened the company's reputation and ability to win contracts. As Tread (2021), businesses that valued performance assessments positioned themselves as industry leaders.

Furthermore, the success of the construction industry indicated whether it was prepared for IR 5.0. This study examined which technologies were used, their cost, and how much time construction industry spent using or experimenting new technology based on performance outcomes. If performance was strong, this study concluded that the construction industry was ready to adopt the new revolution; if not, it suggested the industry was not yet prepared. Several performance measures, such as technological adoption, cost management, and time spent on integrating new technologies, were evaluated to assess IR 5.0 readiness. Performance reviews identified strengths and areas needing improvement. According to Naji et al. (2024), low technological readiness and a lack of standardisation highlighted the necessity of industry-wide standards and technological development investments. According to F Ramadan et al (2023), implementing on-site technologies enhance employees' performance areas like initiative, safety, quality, productivity, and attendance. Therefore, if performance evaluations demonstrated effective technology use, the industry was considered ready for IR 5.0. Otherwise, they revealed areas that required development. Despite the benefits, performance evaluation had its drawbacks as well.

2.3.1 Challenges of Performance Evaluation in Construction

Performance evaluations brought advantages to the construction industry but also presented challenges such as subjectivity and bias. One major issue was the difficulty of objectively assessing individual performance due to the complexity and variability of construction projects. Differences in project scope, budget, and timelines made it hard to apply consistent evaluation standards. As a result, assessments often relied on supervisors’ subjective judgments, which were prone to conscious or unconscious bias. According to Symonds (2023), evaluators may have allowed personal preferences to influence their ratings, leading to unfair or inconsistent outcomes. This undermined employee trust and morale, reducing the effectiveness of performance reviews. Workers who felt their efforts were not recognised often became demotivated, which could lead to increased turnover. According to Goldsberry (2023), addressing this issue required clearer evaluation criteria and bias-reduction training for supervisors. Another challenge involved managing a distributed workforce. Construction teams often worked across multiple sites, making direct supervision and consistent performance tracking difficult. According to Symonds (2023), irregular work schedules and communication breakdowns complicated efforts to maintain oversight, resulting in inconsistent evaluations. These issues highlighted the need for flexible management strategies and effective communication systems to support accurate assessments in diverse working environments.

Additionally, traditional performance metrics, often based on financial outcomes, failed to capture the full complexity of construction projects. The industry recognised the need for non-financial indicators， such as quality, safety, and stakeholder satisfaction, to provide a more complete picture of success. According to Ibrahim, Zayed, & Lafhaj (2024), adopting these new metrics posed difficulties, including data collection challenges, cultural resistance, and the need for strategic alignment. Overcoming these obstacles required a reassessment of existing practices and the development of integrated frameworks that combined both financial and non-financial measures. In conclusion, while performance evaluations offered valuable insights, the construction industry still faced barriers to fair and accurate assessment. Achieving reliable evaluation depended on reducing bias, strengthening communication, and adopting more comprehensive performance frameworks. By addressing these issues, construction industry could enhance productivity, efficiency, and overall project success. Performance could be evaluated based on different aspects, but there was an original core component of performance.

2.3.2 Framework of Performance Measurement in Construction

2.3.2.1 Balance Scorecard

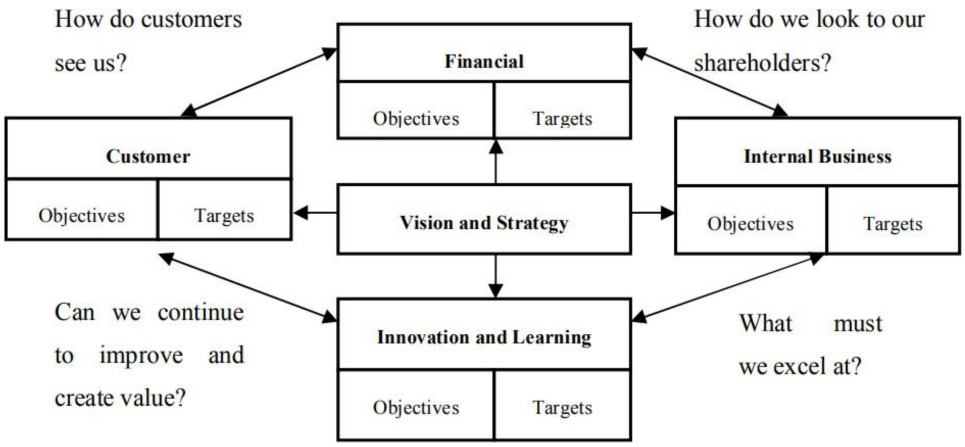


Figure 2.3: The Balanced Scorecard (Source: Işik, 2009).

The construction industry made extensive use of the Balanced Scorecard (BSC) Model, which was first presented by Kaplan and Norton in 1992, to assess and improve organizational performance. Based on Figure 2.3 the BSC framework incorporated four essential viewpoints: internal business, financial performance, customer happiness, and innovation and development (Işik, 2009). According to Kaplan and Norton (1996a), the idea sought to match corporate principles with operational goals, shareholder value and expectations, customer satisfaction, and the goals, skills, and aspirations of individual employees. This concept was especially applicable to the construction industry, as businesses had to maintain their competitiveness by striking a balance between operational efficiency, client demands, profitability, and technological improvements.

The BSC framework was used to gauge how prepared the construction industry was to implement IR 4.0 or IR 5.0 technologies. Organizational flexibility, workforce skill levels, technology infrastructure, and financial capacity were all components of readiness. Businesses with high scores in these categories were more prepared to use digital project management tools, automation, artificial intelligence, and the Internet of Things. According to Luu et al. (2008), competitive pressure, legal requirements, and the perceived advantages of cost savings and efficiency improvements were some of the variables that influenced the construction industry' intentions to adopt new technologies. By striking a balance between immediate financial concerns and long-term innovation objectives, the BSC assisted businesses in carefully planning their shift to advanced building techniques. The efficacy of the BSC in assessing industry preparation and future goals was demonstrated by research conducted by Luu et al. (2008), which combined it with the strategic weaknesses opportunities threats (SWOT) matrix to evaluate the strategic performance of major construction firms in Vietnam. The BSC was considered a recommended option for performance measurement in the construction industry since it was thought to be more thorough and organized than other models, such as the European Foundation for Quality Management's Excellence Model (EFQM) (Robinson et al., 2005). The BSC ensured that construction companies are ready for new technology, sustainability projects, and changing customer demands by coordinating organizational strategy with operational execution.

2.3.2.2 ERQM Excellence Model

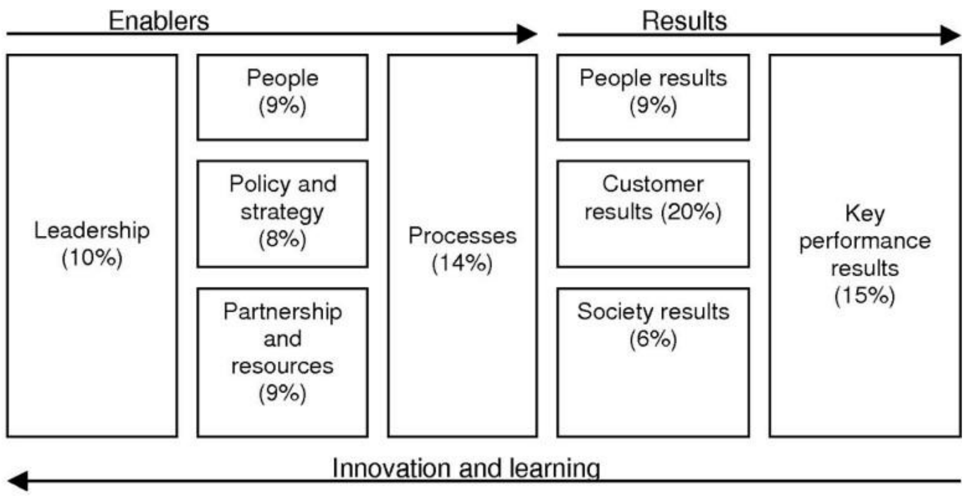


Figure 2.4: EFQM excellence model (Source: Işik, 2009).

Based on Figure 2.4, the European Foundation for Quality Management's (EFQM) Excellence Model was shown to be essential to raising the construction industry’s productivity and effectiveness. It provided businesses with a methodical framework for evaluating and improving their strategy, stakeholder involvement, and leadership. Through the use of cutting-edge technologies like automation, IoT, and BIM, construction companies maximized project efficiency, upheld high standards of quality, and advanced sustainability by putting the EFQM model into practice. By placing a strong emphasis on responsiveness to client needs and efficient communication, the model also promoted customer happiness. Another significant advantage was workforce development, since EFQM promoted ongoing employee involvement and training, which resulted in a more knowledgeable and effective workforce. Additionally, by anticipating possible risks and taking preventative action to guarantee safety and compliance, the model helped with risk management. According to EFQM (2020), organizations that used this model reported increased productivity, better stakeholder interactions, and long-term commercial success. According to Balbastre-Benavent et al. (2011), businesses improved operational excellence and maintained their competitiveness in a changing market by integrating it into the construction industry. According to Kanji and Wong (1998), adopting total quality management frameworks such as EFQM enhanced customer satisfaction, operational effectiveness, and overall project performance in the construction industry. Construction organizations thus exceeded customer expectations, upheld high standards, and achieved sustainable growth by using EFQM as a comprehensive performance monitoring instrument.

2.3.2.3 Key Performance Indicators

Classification Clusters (C)	Metrics (M) for Key Performance Indicators			
Generic classification (C1)	Strategic (M1)	Operational (M2)		
Goal classification based (C2)	Strategic Quantitative (M1)	Strategic Qualitative (M2)	Operational Quantitative (M3)	Operational Qualitative (M4)
Regulation based (C3)	Regulated or Accounting (M1)	Non-regulated or Industry Specific (M2)	Analytical or Company Specific (M3)	
Balanced Scorecard based (C4)	Financial perspective (M1)	Customer perspective (M2)	Internal process perspective (M3)	Learning & growth perspective (M4)
Business Value Model based (C5)	Demand Management aspect (M1)	Supply Management aspect (M2)	Support Services aspect (M3)	

Figure 2.5: KPI Classification Framework (Source: Ganesan et al, 2007).

Additionally, there was another framework that used key performance indicators (KPIs) to gauge the performance of the construction business as shown on Figure 2.5. Both project-level and organizational-level evaluations of the construction industry's performance were made possible by the KPIs methodology. According to Lin and Shen (2007), the KPI framework was initially created by the Construction Best Practice Programme (CBPP) in the late 1990s and enabled businesses to gauge the effectiveness, quality, and general performance of construction projects. According to CBPP-KPIS (2002), key performance indicators were classified into two main levels: project-level indicators, which evaluated aspects such as construction cost, time predictability, defect levels, and client satisfaction; and company-level indicators, which focused on broader measures like safety, profitability, and productivity. According to The KPI Working Group (2000), KPIs were essential for assessing the sustainability, efficacy, and efficiency of building projects. At the project level, KPIs including cost performance, schedule adherence, and defect rates assisted businesses in evaluating their capacity to complete projects within budget, on schedule, and with the anticipated level of quality.

The KPI framework was used to assess how prepared construction companies were to embrace IR 4.0 or IR 5.0 A company's organizational culture, worker capabilities, digital infrastructure, and financial preparedness were all examples of readiness considerations. According to Chan and Chan (2004), a company was more willing to invest in automation, artificial intelligence, and digital technologies if it had good profitability, high productivity ratings, and high safety performance. Companies' prioritization of innovation, customer happiness, and sustainability KPIs reflected their ambition to adopt new technologies. Smart construction methods, AI-driven project management, and IoT-enabled monitoring systems were more likely to be used by construction companies that prioritize cost and time predictability, defect reduction, and client satisfaction. The KPI framework provided a measurable method for evaluating an organization's readiness and capacity to transition to more sophisticated and environmentally friendly building techniques.

2.3.2.4 Contract Administration Performance Framework

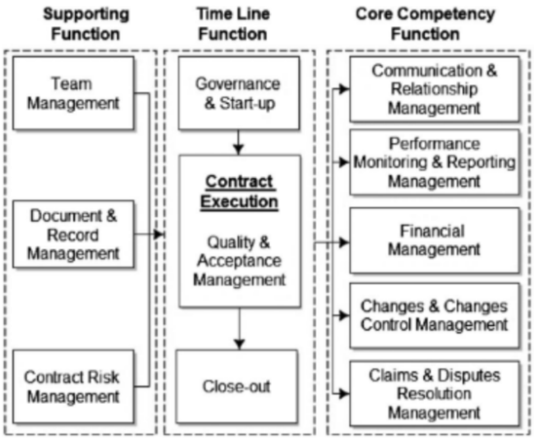
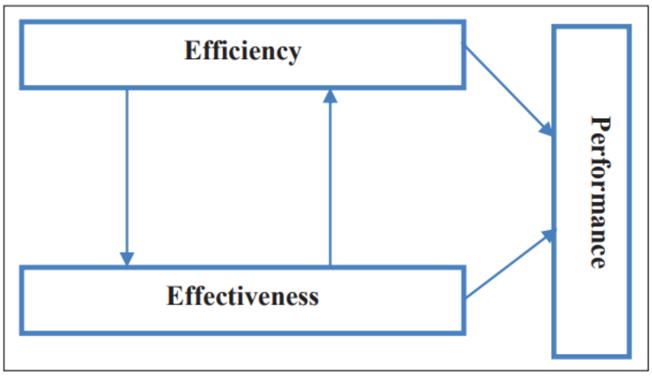


Figure 2.6: Contract Administration Performance Framework (Source: Gunduz and Elsherbeny, 2019).

Based on Figure 2.6, the Contract Administration Performance Framework (CAPF), a structured strategy or model, was utilized to evaluate, track, and enhance the efficacy and efficiency of the contract administration process within a project, especially construction projects. According to Gunduz and Elsherbeny (2019), construction experts' consensus on the 93 contributing criteria influencing contract administration performance formed the basis of CAPF. Figure 2.6 showed the three primary components of the CAPF were the timeline function, core competency supporting, and supporting function.

Figure 2.6 illustrated how the timeline function encompassed contract execution (quality and acceptance management), contract closeout management, governance, and start-up management. This function, which represented the three groups of the project management process (planning, executing, and closing), received additional support from the monitoring and control process groups (the core competency function). The core competency function included financial management, performance monitoring and reporting management, communication and relationship management, change and change control management, and claims and dispute resolution management. The timeline function provided input to and received feedback from the core competency functions. The general construction administration function interacted with the various process groups.

2.3.3 Components of Performance



Source: Ozcan (2008)

Figure 2.7: Component of Performance (Source: Ozcan, 2008).

According to Shradha Gawankar (2015), it was important to remember that effectiveness and efficiency were two aspects of total performance measures that were mutually exclusive, yet they could have had an impact on one another. More precisely, based on Figure 2.7, it was shown efficiency and effectiveness influenced each other, and both could have affected overall performance (Ozcan, 2008). The argument was presented in the appropriate context in Figure 2.7. However, it was conceivable for an organisation to be both effective and inefficient in using its inputs, or it may be efficient yet ineffective.

2.3.4 Formulation of Theoretical Framework

2.3.4.1 Theory of Reasoned Action

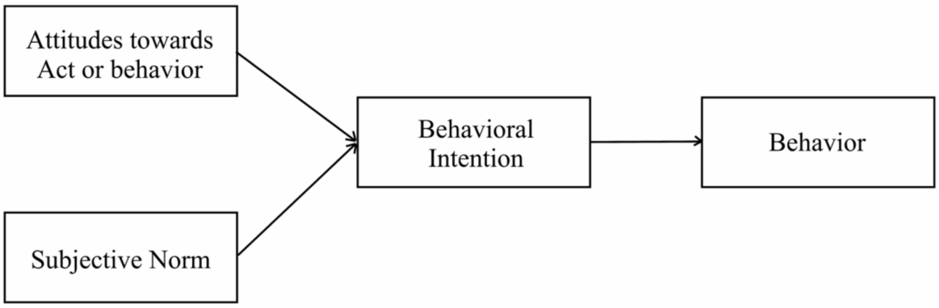


Figure 2.8: Theory of Reasoned Action (Source: Fishbein & Ajzen, 1975).

According to Fishbein and Ajzen (1975), they created the Theory of Reasoned Action (TRA), which offered a fundamental framework for comprehending how personal intentions influenced actual behaviour. According to Figure 2.8, the TRA, that an individual's behavioural intention was influenced by two main factors: subjective norms and attitudes towards the act or behaviour. While attitudes referred to a person's positive or negative evaluation of engaging in the action, subjective norms represented perceived social pressure from important persons (such as peers, superiors, or society) to engage in or refrain from engaging in the behaviour.

According to the hypothesis, a strong intention to act frequently leads to the intended behaviour since behavioural intention was the direct antecedent of actual behaviour. Intention served as a crucial predictor of performance-related behaviours in this situation. Therefore, the TRA supported the notion that better performance outcomes could result from raising construction industry' motivation through optimistic views and encouraging social environment. Organisational, social, and technical studies frequently employed this framework to describe how construction industry made decisions (Fishbein & Ajzen, 1975).

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

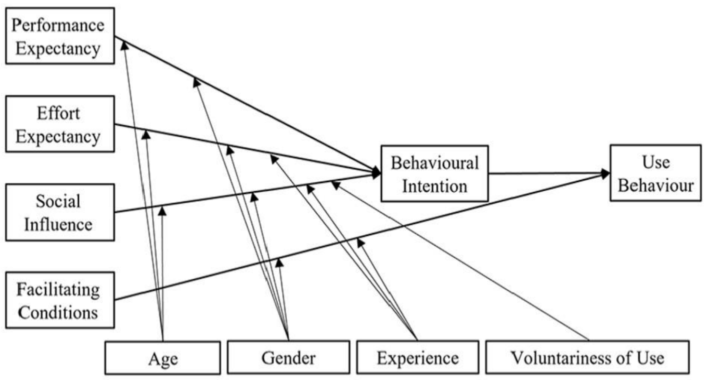


Figure 2.9: Unified Theory of Acceptance and Use of Technology (UTAUT) (Source: Venkatesh, 2003b).

In order to support the relationship between intention, readiness, and performance, this study adopted the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003) as its theoretical framework. The model identified four key constructs, performance expectancy, effort expectancy, social influence, and facilitating conditions, that significantly affected users' behavioural intention. This behavioural intention subsequently influenced actual use behaviour, which reflected performance outcomes.

According to the Figure 2.9, the model also recognised that these associations were moderated by individual factors like age, gender, experience, and voluntariness of use. According to Venkatesh (2003b), a higher intention to adopt or interact with a system or process were believed to result in better performance, and intention was treated as an independent variable in this study. On the other hand, readiness, which is symbolised by facilitating conditions in the model, indicated whether the person or organisation had the resources and assistance required to function well. There was a far higher chance of attaining excellent performance when both intention and readiness were strong. According to Venkatesh (2003b), in order to describe how behavioural and environmental elements interacted to affect performance outcomes in technological or organisational change contexts, the UTAUT model provided a clear and organised foundation.

2.3.4.3 Theory of Organisational Readiness for Change

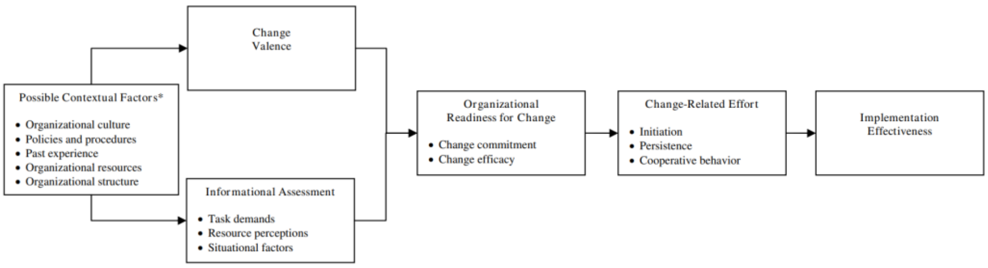


Figure 2.10: Theory of Organizational Readiness for Change (Source: Weiner, 2009).

According to Weiner's (2009) Theory of Organisational Readiness for Change, offered a solid basis for comprehending how readiness affected performance, particularly in industry embracing IR 5.0 and other digital and technological transformations as shown in Figure 2.10. Figure 2.10 illustrated that contextual elements such as organisational culture, structure, resources, and past experiences, along with an internal assessment of task demands and resource availability, all influenced organisational readiness, according to this idea.

These factors contributed to what Weiner (2009) referred as change valence and informational assessment, which in turn affected change commitment and change efficacy, the two key components of organizational readiness. In the context of IR 5.0, construction companies with high readiness were more likely to demonstrate stronger change-related efforts such as initiation, persistence, and cooperative behaviour, ultimately leading to higher implementation effectiveness and performance. Therefore, according to Weiner (2009), this theory supported the idea that readiness was not only a prerequisite for adopting IR 5.0 technologies but also a determinant of how well such innovations enhanced industry performance.

Based on the study, it highlighted the importance of examining performance in relation to readiness and intention during the IR 5.0 evolution. Therefore, RQ_1 was developed:

RQ_1: What are the variables that affect the performance of the construction industry in the IR 5.0 evolution?

2.4 Formulation of Independence Variables

Performance in the construction industry was affected by several factors. Two crucial independent variables, which were readiness and intention, had a significant impact on performance. The construction industry needed to comprehend these factors to improve its overall performance.

2.4.1 Readiness of the Construction Industry in the IR 5.0 Revolution

First, the performance of the construction industry was influenced by numerous factors, one of the elements which was readiness. According to Vladimirovna and Nikolayevna (2019), the readiness referred to the willingness or a state of being prepared. According to Harrison.T (2014), the ability to supply and integrate the capabilities needed by combatant commanders to carry out their designated missions was known as readiness. A key component of readiness was workforce and skill preparedness. The industry required professionals skilled in AI, robotics, IoT, and sustainable tech, yet many workers lacked these skills. Without training, companies faced errors, delays, and resistance due to job security fears. Investment in digital training was essential to support the shift to IR 5.0.

Moreover, according to The Times (2023), companies like Automated Architecture had developed construction robots through portable "microfactories" to address labour shortages and improve productivity. To adopt IR 5.0, the construction industry needed to had integrate advanced technologies such as AI-driven design, robotics, IoT, BIM, and digital twins. These technologies helped automate and monitor projects in real time, enhancing accuracy and efficiency. However, with increased digital integration, managing cybersecurity risks became essential to prevent data breaches and cyberthreats. According to Reuters (2024) stated that while digital twins enabled real-time data analysis, they also posed serious privacy and security challenges. Additionally, construction industry with outdated or incompatible IT infrastructure faced difficulties transitioning to IR 5.0, resulting in inefficiencies, higher costs, and resistance to adopting new technologies. On the other hand, construction industry with updated infrastructure benefited from improved automation, productivity, and smoother integration. Nevertheless, construction industry required time and training to adapt to these technologies. Without this, businesses risked delays, higher expenses, and poor performance. Therefore, to fully benefit from IR 5.0, the construction industry needed a comprehensive strategy that includes staff training, infrastructure modernisation, and strong cybersecurity measures.

According to the Chartered Institute of Building (2024), the performance of the construction industry in IR 5.0 was significantly influenced by its financial readiness. High upfront costs for adopting technologies like robotics, AI, and IoT posed major challenge, especially for small firms. According to SimAnalytics (2024) stated many businesses were reluctant to invest in automation due to concerns over return on investment (ROI) and uncertain short-term gains. This hesitation slowed the transition, affecting productivity and competitiveness. According to Wiley Online Library (2023) stated that outdated financial plans and lack of government support further limited companies' ability to upgrade infrastructure and train staff. On the other hand, construction industry with strong financial backing, clear investment strategies, and access to incentives were more capable of adopting new technologies and improving performance. Therefore, financial readiness was key for successful digital transformation and long-term growth in IR 5.0.

Based on the study, it highlighted the importance of examining performance in relation to readiness during the IR 5.0 evolution. Therefore, the RQ_{2a} was developed:

RQ_{2a}: What is the relationship between the readiness toward construction industry's performance in IR 5.0?

2.4.2 Intention of the Construction Industry in the IR 5.0 Revolution

The next independent variable that influenced whether the construction industry adopted IR 5.0 was intention. According to Anscombe (1956), defined intention as the aim to carry out an action. In this study, intention referred to the construction industry's willingness to embrace IR 5.0. This intention was shaped by construction industry' drive, commitment, and readiness to adopt new technologies. While some companies focused on the benefits gained such as cost savings or improved efficiency, others assessed the value and impact of the technologies. Key factors that influenced intention included perceived benefits, market pressure, competitiveness, and awareness of IR 5.0. Furthermore, some construction industries were hesitant to adopt IR 5.0 if they believed the benefits were not greater than those of IR 4.0. High implementation costs and the need for advanced skills created reluctance, especially without immediate returns (Smith, 2020).

However, industry was more willing to adopt IR 5.0 when they clearly recognised its potential to improve productivity and operational efficiency (Jones, 2019). Thus, intention depended heavily on how the costs and benefits of IR 5.0 were understood. In addition, fear of losing competitive advantage also influenced adoption. The construction industry recognised that failing to adopt disruptive technologies could result in obsolescence (Christensen, 1997). IR 5.0's human-centric and personalised approach aligned with customer expectations, driving businesses to adopt in order to remain relevant. A company's knowledge and understanding of IR 5.0 also played a critical role. When construction industry was aware of its benefits such as enhanced sustainability, performance, and innovation, they were more likely to adopt. On the other hand, poor understanding or misconceptions reduced their intention. For instance, Kavirathna and Perera (2025) reported that IR 5.0 principles, when combined with enabling technologies, could improve environmental performance and align with sustainability goals. Once companies gained clarity, they were better able to select suitable technologies, ensuring smoother integration and maximised benefits. Therefore, increasing awareness and addressing misunderstandings were key steps in encouraging adoption within the construction industry.

Based on the study, it highlighted the importance of examining performance in relation to intention during the IR 5.0 evolution. Therefore, RQ_{2b} was developed:

RQ_{2b}: What is the relationship between the intention toward construction industry's performance in IR 5.0?

2.4.3 Relationship Between Readiness and Intention Toward Performance of IR 5.0 Revolution

In this study, the relationship between readiness and intention played crucial role in the way construction industry affected their performance. As the study mentioned earlier, readiness referred to the construction industry level of preparation to adopt the IR 5.0, while intention referred to the willingness of construction industry to adopt IR 5.0. When both readiness and intention were aligned, construction industry were better positioned to adopt IR 5.0 confidently and effectively. This alignment not only accelerated the adoption process but also contributed to improved performance outcomes such as innovation, productivity, and competitiveness.

Furthermore, a high level of readiness can reinforce a construction industry’s intention to act by reducing uncertainty and increasing confidence in the successful implementation of IR 5.0. Likewise, a strong intention motivated the construction industry to invest in enhancing its readiness. This mutual reinforcement underscored the importance of understanding the relationship between readiness and intention as essential for shaping the transition to IR 5.0.

As indicated in the study, while the precise nature and extent of this relationship were still being explored, it was clear that the interconnection between readiness and intention was likely to influence performance in the construction industry.

RQ_{2a} and RQ_{2b} were developed as follows: “What is the relationship between the readiness toward construction industry’s performance in IR 5.0? and “What is the relationship between the intention toward construction industry’s performance in IR 5.0?”

2.4.4 Impact of Construction Industry Readiness and Intention on Performance in IR 5.0

This study proposed that the combination of readiness and intention significantly influenced the performance of construction industry during the construction industry's transition into IR 5.0. Readiness referred to the preparedness of construction industry in terms of financial capacity, technological infrastructure, workforce skills, and strategic planning. Intention represented their willingness and motivation to adopt and implement IR 5.0 technologies.

This finding suggested that when construction industry demonstrated both a high readiness and a strong intention, they were more likely to integrate advanced technologies and achieve improved performance. These improvements were observed in areas such as innovation, productivity, sustainability, and operational efficiency. However, when either readiness or intention was lacking, the transformation process faced obstacles, which reduced the effectiveness of IR 5.0 adoption. As the study concluded, the analysis confirmed the importance of both readiness and intention in shaping performance outcomes. This relationship underscored the need for a balanced focus on both factors to ensure a successful transformation.

RQ_{3a} and RQ_{3b} were developed as follows: “What is the impact of construction industry’s readiness toward the performance in IR 5.0?” and “What is the impact of construction industry’s intention toward the performance in IR 5.0?”

2.5 Formulation of Conceptual Framework

Based on the literature review above and the development of research questions, the conceptual framework in Figure 2.11 was developed to illustrate the relationship between readiness, intention, and the performance of the construction industry in the IR 5.0 evolution.

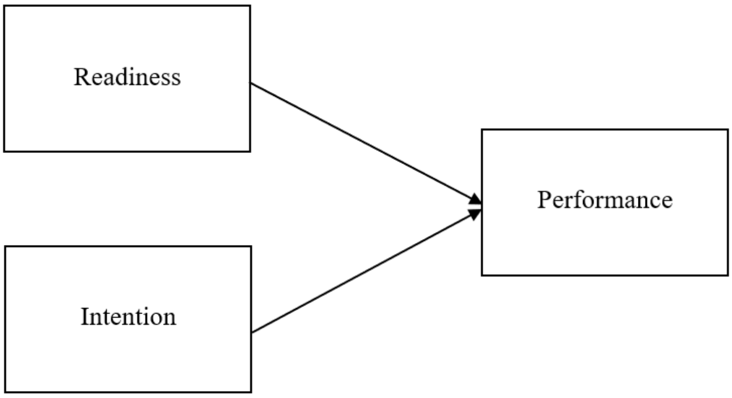


Figure 2.11: Conceptual Framework of Performance Influenced by Readiness and Intention.

From the formulation of the conceptual framework, the following hypotheses were developed to measure the research questions:

H_1 – The readiness and intention are the factors affecting the quantitative study on the performance of construction industry in IR 5.0 evolution.

H_{2a} – There is a significant relationship between readiness toward construction industry's performance in IR 5.0

H_{2b} – There is a significant relationship between intention toward construction industry's performance in IR 5.0

H_{3a} – There is a significant impact of construction industry's readiness toward the performance in IR 5.0.

H_{3b} – There is a significant impact of construction industry's intention toward the performance in IR 5.0.

CHAPTER 3

METHODOLOGY AND WORK PLAN

3.1 Introduction

The construction industry was greatly impacted by the rapid technological breakthroughs of the modern era, which increased productivity, automated processes, and enhanced project management. Notwithstanding these advancements, the industry still faced a number of challenges that impaired its general effectiveness and expansion. According to Brady Ware & Company (2025), labor shortages, supply chain interruptions, inflation, cost increases, economic instability, adoption of new technologies, and sustainability issues as the main obstacles faced in 2025.

Among these, the labour shortage was the primary problem confronting the construction industry. The shortage of skilled labour worsened as more experienced workers retired and fewer young professionals entered the industry. Approximately 88% of contractors reported they had trouble obtaining qualified labour, according to the Associated General Contractors of America (2014). Lack of personnel frequently caused project delays, and in the worst cases, it increased labour costs.

Furthermore, one of the challenges for the construction industry which was the adoption. It was not an easy job to adopted new revolution, as construction industry required financial resources to purchase new technology. In addition, the construction industry had to invest time in learning how to use and implement these technologies, as well as understanding how they could improve efficiency and effectiveness. Transferring information through technology also posted significant difficulties. The increasing pressure to adopt innovations such as BIM, drones, and AI was undeniable. Moreover, integrating various technologies proved to be challenging and required significant investment in hardware, software, and training.

3.2 Research Design

Both quantitative and qualitative research approaches were taken into consideration in this study. But because it facilitated systematic data collection through surveys and statistical analysis of the variables, performance, intention, and readiness the quantitative method was the focus. The study's choice of methodology ensured that the survey questions were designed to produce quantifiable data, which facilitated the analysis of relationships and effects in the context of IR 5.0 adoption in the construction industry.

3.2.1 Qualitative Research

This study recognized two main research types: qualitative and quantitative. According to Sreekumar (2023), qualitative research referred to the process of gathering, evaluating, and interpreting non-numerical data. Examples of such data included colour preferences among students and the types of cars available in the market. The results of qualitative research were expressed verbally and helped in understanding construction industry' subjective opinions about certain events or topics. Unlike quantitative research, which focused on numerical measurements, qualitative research aimed to explore the "why" and "how" behind human behaviour. It was exploratory in nature and often used to generate hypotheses or theories. Sreekumar (2023), that qualitative data typically came in the form of text, audio, video, or photographs. Common qualitative approaches included narrative, phenomenology, grounded theory, ethnography, and case study. This study adopted grounded theory, where the theory was developed from real-world evidence rather than starting with a hypothesis.

Several qualitative methods were used. In-depth or one-on-one interviews allowed this study to understand respondents' personal views and experiences. These interviews were often semi-structured and conducted face-to-face or over the phone. Document analysis or literature review involved examining existing written sources such as reports, policies, and research papers. Focus groups, typically involving six to ten construction industry, were held under a moderator's guidance to explore opinions and ideas. Though potentially costly, they could be conducted in person or online. Lastly, qualitative observation was used in this study to gather information by observing behaviours and interactions in natural settings, using all five senses.

3.2.2 Quantitative Research

According to Bhandari (2020), the process of gathering and analysing numerical data was known as quantitative research. It helped construction industry identify patterns, make predictions, test causal relationships, and generalize findings to larger populations. Construction industry also used quantitative research in scientific, business, and social contexts to test hypotheses, measure variables, and draw objective conclusions. According to Bhandari (2020), quantitative method consisted of three types: descriptive, correlational, and experimental research. Descriptive research provided a general overview of study variables, correlational research examined relationships between variables, and experimental research involved manipulating variables to observe their effects while controlling external factors. One of the key characteristics of quantitative research was its reliance on numerical data, allowing for statistical analysis. It aimed to be objective, focusing on quantifiable variables. According to USC Libraries (2025), quantitative research sought to produce generalizable and reliable results by concentrating on measurable aspects. Data collection methods included questionnaires, databases, and measuring tools. The data were analysed using mathematical and statistical techniques. According to Voicedocs (2022), one of the main advantages was the ability to work with large sample sizes, which reduced bias and improved accuracy.

Quantitative research offered several benefits to construction industry. It enabled quick data collection and analysis, saving time and resources. With the help of various software programs, construction industry was able to process large datasets efficiently. The use of closed-ended questions such as “yes” or “no” made data analysis simpler and more accurate. Furthermore, quantitative surveys were considered more engaging, as their straightforward design encouraged higher response rates compared to open-ended formats. According to Vanderpoel (2024), effective surveys were brief, relevant, and avoided leading or ambiguous questions. Quantitative research also required less time and effort from participants and could be conducted online, making it more convenient than qualitative in-depth interviews that needed a specific setting. Despite its strengths, quantitative research also had limitations. It often lacked depth and context, as it primarily focused on "what" rather than "why." According to Horberry, R (2024), this approach missed underlying motives and personal insights due to its structured and closed-ended nature. It also offered limited flexibility, with fixed questionnaires that could not easily be modified during the research process. Another issue was survey response bias; participants might provide socially acceptable answers rather than truthful ones. Low response rates further reduced the reliability of the data. According to Kibuacha (2024), small sample sizes risked generating unrepresentative and biased findings. Lastly, quantitative research required large sample sizes to ensure generalisability, which could be expensive and time-consuming. The distinction between quantitative and qualitative research was summarized in Table 3.1. The data gathered in this study included a variety of theoretical types.

Table 3.1: Differences Between Quantitative Research and Qualitative Research.

Parameter	**Quantitative Research**	**Qualitative Research**
Purpose and design	- Test theories and hypothesis - Identify causal relationships - Quantifiable and measurable - More structured	- Explore concepts and ideas - Formulate hypotheses or theories - Build a deeper understanding of the phenomenon - Focus more on subjective and descriptive analysis - Offer detailed descriptions of complex phenomena
Research question	- More conclusive question like What, When, Where - Example: On a scale of 1 to 5, how would you	- Exploratory questions like How or Why - Example: What are the biggest

	rate the impact of labour shortages on project delays in the construction industry? (1 = No impact, 2 = Minor impact, 3 = Moderate impact, 4 = Significant impact, 5 = Severe impact)	challenges you had experienced in adopting new technologies in the construction industry, and how had they impacted your projects?
Sample Size	Large	Small
Data	- Structured - Measurable - Numeric form	- Unstructured - Not measurable, cannot be quantified - Could be text or images
Data collection method	Methods can include experiments, controlled observations, questionnaires, and surveys with rating scales or close-ended questions. These methods can be experimental, quasi-experimental, descriptive, or correlational.	Methods can include semi-structured interviews or surveys with open-ended questions, document studies or literature reviews, focus groups, case study research, and ethnography.
Data analysis	- Deductive: Hypothesis formulated at the start - Exact measurement - Statistical analysis with tools like Excel, SPSS, or R	- Inductive: Hypotheses formed after data collection - Categorization of data into patterns - Methods: Content analysis, grounded

		theory, thematic analysis

3.3 Data Collection

This study used a quantitative research approach, concentrating on structured data collecting to measure the variables of readiness, intention, and performance in the context of IR 5.0 adoption within the construction industry, in order to obtain significant evidence for analysis. The most important element in the study was data. According to GeeksforGeeks (2025), data was a collection of facts, information, and statistics, and it could take various forms, such as text, numbers, sound, images, and more. The primary focus of the study was data, as data collection enabled construction industry to generate high-quality evidence to support their claims. According to Wilson (2022,) explained making educated decisions required high-quality data. Additionally, there were various data collection methods, including primary and secondary data. Depending on this study unique needs and situations, construction industry employed different methods of data collection. Each method served different purposes. By combining these techniques, the study aimed to produce valid and trustworthy results that helped comprehend how the construction industry performed in the IR 5.0 era.

3.3.1 Primary Data

There were various types of data collection methods used in this study. One key strategy was the collection of primary data. According to Hassan (2024) stated primary data referred to information that was originally gathered by this study and specifically designed to achieve the study's objectives. This data was collected independently and was not obtained from any secondary resources. Next, several methods were available for collecting the primary data including surveys, interviews, observations, case studies and action research and experiments.

In this study, the primary data was collected using questionnaires. These instruments were designed to effectively gather relevant and structured related to readiness, intention, and performance in the context of IR 5.0 adoption.

The questionnaire included multiple-choice items and Likert-scale questions. To maintain accuracy and reliability, the questionnaire was developed based on expert feedback and previous research. A pilot test was conducted to ensure clarity and effectiveness. Responses were gathered systematically to minimize bias and errors. Ethical standards were strictly followed during the data collection process, participants were informed of the study's purpose, their right to withdraw at any time, and were asked to give informed consent. All personal information was kept confidential. This study relied primarily on primary data to analysed the performance of the construction industry in the IR 5.0 era and to assess the impact of readiness and intention. Using primary data ensured accurate analysis and enhanced the validity and reliability of the findings. A more precise evaluation of how readiness and intention affected industry performance was made possible through this approach.

3.3.2 Secondary data

This study supported the analysis of the construction industry's performance in the IR 5.0 evolution by using secondary data in addition to primary data. According to Hassan (2024), secondary data referred to information that had been gathered, organized, and published by others for purposes unrelated to the current research. The goal of using secondary data in this study was to save time and resources. Since the focus was on the performance of the construction industry in IR 5.0, using existing materials helped avoid the need to create or locate new data from scratch. Secondary data was valuable due to its longitudinal nature, which allowed the study to analyse industry trends over time. It was also easily accessible through reports, publications, and databases, making data collection more efficient and cost-effective.

According to Kothari (2004), sources of secondary data included the internet, unpublished documents, and published materials. Government websites, industry publications, and online databases provided useful insights, while unpublished sources such as dissertations and internal reports offered unique data. Published materials, including books and journals, contained verified information that supported the research. According to Creswell & Creswell (2017), historical statistics enabled the study to examine long-term patterns, offering a broader view of industry performance. However, secondary data also had limitations, including potential relevance issues, outdated information, and possible bias, all of which could have affected the accuracy and usefulness of the findings. Therefore, the study critically evaluated each source to ensure the reliability and relevance of the data in understanding how readiness and intention influenced performance in the construction industry under IR 5.0.

3.4 Sampling data

This study primarily used quantitative methods, and an essential step was selecting the appropriate sampling technique and sample size for data collection. As previously stated, this study relied on primary data. Primary data was collected firsthand by construction industry, making it essential for obtaining accurate and relevant information. To ensure effective data collection, the study required a clear understanding of the appropriate sampling method and sample size to choose a representative group from the construction industry, thereby ensuring data reliability and minimizing bias. The target group within the construction industry was identified, and the sample size had a significant impact on data collection and analysis. According to Enago Academy (2019), sampling played a crucial role in obtaining meaningful research findings. A well-selected sample ensured accurate and reliable results while saving time and resources. Before applying any sampling technique, this study determined the appropriate sample size to serve as the target group for data collection and analysis. Therefore, to provide an effective examination of how readiness and intention influenced performance in the construction industry during the IR 5.0 evolution, this study selected an adequate sample size prior to adopting a specific sampling technique.

3.4.1 Sampling size

According to Coursera Staff (2024), the sample size was the number of observations or participants in a study or experiment. Choosing a suitable sample size as essential, as it ensured that the data gathered was accurate and statistically valid while also providing a clear focus on the goals of the study. A precise sample size reduced sampling mistakes, improved the accuracy of findings, and permitted extrapolation to the larger population. According to the

Institute for Work & Health (2021), a study's sample size affected its ability to draw conclusions as well as the accuracy of its estimates.

In this study, which focused on the performance of the construction industry in the IR 5.0 evolution, finding the right sample size was crucial for obtaining insightful results from this study, which focusses on the construction industry. While an overly large sample could have been resource-intensive without yielding proportionate benefits, a sample that was too small might have produced biassed or inconclusive. An excessively large sample offered only modest improvements in accuracy after a certain point and was considered unethical due to needless participant involvement, as noted in an article from the Journal of Educational Evaluation for Health Professions (Jeong et al., 2019).

There were several ways to calculate sample size, and each was suited to particular study designs and goals. G*Power was chosen as the suitable instrument for this study. G*Power was a free program used to compute statistical power and sample sizes for several statistical tests, such as chi-square, F, and t tests. According to Faul et al (2007), due to its accuracy and efficiency, it was frequently used in research and featured an easy-to-use interface. Examining how readiness and intention affected performance in the construction industry was made easier with the use of G*Power, which helped this study obtain a statistically valid and ethically acceptable sample.

3.4.2 Determination of Sample Size

The main purpose of the sample size technique was to allow researchers to choose the number of participants necessary for efficient data collection and analysis. The sample size was crucial to ensuring accurate and reliable results in this study, which examined how the construction industry performed in the IR 5.0 era. To achieve this, the sample size was determined using the G*Power technique.

3.4.2.1 Sample Size Determination Using G*Power Software

According to Faul et al. (2007), G*Power was developed by Franz Faul, Edgar Erdfelder, Axel Buchner, and Albert-Georg Lang. G*Power was a free statistical program that enabled this study to determine the necessary sample size using power analysis. It was recommended for sample size calculation and widely recognized in academic research. An article from the Journal of Educational Evaluation for Health Professions (JEEHP) highlighted G*Power as a valuable tool for sample size estimation and power analysis. It emphasized that G*Power was free, user-friendly, and supported various statistical methods such as F-tests, t-tests, chi-square tests, and Z-tests. Furthermore, Faul et al. (2007) emphasized the significance of G*Power as a useful resource for research, calling it a “great statistical program that researchers should use in their everyday practice,” particularly for calculating sample sizes and conducting power analyses. Many academics across various fields chose G*Power for its accessibility and ease of use. G*Power not only helped this study calculate an appropriate sample size, but it also offered several advantages. According to Faul et al. (2007), G*Power was widely used to accurately estimate the required sample size, ensuring sufficient statistical power to detect meaningful effects. Kang (2021) noted that by determining the correct sample size, G*Power helped reduce errors in data analysis, including Type II errors, when a study fails to detect a true effect. This was essential for maintaining the reliability and validity of research findings, as an inadequate sample size could lead to inconclusive or misleading results.

Additionally, Faul et al. (2007) stated that G*Power assisted researchers in conserving time and resources by preventing unnecessary data collection, thus reducing research costs. It provided a cost-effective and efficient method for determining sample sizes, ensuring that studies were neither overpowered nor underpowered. According to Erdfelder et al. (2009), the software supported a variety of statistical tests, including chi-square tests, regression analyses, ANOVA, and t-tests, making it suitable for various study designs. Its flexibility allowed researchers to tailor sample size calculations to the specific needs of their studies, thereby enhancing the accuracy and credibility of results Overall, G*Power was a valuable tool for this study, which aimed to conduct efficient and effective research with reliable and valid results. Its ability to optimize sample size determination ensured statistical soundness while minimizing unnecessary resource expenditure, making it an essential tool in quantitative research. Several formulas were also available to verify the accuracy of G*Power’s calculations, providing a reliable means of confirming its results.

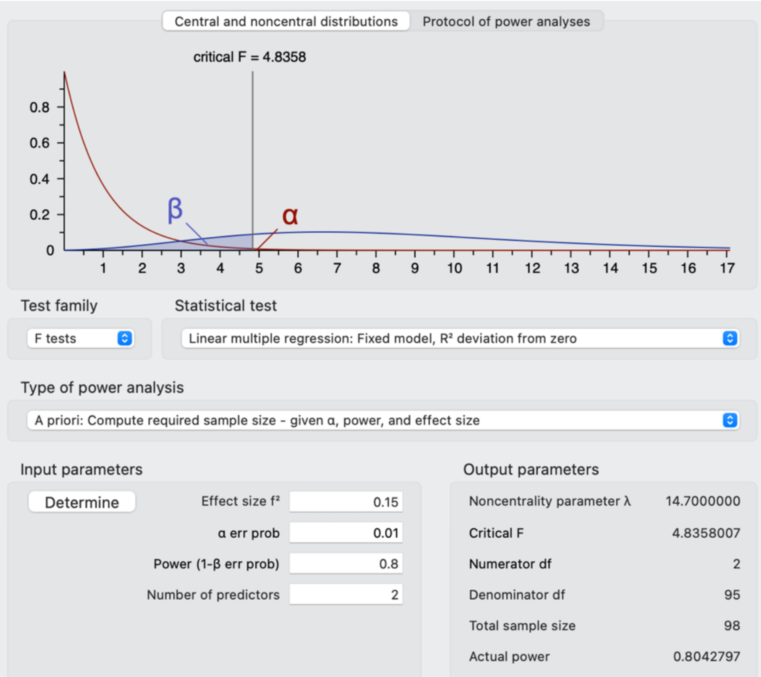


Figure 3.1: Sample Size Estimation Graph from G*Power for Regression Analysis.

Based on Figure 3.1, this study used G*Power with the test type "Linear multiple regression: Fixed model, R^2 deviation with zero" applied F tests to conduct power analysis. The selected analysis type was "A prior: Compute required sample size - given α, power, and effect size". This power analysis helped determine the required sample size without needing the population size, making it suitable for this study where the population size was unknown. The input parameter included an effect size $f^2 = 0.15$, alpha error probability = 0.01, Power ($1 - \beta$ err prob) = 0.8 and two pcredictors. According to Cohen (1988) state small, medium and large effect size were defined as f^2 = 0.02, 0.15 and 0.35 respectively. This study used a medium effect size of 0.15 due to lack of prior information. According to Cohen (1988) stated when no prior information was available, researchers were advised to adopt a medium effect size as the standard estimate. Next, this study set the confidence level of 99%, which resulted in an alpha error probability of 0.01 as shown in Formula (3.1) and Formula (3.2). The alpha error probability was calculated using the following formula:

$$\alpha = 1 - \text{Confidence level} \tag{3.1}$$

$$\alpha = 1 - 0.99 = 0.01 \tag{3.2}$$

In G*Power, this study set power at 0.80, following by the Cohen’s standard. According to Cohen (1988), power 0.80 was conventionally accepted as a reasonable balance between Type I and Type II error risks. Lower power would have increased the risk missing a true effect, while higher power would have required much larger sample size, which would have been impractical. Since this study included two independence variables, the number of predictors was set to 2.

Based on Figure 3.1, a minimum sample size of 98 was required to achieve 80% power, detect a medium effect size (f^2 = 0.15), with 2 predictors, and a 99% confidence level (α = 0.01), as presented in Formula (3.2). The noncentrality parameter (λ = 14.70) indicated the expected effect strength, and the critical F-value (4.84) represented the threshold for reject the null hypothesis. The actual power of 0.80 confirmed the study design was adequate.

3.4.2.1.1 Multiple Linear Regression

To validate the G*Power accuracy this study applies traditional power analysis formulas to manually compute sample size and power. The software's dependability is validated if the manually determined values correspond to G*Power's output. By contrasting G*Power's sample size computations with those obtained using accepted statistical formulas, this study can verify the accuracy of the program.

Multiple linear regression contained a manual formula that could be used to calculate the required sample size. According to Bausell and Li (2002), the Z-based approximation formula allowed researchers to independently verify that the sample size estimated by G*Power fell within a valid range. This approach supported academic justification, strengthened methodological defense, and enabled manual cross-checking of the software-generated values. The Z-based formula was particularly effective when dealing with moderate to large sample sizes and offered a practical alternative to the more complex noncentral F-distribution method used by G*Power. The manual calculation formula was stated as follows:

$$N = \frac{(Z_{1-\alpha} + Z_{1-\beta})^2}{f^2} + k + 1 \tag{3.3}$$

where

N = sample size

$Z_{1-\propto}$ = Z-score corresponding to the chosen significance level (α)

$Z_{1-\beta}$ = Z-score corresponding to the statistical power (1–β)

f^2 = effect size

k = number of predictor variables

In this Formula (3.3), N represents the required sample size; $Z_{1-\propto}$is the Z-score corresponding to the chosen significance level (α), and $Z_{1-\beta}$ is the Z-score corresponding to the statistical power (1–β). The term f^2 denotes the effect size, and k indicates the number of predictor variables in the regression model. For this study, a medium effect size was assumed with f^2 = 0.15, a 99% confidence level was set (α = 0.01, hence $Z_{1-\propto}$ = 2.326), and a statistical power of 0.80 was targeted (β = 0.20, hence $Z_{1-\beta}$ =0.842). With two predictors (k =2), the formula was computed as follows:

$$N = \frac{(2.326 + 0.842)^2}{0.15} + 2 + 1$$

$$N = \frac{(3.168)^2}{0.15} + 3$$

$$N = 66.913 + 3$$

$$N = 70$$

Based on the manual computation using the Z-based approximation formula for linear multiple regression, the minimum sample size was calculated to be 70.

3.4.3 Comparison with Other Statistical Software

The accuracy of G*Power was verified by comparing it to other statistical programs like R, SPSS, and SAS to see if its minimum sample size estimates matched those made with other reliable programs. By performing comparable statistical tests on other software systems and comparing the outcomes, in this study evaluated the dependability of G*Power.

Discussions on Cross Validated, for instance, described instances in which academics had contrasted G*Power with R, namely the webpower package. These comparisons showed that rather than faults in G*Power itself, discrepancies in sample size estimates frequently resulted from variances in default settings, rounding techniques, or effect size computations. In this study, it was discovered that G*Power generated results that closely resembled those of R and other applications, verifying its accuracy, by standardising effect size definitions and ensuring that the same statistical parameters (e.g., alpha level, power, and variance) were utilised (Cross Validated, 2024).

As a result, G*Power is verified empirically by comparisons with other statistical techniques in addition to theoretical formulations. In this study are reassured that G*Power is a trustworthy tool for power analysis and sample size determination thanks to this cross-verification procedure.

3.4.3.1 R Programming Language for Statistical Analysis

R was a free, open-source programming language and software environment that was widely used for statistical computing, data analysis, and graphical visualization. R was developed based on the S programming language, which was originally created at Bell Labs, and it later became a standard tool in statistics and data science. According to the American Statistical Association (2022), practitioners were advised to apply methods and data that were suitable, unbiased, and appropriate to the context, aiming to ensure outcomes that were accurate, meaningful, and reproducible. R supported these principles effectively because all analysis steps were scripted, enabling full transparency. These scripts could be shared, reviewed, and re-executed with ease. According to W.N. Venables and B.D. Ripley (2002), R eliminated licensing costs for students and researchers and provided a wide variety of statistical and graphical techniques. R supported a range of statistical analyses, including linear and multiple regression, ANOVA, Multivariate Analysis of Variance (MANOVA), and non-parametric tests. For data visualization, R offered high-quality plots through packages like ggplot2 and base graphics, which allowed for fully customizable, publication-ready visuals. R was also widely used in academic research, particularly for tasks such as sample size calculation, power analysis, and simulation studies.

```
> # Load packages
> library(pwr)
> library(grid)
> library(gridExtra)
> library(ggplotify)
>
> # Define inputs
> effect_size <- 0.15
> alpha <- 0.01
> power_target <- 0.80
> predictors <- 2
>
> # Power analysis to calculate required sample size
> test <- pwr.f2.test(u = predictors, f2 = effect_size, sig.level = alpha, power = power_target)
>
> # Dynamically extract values
> numerator_df <- predictors
> denominator_df <- 95  # You want this fixed at 95
> total_sample_size <- denominator_df + predictors + 1
> critical_f <- round(qf(1 - alpha, numerator_df, denominator_df), 2)
> noncentral_param <- round(effect_size * total_sample_size, 2)
> actual_power <- round(test$power, 4)
>
> # Create data for power curve
> n_values <- seq(80, 120, 1)
> powers <- sapply(n_values, function(n) {
+     v <- n - predictors - 1
+     if (v > 0) {
+         pwr.f2.test(u = predictors, v = v, f2 = effect_size, sig.level = alpha)$power
+     } else {
+         NA
+     }
+ })
```

Figure 3.2: Power Curve and Summary Output for Multiple Regression (f^2= 0.15, α = 0.01, Power = 0.80, 2 Predictors).

```
> # Create the base R plot function
> power_plot <- function() {
+     plot(n_values, powers, type = "l", lwd = 2, col = "blue",
+          main = paste0("Power Curve (Multiple Regression)\nf² = ", effect_size, ", α = ", alpha, ", Predictors = ", predictors),
+          xlab = "Sample Size", ylab = "Power", ylim = c(0, 1))
+     abline(h = power_target, col = "red", lty = 2)
+     abline(v = total_sample_size, col = "darkgreen", lty = 3)
+     points(total_sample_size, power_target, pch = 19, col = "blue")
+     text(total_sample_size, power_target + 0.02,
+          labels = paste0("n = ", total_sample_size, ", Power = ", power_target),
+          pos = 3, col = "blue", cex = 0.8)
+ }
>
> # Dynamic summary text (no hardcoded numbers)
> summary_text <- textGrob(
+     paste0(
+         "Effect size f² = ", effect_size, "\n",
+         "Alpha error probability = ", alpha, "\n",
+         "Power (1 - β) = ", actual_power, "\n",
+         "Number of predictors = ", predictors, "\n",
+         "Total sample size = ", total_sample_size, "\n",
+         "Numerator df = ", numerator_df, "\n",
+         "Denominator df = ", denominator_df, "\n",
+         "Critical F = ", critical_f, "\n",
+         "Noncentrality parameter = ", noncentral_param
+     ),
+     gp = gpar(fontsize = 12), x = 0.05, hjust = 0
+ )
>
> # Combine summary and graph like G*Power output
> grid.arrange(summary_text, as.grob(~power_plot()), ncol = 1, heights = c(1, 2))
```

Figure 3.3: Power Analysis Output and Power Curve for Multiple Linear Regression with Medium Effect Size (f^2= 0.15, α = 0.01, Power = 0.80, 2 Predictors).

Effect size f² = 0.15
Alpha error probability = 0.01
Power (1 - β) = 0.8
Number of predictors = 2
Total sample size = 98
Numerator df = 2
Denominator df = 95
Critical F = 4.84
Noncentrality parameter = 14.7

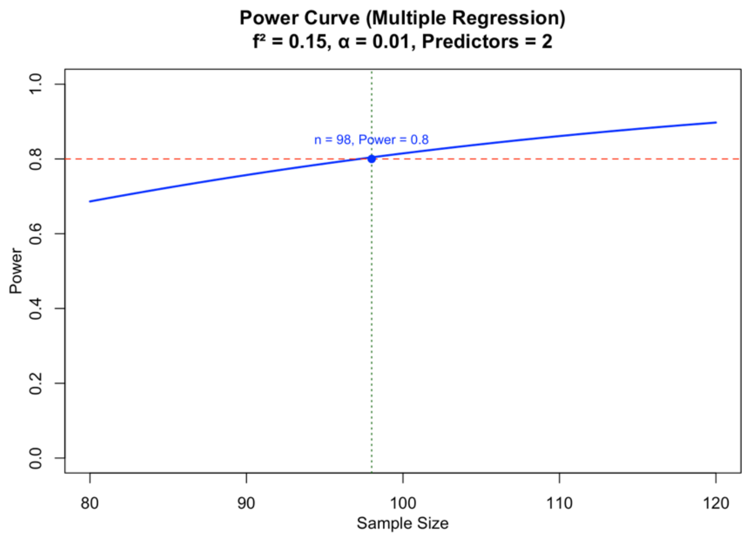


Figure 3.4: Power Curve for Multiple Linear Regression Analysis.

After conducting the procedures illustrated in Figure 3.2 and Figure 3.3, the results were obtained. Based on Figure 3.4, the minimum sample size was determined to be at least 98 respondents. The input parameters used in R, effect size (f^2= 0.15), alpha error probability (α = 0.01), and number of predictors (2), were consistent with those used in G*Power. The results, including the numerator degrees of freedom, critical F-value, noncentrality parameter, and total sample size, aligned exactly with the G*Power output. This confirmed that R supported the conclusion that a minimum of 98 respondents was needed to achieve 80% statistical power at a 99% confidence level. This sample size was essential to ensure accurate estimation when assessing how construction industry adopted IR 5.0.

3.4.3.2 Daniel Soper Sample Size Calculator

Daniel Soper's sample size calculator was a free, web-based statistical tool designed to determine the minimum sample size required for conducting Structural Equation Modeling (SEM), multiple regression, and ANOVA. In addition, the calculator was able to perform t-tests, chi-square tests, and F-tests. The sample size calculator for Structural Equation Models was developed by Dr. Daniel Soper. The A-priori Sample Size Calculator provided a practical and academically supported method for determining sample size. According to Statistics Solutions (2025), the tool was described as “user-friendly” and was based on established research by Westland (2010), which highlighted its value in producing reliable and properly powered SEM study designs.

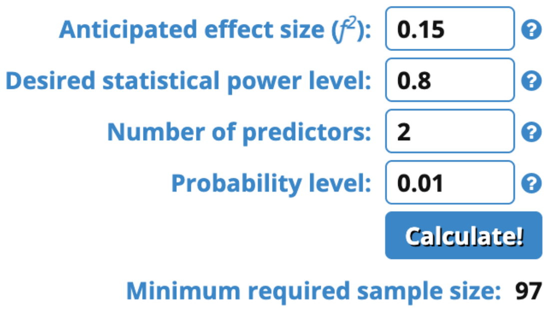


Figure 3.5: A-prior Sample Size Calculator for Multiple Regression.

Based on Figure 3.5, Daniel Soper’s sample size calculator was shown to be capable of conducting analysis using input parameters such as effect size (f^2= 0.15, medium), desired statistical power level = 0.80, probability level = 0.01, and number of predictors (k) = 2. After the calculation, the minimum required sample size was determined to be 97.

Table 3.2: Cross-Validation of Sample Size Estimates Using G*Power, R, and Daniel Soper's Calculator.

Parameter	**G*Power**	**Manual Calculation – Multiple Linear Regression**	**R**	**Daniel Soper Size Calculator**
Effect Size (f^2)	0.15	0.15	0.15	0.15
Alpha Error probability (α)	0.01	0.01	0.01	0.01

Power (1 - β)	0.8042797	0.80	0.80	0.80
Number of Predictors	2	2	2	2
Numerator Degrees of Freedom	2	-	2	2
Denominator of Degrees	95	-	95	94
Critical F-Value	4.8358007	-	4.84	4.8673
Noncentrality parameter (λ)	14.7000000	-	14.7	14.55
Minimum sample size	98	70	98	97

Table 3.2 compared the results of four tools, G*Power, Multiple Regression manual calculation, R, and Daniel Soper's Sample Size Calculator, that were used to determine the minimum required sample size for a multiple regression analysis. Using the same input parameters (effect size = 0.15, α = 0.01, power = 0.80, and 2 predictors), all four tools and methods produced consistent results. Manual calculation – Multiple Linear Regression recommended minimum sample size was 70, G*Power and R recommended a minimum sample size of 98, while Daniel Soper's calculator suggested 97. Given the slight variation, this study recommended collecting at least 98 respondents to ensure adequate statistical power for the analysis.

3.4.4 Sampling Collection Techniques

Instead of surveying the entire population, this study can gathered data from a subset by using sampling, which was an essential phase in the research process. It guaranteed that data was manageable while preserving representativeness, boosted productivity, and lowered expenses (Saunders, Lewis, & Thornhill, 2019). Sampling techniques were typically divided into two basic categories: probability sampling and non-probability sampling. In the study, stratified sampling and purposive sampling were selected as the sampling techniques used in the study. The reason that purposive sampling was selected was because the study already knew the area needed to collect data in, which was the construction industry, and other than that, the construction industry had different education levels and skill levels, and labour had different views for IR 5.0. Both techniques can helped this study be more efficient in the sampling. The goals of the study, the resources at hand, and the requirement for generalisability all influenced which of these approaches was best.

3.4.4.1 Probability Sampling

Probability sampling was a method often used in surveys, quality control, medical research, education studies, market research, and political polls. According to Nikolopoulou (2022), probability sampling was a technique in which a sample, or a subset of the population under study, was chosen at random. It was also known as random sampling. For it to be considered random, every research unit had an equal chance of being selected. This method helped ensure fairness and reduced bias, producing accurate and generalizable results, ultimately supporting reliable conclusions in the study. According to Edward (2024), the methodical process of probability sampling guaranteed that each participant had an equal chance of being chosen, which improved the validity and dependability of study findings. There were several types of probability sampling, including simple random sampling, stratified sampling, systematic sampling, and cluster sampling.

3.4.4.1.1 Simple Random Sampling

According to Scribbr (2023), every member of a population had an equal chance of being chosen for the sample when using simple random sampling, a probability sampling technique. One of the most impartial selection processes, this strategy guaranteed equity since no one as given preference over another. According to Mindthegraph (2023), this study can used computer-based algorithms, random number generators, or drawing lots to create a random sample. According to SurveyLab (2023), this method's simplicity and unpredictability provided precise and broadly applicable results, which was particularly crucial for extensive surveys or experiments. Random sampling guaranteed that the sample was representative of the entire population and helped lower the chance of bias in situations where the population was huge. This was especially helpful for research that sought to make generalisable findings. Because representative samples were necessary for drawing reliable conclusions, simple random sampling was therefore frequently employed in a variety of domains, including as market research, public opinion surveys, and clinical trials (Scribbr, 2023). Simple random sampling was also a flexible technique in research design because it was simple to use and does not require prior knowledge of the population's characteristics.

3.4.4.2 Non-probability Sampling

According to Scribbr (2023), non-probability sampling was a technique that frequently produced biassed results since not every member of a population has an equal chance of being chosen. In exploratory or qualitative research, where the objective is to acquire insights rather than generalise data, this technique was frequently employed (Mindthegraph, 2023). According to SurveyLab (2023), Convenience sampling (picked participants who were easily reachable), purposive sampling (picked participants according to predetermined criteria), snowball sampling (relied on participants to recruit others), and quota sampling (picking participants to reach predetermined quotas) were examples of non-probability sampling types. According to Scribbr (2023), non-probability sampling was quicker and less expensive than probability sampling, but it was less accurate and could result in selection bias.

3.4.4.2.1 Snowball Sampling

According to Scribbr (2023), a non-probability sampling technique called "snowball" sampling involved current participants enlisting new ones, producing a "snowball" effect. According to Mindthegraph (2023), this method enabled this study to reach construction industry who would normally have been hard to locate or get in touch with, making it especially helpful for studies involving hard-to-reach populations like drug addicts, the homeless, or other marginalised groups. According to SurveyLab (2023), like a snowball expanding as it rolled down a hill, the process began with a small number of initial participants, and as they recommended others, the sample size grew. In qualitative research, where the emphasis was more on in-depth comprehension than statistical representation, this approach was frequently used. By examining social networks and relationships within particular groups, snowball sampling enabled this study to gain important insights into experiences and behaviours that might have been difficult to record using traditional techniques. According to Scribbr (2023), despite being economical and useful, snowball sampling could introduce bias since participants might only have recommended construction industry who were similar to them, which could have resulted in a sample that was not entirely representative of the population. In qualitative research, it was nonetheless a useful tool despite this shortcoming, especially when examining hidden or sensitive topics where typical sampling techniques were impractical (Mindthegraph, 2023).

3.4.4.2.2 Purposive Sampling

According to Scribbr (2023), purposive sampling was a non-probability sampling method where participants were selected based on specific characteristics or qualities that were relevant to the research. It was often referred to as judgemental or selective sampling. According to Mindthegraph (2023), this method was especially helpful in qualitative investigations because it enabled this study to concentrate on construction industry who possessed specific information, experiences, or expertise relating to the research issue. Instead of using random selection, this study used purposive sampling to deliberately choose participants who fitted specified criteria in order to obtain rich, in-depth information on particular phenomena (SurveyLab, 2023). For instance, only construction industry who had received cancer treatment were included in a study on the experiences of cancer survivors. According to Scribbr (2023), purposive sampling offered useful in-depth information, but it could also introduce bias because the sample might not have been representative of the wider population, which limits the generalisability of the results. According to Mindthegraph (2023), purposive sampling was frequently employed in case studies, expert interviews, and pilot studies where this study needed particular data or insights, notwithstanding this drawback. Following the calculation of the sample size based on the sampling technique chosen by the this study, data collection was carried out to collect the date. However, it was equally crucial for this study to choose the right tool to use when gathering data.

3.5 Research Instrument

In this study, a variety of study instruments were utilised, including pre-determination test, pilot test, and questionnaires, to gather data. In this study, the research instrument that was used was the questionnaire. Different research instruments had a variety of advantages and disadvantages.

3.5.1 Instrument Testing

In this study, in addition to choosing the questionnaire as the data collection method, it was essential to ensure the reliability and validity of the questionnaire. According to Bullen and Bullen (2022), before using the survey questionnaire to collect data, it was important to test it. Pretesting and piloting helped identify questions that construction industry might not have understood or any issues with the questionnaire that could have led to biased responses. According to Morrison (2019), that reliability, or consistency, referred to the extent to which an instrument yielded the same results if the measurement was repeated under similar conditions. Next according to Assessment (2013), validity, which was also rephrased as "truthfulness" or "accuracy," was the idea that the questionnaire measured what it claimed to measure. The pre-test and pilot test were able to help ensure the construction industry of IR 5.0 questionnaire's reliability and validity.

3.5.2 Pre-test

In this study, a pre-test was conducted to examine the clarity, wording, and overall structure of the questionnaire developed to measure the performance of the construction industry in the context of IR 5.0. The pre-test involved a small group of respondents who were familiar with the construction industry, and their feedback was used to identify any ambiguous, confusing, or irrelevant items in the questionnaire. This process helped ensure that all questions were clearly understood and accurately reflected the variables of intention, readiness, and performance. Based on the feedback received, necessary adjustments were made to improve the questionnaire before proceeding to the pilot test phase.

According to van Teijlingen and Hundley (2001), pre-testing a questionnaire is essential for detecting problems with wording and structure before a full-scale pilot was conducted. Similarly, according to Peat et al. (2002) emphasized that pre-testing enhanced the internal validity of a questionnaire by identifying items that might not functioned as intended. According to Nur Sukinah Aziz and Adzhar Kamaludin (2015) pretesting was crucial for locating issues with the questionnaire. Confusion with the question's broad meaning and misunderstandings of specific terminology or concepts were examples of issues with question content. Once the questionnaire design was completed to measure the performance of the construction industry in the context of IR 5.0, this study conducts a pre-test. To ensure the instrument was clear, relevant, and accurately captureed the intended variables such had intention, readiness, and performance. The pre-test was carried out with a small group of respondents from the construction industry. Their feedback was used to refine the wording, structure, and logic of the questionnaire before it proceeded to the pilot test phase.

3.5.3 Pilot Test

To ensure the questionnaire's reliability and validity, this study conducted a pilot test. According to Dovetail Editorial Team (2023), a pilot study was an initial investigation carried out before to a more extensive study. The pilot test helped in this study guide the direction of the quantitative study of performance of construction industry. It included providing insights into the study overall feasibility, and any challenges that in the quantitative study on the performance of construction industry might have faced once it was implemented. The reason for conducting pilot testing was to shape the direction of the quantitative investigation on the performance of the construction industry within the IR 5.0 revolution. It allowed for a better understanding of the research methods and provided a clearer picture of how the actual data collection process would unfold. According to Dovetail Editorial Team (2023), pilot testing helped identify and prevent potential errors that might have affected the reliability of the results or hinder the successful completion of the study. It also served to evaluate the feasibility and practicality of the research design based on the current data and available resources. Furthermore, it provided early insights into the possible trends and outcomes of a full-scale study, supporting more informed decision-making as the research progressed. According to van Teijlingen and Hundley (2002), pilot studies were a crucial part of a well-designed investigation. Although it does not ensure success in the primary trial, conducting a pilot study increased the likelihood. Other than the pilot tests, other test was able to ensure the questionnaire for the performance in the construction industry in IR 5.0 was reliable and valid was the pre-test. To assess internal consistency reliability, Cronbach's Alpha values were examined for each construct. As shown in Table 3.3, a value of 0.70 or above is generally considered acceptable, indicating that the items consistently measure the intended construct (Hair et al., 2022).

Table 3.3: Cronbach's Alpha Scores value (Source: Taber, 2018).

Cronbach's Alpha	**Internal Consistency**
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

3.5.4 Questionnaire Descriptive

According to Bhat (2023), a questionnaire was a research tool designed to collect data from respondents. It contained a series of questions or prompts. Typically, a research questionnaire included a combination of open-ended and closed-ended questions. In this study, which was a quantitative study on the performance of the construction industry in the IR 5.0 evolution using a conceptual model, the study utilised a questionnaire to collect data related to intention, readiness, and performance. A survey always included a questionnaire, but a questionnaire might or might not have been part of a survey. The advantages of questionnaires included wide content availability and cost-effectiveness. According to Olivia & Olivia (2023), questionnaires reached a broad and diverse audience, and online platforms enabled survey distribution across Malaysia. Questions could be designed for multilingual accessibility, for example, Google Forms allows translation.

Furthermore, online questionnaires allowed efficient data collection from various stakeholders without travel or printing costs. Respondents could remain anonymous, and many tools complied with privacy regulations. The disadvantages included limited context. Important data that might have been obtained through interviews or observation could have been overlooked. After evaluating all instruments, this study chose the questionnaire as the most suitable tool due to its efficiency, reach, and cost-effectiveness in the context of IR 5.0.

According to Olivia and Olivia (2023), questionnaires were a cost-effective way to collect information. Researchers did not need to hire personnel for data checks or travel to multiple locations. In this study, data was gathered through online questionnaires, eliminating the need for printing or shipping costs. Respondents could complete the questionnaire anonymously. Moreover, many survey platforms complied with essential privacy and data security regulations. The disadvantage of questionnaire was its limited context. Only a limited amount of context for the research issue was provided by questionnaires. Important information that could have been obtained by alternative data collection techniques, such interviews or observation, might have been overlooked in this study. After evaluating the advantages and disadvantages of various research instruments, in this study used a questionnaire. Compared to other methods, questionnaire was the most suitable tool for collecting data efficiently within a short timeframe, across distant locations, and at a lower cost making it ideal for reaching the data collection target in the construction industry for this IR 5.0 related study. Once this study decided to use the questionnaire, it conducted tests to ensure that the questions were reliable in measuring the performance of the construction industry in the IR 5.0 revolution.

3.6 Descriptive Measurement

According to Uma Sekaran and Roger Bougie (2016), descriptive measurement summarized and organized the characteristics of the data set, which meant providing an overview of the data collected. In this study, descriptive measurement was conducted using two types: frequencies and percentages. According to (Creswell, 2017), the highest and lowest values of each category of data were identified. The data set consisted of responses and observations from the sample. The descriptive measurement covered respondent's demographic information, including gender, position, working experience, and high education level, as well as variables related to readiness and intention.

3.6.1 Construct Measurement Scale

The instrument utilised in this study to measure abstract ideas such as performance, intention, and readiness, all of which were crucial for evaluating the performance of the construction industry in the context of IR 5.0, was referred to as a construct measuring scale. Since these conceptions entailed behavioural and psychological components, they could not be directly observed. For example, readiness encompassed a construction industry's preparedness to adopt new technologies, while intention reflected the willingness or mindset towards innovation. These concepts were complex and multi-dimensional; therefore, a structured measurement scale, such as a Likert scale, was used to translate them into measurable items. This allowed the study to gather quantitative data that accurately reflected construction industry's perceptions and responses. According to Sekaran and Bougie (2019), the construction industry emphasised the importance of operationalizing abstract constructs through reliable and valid measurement scales. Several types of construct measurement scales were identified, among which the nominal and ordinal scales were applied in this study. The nominal scale was used to categorize demographic information such as gender and job role without implying any order. Meanwhile, the ordinal scale was used to measure constructs like intention and readiness, where respondents ranked the construction industry's readiness in a meaningful order. This allowed the study to assess the varying levels of performance among construction industry stakeholders in the context of IR 5.0 adoption.

According to Bobbit (2023), the nominal scale was used to assign labels to variables without involving numerical values. Data was usually categorised into discrete groups using these variables, which were strictly categorical in nature. In this study, the nominal scale included gender, current latest position, construction industry, highest education level, and current company location. These were recorded purely as categories, without any ranking or numerical meaning. These variables served the purpose of segmenting respondents based on background characteristics that might have influenced their views or performance in relation to IR 5.0 adoption. However, these categories carried no ranking or quantitative meaning; they were simply used to differentiate groups for comparative analysis. This allowed the study to explore whether differences in demographic or organizational attributes were associated with variations in readiness, intention, or performance within the construction industry. Other than the nominal scale, an internal scale was also applied in this study.

This study also used the interval scale in addition to the nominal scale. Although it lacked a true zero point, the interval scale was used for variables that had both order and equal distances between contiguous categories. More accurate measurements and mathematical operations, such as addition and subtraction, were made possible by this scale (Sekaran & Bougie, 2019). Construction industry respondents determined their degree of agreement or perceived influence on a scale (e.g., 1–5 or 1–7) with equal intervals between each level of agreement in order to evaluate their views or perceptions about IR 5.0. In this study, data analysis and calculations were carried out using the Statistical Package for the Social Sciences (SPSS) and Partial Least Squares Structural Equation Modeling (PLS-SEM) after data collection was completed. In the context of IR 5.0 implementation in the construction industry, SPSS and PLS-SEM enabled efficient handling of quantitative data, allowing the application of descriptive and inferential statistical techniques to assess the correlations between factors such as intention, readiness, and performance.

3.7 Description Measurement of Using Statistical Package for The Social Sciences

According to Awati (2024), SPSS was a tool from IBM. This instrument was initially introduced in 1968. The primary purpose of this software was to analyse data statistically. SPSS was widely recognized for its user-friendly interface and its ability to manage and analyse quantitative data efficiently. It also supported a wide range of statistical procedures, including descriptive statistics, correlation, ANOVA, regression, and more. SPSS allowed data to be organized into meaningful formats using tables and graphs. Furthermore, SPSS was able to conduct descriptive analysis to understand the demographic profiles of respondents.

In this study, descriptive analysis with SPSS was crucial because it provided a clear and structured summary and explanation of the respondents' demographic data. Variables including gender, most recent or current employment status, highest level of education, company location (state), and age group were all analysed using SPSS. SPSS was used to process these variables, which were assessed using nominal and ordinal scales, and produced visual displays such as bar charts and histograms, as well as frequencies and percentages. For example, a histogram displayed the age distribution within the sample, while a bar chart showed the respondents' distribution across various educational levels. An overall view of the profiles of the respondents was provided by this descriptive analysis, which also aided in spotting major trends in the data. Furthermore, ensuring that the dataset was thoroughly understood before examining the relationships between factors such as intention, readiness, and performance in the context of IR 5.0 adoption in the construction industry laid the foundation for further inferential statistical analysis. A critical aspect of the assessment model in this study was the validation of the measurement scales' validity and reliability using SPSS. SPSS ensured the accuracy and validity of the data for subsequent analysis by using Cronbach's Alpha for reliability and factor analysis for validity. According to Andy Field (2012), Cronbach's Alpha was the most used indicator of internal consistency (or "reliability"). It was particularly used when a survey or questionnaire included multiple Likert items that combined to form a measure, and construction industry aimed to assess the reliability of the scale.

3.8 Partial Least Squares Structural Equation Modeling

According to Table 3.4, the goals, data needs, and applicability of the measurement models in Partial Least Squares Structural Equation Modeling (PLS-SEM) and Covariance-Based Structural Equation Modeling (CB-SEM) were distinctly different. According to Hair et al. (2017), CB-SEM was intended for theory testing and model confirmation by minimizing the differences between observed and estimated covariance matrices, whereas PLS-SEM was focused on prediction and theory development by maximizing the explained variance in dependent variables. According to Hair et al. (2019), CB-SEM generally required large sample sizes and assumed multivariate normality, while PLS-SEM was suitable for small sample sizes and non-normal data. Additionally, according to Sarstedt et al. (2014), CB-SEM's covariance-based estimation is more appropriate for reflective constructs, whereas PLS-SEM was effective for both reflective and formative measurement models. These distinctions helped researchers choose the appropriate SEM technique based on their study's objectives and data characteristics.

Table 3.4: Differences Between PLS-SEM and CB-SEM.

Criterion	**PLS-SEM**	**CB-SEM**
Research Objective	Prediction oriented	Parameter oriented
Approach	Variance	Covariance
Assumption	Non-parametric	Parametric
Implication	Optimal for prediction	Optimal for parameter estimation
Model complexity	Large complexity	Small to moderate complexity
Sample size	Minimum of 30 - 100	Based on power analysis
Software	SmartPLS, WarpPLS, PLS-Graph	Amos, Lisrel, MPlus

According to Stein, Morris, and Nock (2011), CB-SEM was the appropriate method when the goal of the study was theory testing and confirmation. In contrast, PLS-SEM was suitable when the goal was theory development and prediction. This study used PLS-SEM for further data analysis to provide an insightful examination of the relationships between readiness, intention, and performance in the construction industry. PLS-SEM was a statistical method used to examine complex relationships between latent variables, particularly when the main objectives were theory construction and prediction. According to Sarstedt, Ringle and Hair (2021), conceptual variables that were defined in this study's theoretical models were represented by latent variables, also known as constructs, which were components of statistical models. In this study, the latent variables were readiness, intention and performance. According to Sarstedt, Ringle and Hair (2021), PLS-SEM was appropriate for exploratory research and studies with changing theoretical frameworks since it focussed on optimising the explained variance of the dependent variables (performance). Small to medium sample sizes, non-normal data, and intricate models with numerous constructs and indicators were all areas in which it excelled.

3.8.1 Partial Least Squares Structural Equation Modeling Algorithm

PLS-SEM was a powerful statistical technique used to examine complex relationships between latent and observable variables. The linkages between readiness, intention, and performance, all crucial to the construction industry's adoption of IR 5.0, were evaluated in this study with the help of PLS-SEM. According to Hair et al. (2017), through a methodical and iterative estimation of both the measurement (outer) model and the structural (inner) model, the approach maximised the explained variance of the dependent constructs. According to Hair et al (2021), there were four main steps in the process: (1) figuring out the outer weights for reflective indicators or the outer loadings for formative indicators; (2) estimating the scores of latent variables; (3) figuring out the path coefficients between latent constructs; and (4) updating the weights until convergence. Because it could handle small to medium sample numbers, non-normal data, and complex model structures with ease, this algorithm worked well for the current investigation. This study's application of PLS-SEM yielded useful findings for those involved in the building business by determining the direction and intensity of correlations between components that affected the effective integration of IR 5.0.

3.8.2 Path Model with Latent variables

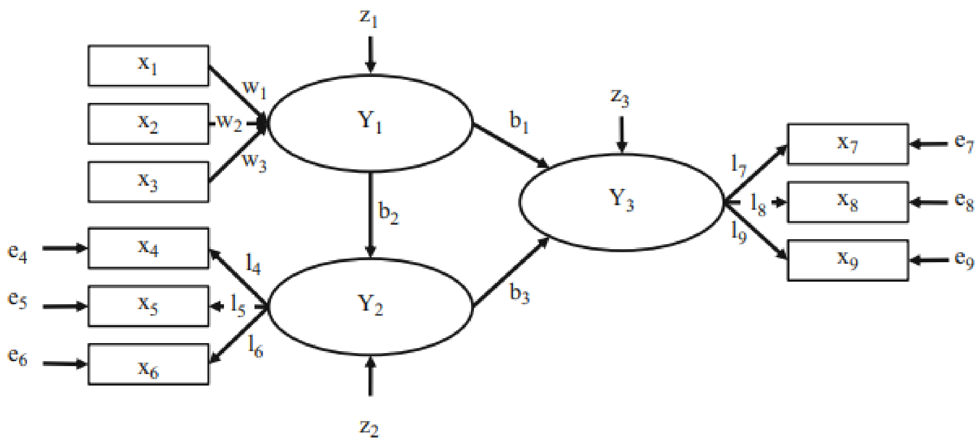


Figure 3.6: Path Model with Latent Variables (Source: Sarstedt, Ringle and Hair, 2021).

According to Sarstedt, Ringle, and Hair (2021), the dependent variable was represented by any latent variables on the right side of the path model, while the independent variables were represented by the latent variables on the left. In path models, constructs were represented by ovals or circles (Y1 to Y3) connected by single-headed arrows that signified causal-predictive linkages. The indicators were directly measured or observed variables that represented the raw data (e.g., respondents' replies to a questionnaire). These indicators were also frequently referred to as manifest variables or items and represented conceptual variables defined in their theoretical models in this study. According to Figure 3.6, it displayed the hypothesis and variable relationships that were estimated in a structural equation modelling analysis. Moreover, according to Sarstedt, Ringle, and Hair (2021), PLS-SEM provided versatility in model construction by handling both reflective and formative measurement models.

3.8.3 Assessment Model Test

In statistical analysis, assessing model test was a crucial step, especially in PLS-SEM. In this study can test theoretical models and hypotheses were tested by using these techniques to evaluate intricate interactions between several variables. Before conducting more complex analyses, the assessment model test ensured that the constructs of intention, readiness, and performance were precisely quantified in the context of this study, which investigated the adoption of IR 5.0 in the construction industry. According to Hair et al (2021), it was demonstrated that the items used to measure the constructs accurately reflected the theoretical ideas under study, the validity of these measurement scales was essential. Reliability ensured that the measurement scales consistently yielded stable and consistent outcomes in a variety of settings (Cronbach, 1951). The conclusions derived from the analysis were jeopardised in the absence of strong reliability and validity; Therefore, these tests were essential to this study's overall integrity. Prior to testing relationships and hypotheses, the correctness and robustness of the model were ensured by the two primary forms of assessment model tests: measurement model assessment and structural model assessment.

3.8.4 Reflective Construct

According to Hair et al. (2022), a reflective construct was a latent variable that existed first and subsequently caused the observed indicators. In this study, the latent variables were readiness and intention, each of which was measured through a set of indicators that reflected their underlying nature. The causality flowed from the construct to the indicators, meaning that changes in the latent variable were expected to be mirrored in the responses to its corresponding items. For example, the construction industry's level of readiness influenced how the respondents answered the survey questions, such that a higher readiness level was likely to result in higher agreement with statements related to technological capability, employee training, and adaptability to Industrial Revolution 5.0 requirements.

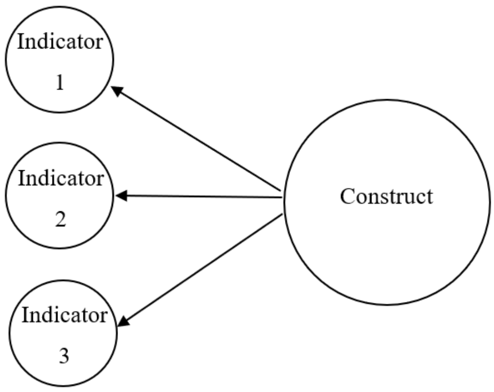


Figure 3.7: Reflective Construct (Source: Hair, 2022).

Based on Figure 3.7 it shows that the indicator were the effects or symptoms of the construct. This meant that the indicators shared a common theme and measure the same underlying concept. For the reflective measurement, the focus was on assessing validity and reliability. According to Hair et al (2022), the reflective measurement ensured that the indicators consistently represented the underlying construct and that the measurement accurately captured the concept it was intended to measure. In addition to the reflective construct, a formative construct was also employed in PLS-SEM.

3.8.5 Formative Construct

According to Hair et al (2022), a formative construct was a latent variable that was caused by its indicators, rather than the other way around. Indicators represent dimension or facets that collectively from the construct. Unlike reflective construct, the indicator in a formative construct did not necessarily correlate with each other, and the removal of an indicator would have altered the meaning and scope of the construct.

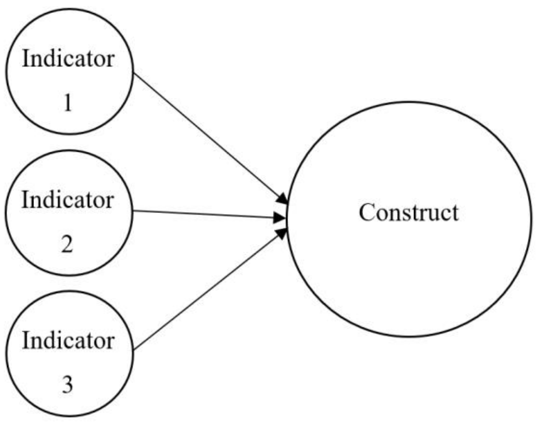


Figure 3.8: Formative Construct (Source: Hair, 2022).

Based on Figure 3.8, the relationship between the indicators and the construct in a formative measurement model was clearly illustrated. This indicated that the construct was formed or built by its indicators, and each indicator represented a distinct dimension that contributed to the overall meaning of the construct. For example, the construct “readiness” in the construction industry could have been formed by indicators such as technological capability, workforce skill level, and financial resources. Each of these indicators added unique information to the construct, and a change in any one of them would have altered the overall interpretation of performance.

3.8.6 Measurement model

In the context of this study, the measurement model specified how latent variables such as readiness, intention, and performance were measured through their respective indicators. According to Sarstedt, Ringle, and Hair (2021), measurement models could be categorized into two types: reflective and formative. In reflective models, indicators were considered manifestations of the underlying construct, where changes in the latent construct led to changes in the indicators. These latent variables were operationalized using reflective measurement models, meaning that the indicators reflected the variations in the underlying construct. According to Mohamad, Bin and Afthanorhan (2014) state the approach was particularly suitable when the indicators were interchangeable and measured the same underlying concept. To ensure the validity and reliability of the constructs, the reflective measurement model was evaluated using a number of important criteria. Convergent validity, discriminant validity, internal reliability, and indicator reliability were a few of these requirements.

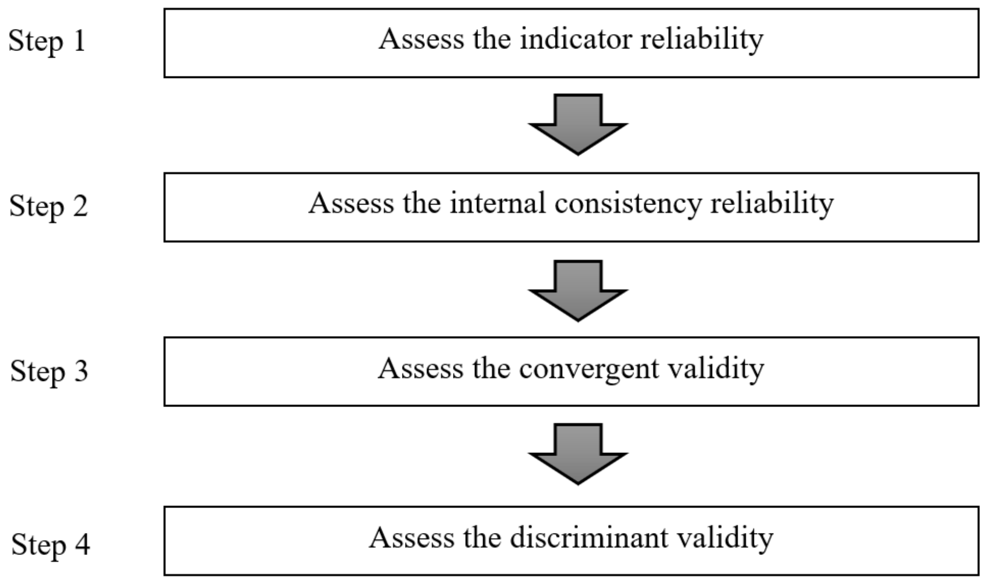


Figure 3.9: Reflective Measurement Model Assessment Procedure (Source: TomassMHultt, 2021).

Assess the Indicator Reliability – Outer Loadings

As depicted in Figure 3.9, the evaluation process for the reflective measurement model comprised four primary stages: assessing indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. According to TomassMHult (2021), indicator reliability referred to the degree to which each indicator explained the variance in its underlying construct, thereby reflecting its dependability. Drawing on the guidelines in Table 3.5, Hair et al. (2022) recommended assessing indicator reliability by examining the outer loadings. Outer loadings of 0.70 or higher indicated strong reliability, meaning that the indicator explained at least 50% of the variance in the construct. Indicators with loadings between 0.40 and 0.70 could be retained if they were theoretically important and their removal did not substantially improve composite reliability (CR) or average variance extracted (AVE). However, indicators with loadings below 0.40 were considered to have insufficient reliability and were removed. This systematic evaluation ensured that constructs such as readiness, intention, and performance were measured with precision in the context of this study.

Table 3.5: Standard for Indicator Reliability (Source: Hair et al, 2022).

Outer Loading Range	**Interpretation**
Outer loadings ≥ 0.70	Strong reliability, indicator explains at least 50% of the construct's variance.
$0.40 \leq$ Outer loadings ≤ 0.70	Moderate reliability, keep if theory supports and removal does not improve CR or AVE.
Outer loadings < 0.40	Low reliability, indicator explain less than 16 % of variance.

Assess the Internal Consistency Reliability – Composite Reliability (rho_a)

According to Hari et al (2022), the assessing internal consistency reliability aimed to determine whether the indicators for a construct measured the same underlying concept consistently or not. Internal consistency reliability was evaluated using both Cronbach's Alpha and composite reliability (CR).

According to Hari et al (2022), Cronbach's Alpha (α) measured the degree to which a set of indicators consistently represented the same construct whereas CR also measured internal consistency reliability but used the actual outer loadings from the PLS-SEM model. In this study, internal consistency reliability was assessed for the constructs of readiness, intention and performance in the construction industry to ensure that the indicators for each construct were consistent and reliable for measuring the underlying variables. Based on the results in Table 3.6, Cronbach's Alpha values above 0.70 were considered acceptable.

Table 3.6: Cronbach's Alpha Scores Value (Source: Taber, 2018).

Cronbach's Alpha (α)	**Interpretation**
$\alpha \geq 0.9$	Excellent
$0.9 > \alpha \geq 0.8$	Good
$0.8 > \alpha \geq 0.7$	Acceptable
$0.7 > \alpha \geq 0.6$	Questionable
$0.6 > \alpha \geq 0.5$	Poor
$0.5 > \alpha$	Unacceptable

Based on Table 3.7, the CR (rho_a) values between 0.70 and 0.90 indicated satisfactory reliability, and values above 0.95 suggested possible item redundancy.

Table 3.7: Standards for Composite Reliability Values (Source: Hair et al, 2022).

Composite Reliability (rho_a)	**Interpretation**
≥ 0.70	Minimum acceptable for establish constructs
0.60 – 0.70	Acceptable only in exploratory research
0.80 – 0.90	Good internal consistency reliability
> 0.95	Problematic

Assess the Convergent Validity – Average Variance Extracted (AVE)

According to Hair et al (2022) and Fornell and Larcker (1981), Average Variance Validity (AVE) was used to assess the convergent validity of the constructs. Which measure whether the indicators of a construct truly represent the same underlying concept. Based on Table 3.8, AVE value of 0.50 of higher were considered acceptable. Indicating that at least 50% of the variance in the indicators was explained by that latent construct. Values between 0.40 and 0.49 were considered marginal but acceptable if other reliability measures such as CR and Cronbach's Alpha, were strong while value below 0.40 indicated poor convergent validity. In this study, AVE was calculated for the constructs of readiness, intention, and performance in the construction industry to verify whether their indicators consistency measured the intended variables.

Table 3.8: Standards for Average Variance Validity (Source: Hair et al, 2022).

Average Variance Extracted (AVE)	**Interpretation**
AVE $\geq$ 0.50	Acceptable
0.40 $\leq$ AVE $<$ 0.50	Marginal
AVE $<$ 0.40	Poor

Assess the Discriminant Validity

Discriminant validity was evaluated using the Fornell-Larcker criterion, which, as described by Fornell and Larcker (1981), required that the square root of a construct's AVE be greater than its correlations with any other construct in the model. According to Henseler, Ringle & Sarstedt (2015), the Heterotrait-Monotrait (HTMT) ratio of correlations was employed as a more recent and robust method to assess discriminant validity. HTMT was used because previous research indicated that the Fornell-Larcker criterion and cross-loadings did not always reliably detect discriminant validity issues, particularly in complex models or when constructs were highly correlated. In this study, the reflective measurement model was applied to the constructs of readiness, intention, and performance, ensuring both the validity and reliability of the latent variables. The indicators for these constructs were finalized during the subsequent stages of the research through a comprehensive review of existing literature and expert consultations. This methodological approach laid a solid foundation for analysing the influence of readiness and intention on performance in the context of IR 5.0 adoption within the construction industry.

To explore the structural relationships between readiness, intention, and performance within the framework of IR 5.0 adoption, employing advanced modelling techniques such as PLS-SEM was crucial. This study laid a robust foundation for utilizing PLS-SEM to examine the influence of these constructs on IR 5.0 adoption in the construction industry, with PLS-SEM ensuring the validity and reliability of the measurement scales. In this study, the specific indicators for readiness, intention, and performance related to IR 5.0 adoption by the construction industry were identified and confirmed in a later phase of the research, following extensive data collection and expert validation. PLS-SEM was particularly suited for this research, as it allowed for the evaluation of both measurement accuracy and the strength of structural relationships, even in the presence of data constraints or model complexity. It provided a comprehensive understanding of how readiness and intention impacted performance outcomes in the construction industry.

3.8.7 Structural Model (Inner Model)

A key aspect of data analysis using Partial Least Squares Structural Equation Modelling (PLS-SEM) was the evaluation of the structural model, which examined the proposed relationships between latent constructs in the study framework. After the reflective measurement model had confirmed the validity and reliability of the constructs, the structural model assessment was employed in this study to explore the influence of the independent variables, intention and readiness, on the dependent variable, performance, in the context of the construction industry adoption of IR 5.0. The procedure for this structural model evaluation was also integrated into the assessment process.

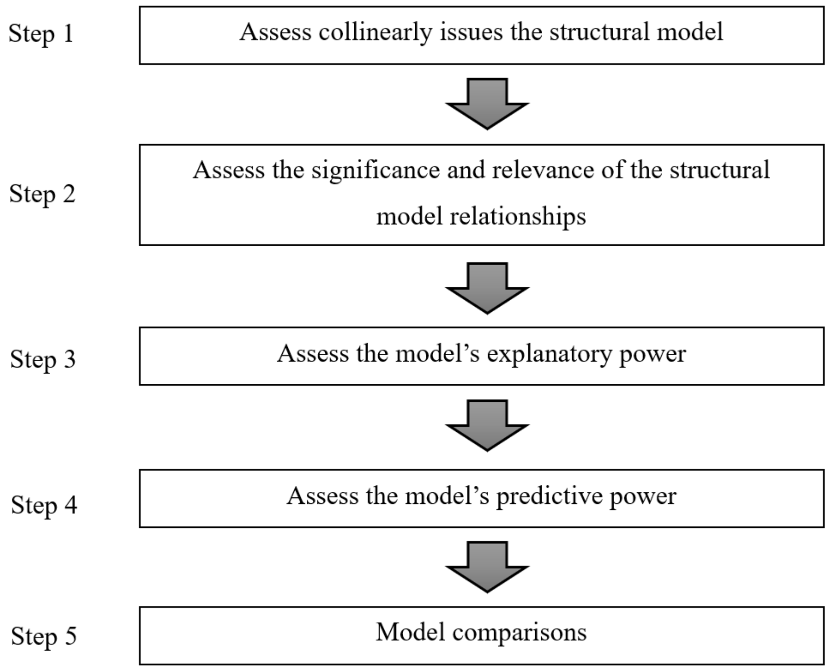


Figure 3.10: Structural Model Assessment Procedure (Source: TomassMHultt, 2021).

To assess the strength, direction, and explanatory power of the structural relationships, Figure 3.10 outlined the following steps: addressed collinearity issues within the structural model, evaluated the significance and relevance of the structural relationships, assessed the model's explanatory power, examined the model's predictive relevance, and performed model comparisons. According to Hair et al. (2022), structural model evaluation was crucial in confirming whether the data had supported the study's proposed theoretical framework.

Assess Collinearity Issues Within the Structural Mode

According to Sarstedt and Mooi (2019), predictor constructs, which were the independent variables in a structural model used to describe or forecast the dependent variable, were the source of multiple regression equations that provided structural model coefficients. In this study, performance was the dependence variable that was influenced by the predictor constructs of intention and readiness. According to Hair et al. (2019), collinearity occurred when two or more predictor variables had a high degree of correlation, making it challenging to evaluate each predictor's individual contribution. According to Sarstedt & Mooi (2019), intercorrelations showed the direction and degree of the linear link between two variables. Collinearity could have been introduced by high intercorrelations between predictor constructs, which could have skewed standard errors and point estimates. According to Becker et al. (2015) and Mason and Perreault (1991), the VIF was used to assess collinearity, where VIF values exceeding 5.0 indicated serious collinearity concerns, and values between 3.0 and 5.0 indicated moderate collinearity concerns, as shown in Table 3.9. According to Hair et al. (2022), when collinearity was detected, this study addressed it by merging constructs or creating higher order constructs. In this study, collinearity was assessed among the predictor constructs, readiness and intention, to ensure that the structural paths leading to performance in the construction industry were not biased by multicollinearity.

Table 3.9: VIF Value Thresholds for Assessing Collinearity in PLS-SEM (Source: Hair et al, 2022).

VIF Value	**Risk Level**	**Interpretation**
≤ 3.0	Ideal	No collinearity issues
3.01 – 5.0	Acceptable	Mild collinearity
> 5.0	Problematic	Multicollinearity present

Assess the Significance and Relevance of the Structural Relationships

Based on Figure 3.10, this study used bootstrapping techniques to ascertain the statistical significance of the path coefficients in the model to evaluate the importance and applicability of the structural model links. According to Hair et al. (2022), the null hypothesis (H_0) that the path coefficient (β) was equal to zero was tested, and standard errors were estimated via bootstrapping. Based on Table 3.10, a path coefficient's p-value (p) was used to determine its significance; values less than 0.05 were considered statistically significant. In addition, t-values (t) greater than 1.96 indicated significance at the 5% level, while t-values greater than 2.58 indicated significance at the 1% level (two-tailed tests). The magnitude of the path coefficients, which indicated how strongly the constructs were related to one another, was also examined to assess the importance of the structural relationships. According to Cohen (1988) and Hair et al. (2022), β values of 0.10, 0.30, and 0.50 represented small, moderate, and strong effects respectively. In this study, these thresholds were used to interpret the influence of intention (β_2) and readiness (β_1) on the dependent variable, performance (β_3), in the context of the construction industry's adoption of IR 5.0. Effect size was a measure that quantified the practical impact of an independent variable on a dependent variable, complementing statistical significance tests. In the context of multiple regression or PLS-SEM, Cohen's (f^2) was commonly used to determine how much a specific predictor contributed to the explained variance of the dependent variable (Cohen, 1988). Based on Table 3.10, an f^2 value below 0.02 indicated a negligible effect, values between 0.02 and 0.14 represented a small effect, values between 0.15 and 0.34 indicated a medium effect, and values 0.35 or higher denoted a large effect. This measure allowed the study to assess both the statistical significance and practical impact of predictors. Confirming the validity of the structural model and ensuring that the proposed linkages between variables were both statistically reliable and practically useful depended on how significant and relevant these interactions were.

Table 3.10: Standard Threshold Values for Evaluating Structural Relationships (Source: Hair et al., 2022; Cohen, 1988).

Criteria	**Threshold**	**Interpretation**
p-value (p)	< 0.05	Significant at 5% level
	< 0.01	Significant at 1% level
t-value (two-tailed) (t)	> 1.96	Significant at 5% level
	> 2.58	Significant at 1% level
Path coefficient (β)	≥ 0.10	Small Effect
	≥ 0.30	Moderate Effect
	≥ 0.50	Strong Effect
Effect Size (f^2)	< 0.02	Very Small
	0.02 – 0.14	Small
	0.15 – 0.34	Medium
	≥ 0.35	Large

Assess the Model's Explanatory Power (R^2)

The coefficient of determination (R^2) of the endogenous construct or constructs was the next stage in assessing the structural model. According to Shmueli & Koppius (2011), R^2 served as a gauge of the model's explanatory capacity, or in-sample predictive power, and denoted the variation explained in each of the endogenous constructs. According to Rigdon (2012), higher values of R^2 suggested better explanatory power, which measured how effectively the model predicted performance outcomes. Higher values indicated a better model fit. R^2 values typically ranged from 0 to 1. According to Hair, Ringle, and Sarstedt (2011), R^2 values of 0.75, 0.50, and 0.25 were regarded as significant, moderate, and weak, respectively, as shown in Table 3.11. According to Sarstedt and Mooi (2019), the more predictor constructs included in the model, the higher the R^2 value tended to be. In the context of the study, readiness and intention were the predictor constructs used to explain the variation in performance. In addition to R^2, this study also assessed the f^2 effect size, which quantified the influence of removing a readiness or intention on the R^2 value of the performance. According to Hair, Ringle, and Sarstedt (2011), that f^2 measured how much each predictor construct contributed to explaining the variation in the dependent construct. Based on Table 3.11, an f^2 value of 0.02 represented a small effect, indicating only a minimal contribution of the predictor to the explained variance. A value of 0.15 represented a medium effect, reflecting a moderate influence on the dependent construct, while a value of 0.35 or above represented a large effect, suggesting a substantial impact on the variance explained. These thresholds represented useful benchmarks for confirming the relative importance of the predictors in the structural model.

Table 3.11: Threshold Values for Coefficient of Determination (R^2) & Effect Size (f^2) (Source: Hair, Ringle, & Sarstedt, 2011).

R^2 Value	**Interpretation**	**f^2 Value**	**Interpretation**
≥ 0.75	Substantial	0.35	Large
0.50 – 0.75	Moderate	0.15	Medium
0.25 – 0.50	Weak	0.02	Small

Assess the Model's Predictive Power (Q^2)

According to Hafiz Hanafiah (2020), evaluating the predictive power of the model was an essential phase in assessing the real-world usability of a structural model, particularly in understanding its ability to forecast outcomes for new or unseen data. Shmueli et al. (2019) stated that predictive power was distinct from explanatory power, represented by Q^2, as it emphasized out-of-sample prediction rather than merely fitting the model to existing data.

In this research, the $PLS_{pretict}$ procedure was used to assess predictive power. This procedure incorporated methods such as k-fold cross-validation to generate prediction errors using metrics like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Q^2 predict (Hair et al., 2022). According to Hair et al. (2022), a Q^2 predict value greater than 0 indicates predictive relevance for the corresponding endogenous construct, while a value of 0 or below suggests no predictive relevance, as outlined in Table 3.12. Additionally, lower RMSE or MAE values compared to a linear regression benchmark suggested strong predictive capability. This assessment was crucial in determining whether the constructs of readiness and intention significantly predicted performance within the context of IR 5.0 adoption in the construction industry, thereby ensuring that the model remained robust and applicable beyond the current dataset.

Table 3.12: Q^2 Predict Standard Values (Source: Hair et al, 2022).

Q^2 Value	Interpretation
$Q^2 > 0$	Has predictive relevance for that construct
$Q^2 \leq 0$	No predictive relevance for that construct

Model Comparison

The last phase of the structural model assessment entailed comparing various models to determine which one most effectively elucidated or forecasted the relationships among constructs. According to Sarstedt and Mooi (2019), model comparison aided in evaluating whether a more intricate model provided significantly better explanatory or predictive capabilities compared to a simpler version. According to Hair et al. (2022), this study utilized model comparison metrics such as the coefficient of determination (R^2), predictive relevance (Q^2 predict), and information criteria including the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). These metrics weighed model fit against complexity, where lower AIC and BIC values indicated a more favourable model structure.

According to Sharma et al. (2019), AIC and BIC penalized on models that were excessively complex, thereby minimizing the likelihood of overfitting. This investigation employed model comparison approaches to assess alternative structural paths concerning readiness, intention, and performance to ensure the selection of the most robust and theoretically significant model. According to the final statistical analysis, once the complete dataset was processed and the results were finalized, the study's findings, such as the importance of each path and the overall model's explanatory power, were further evaluated and discussed, offering a fuller understanding of the dynamics of IR 5.0 adoption. The study then included a flowchart that illustrated the study's progression.

3.9 Flowchart

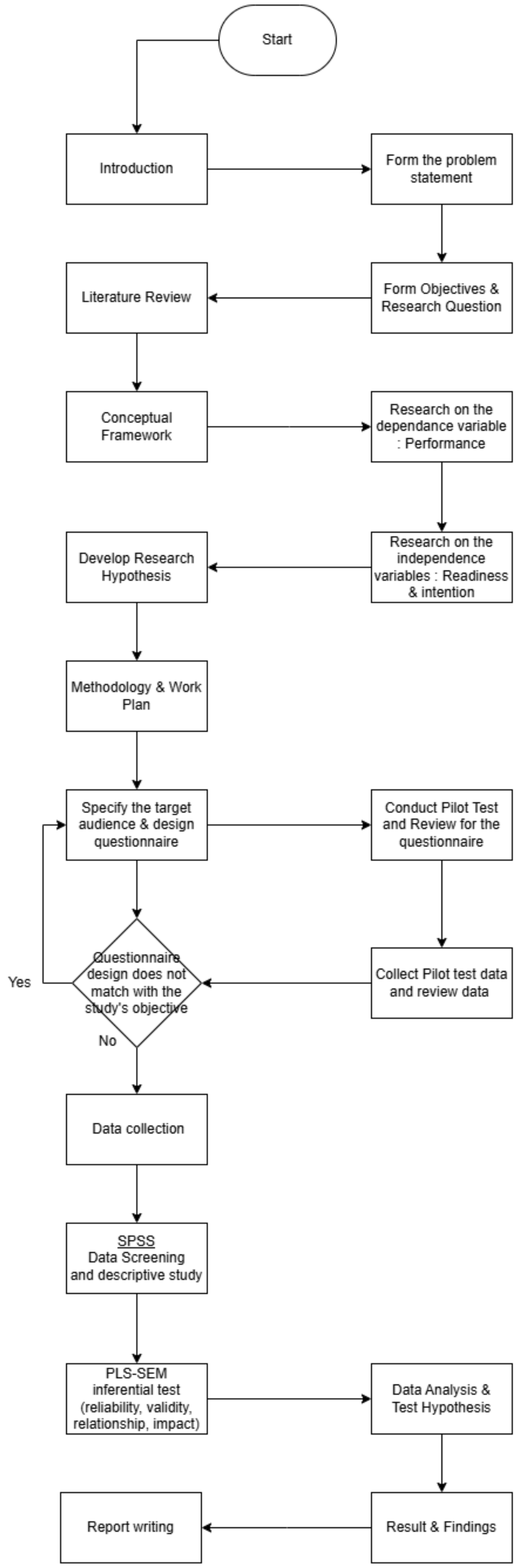


Figure 3.11: A Quantitative Study on the Performance of Construction Industry in the IR 5.0 Evolution's Flowchart.

Based on Figure 3.11 shown in the beginning, this study included an introduction, which provided a brief overview of the quantitative study on the performance of the construction industry in IR 5.0. It allowed readers to have a clear and general understanding of the study. After that, this study formed the problem statement, which identified the problems currently faced by the construction industry. It helped the study establish a clear foundation to develop the objectives and research questions. The objectives and research questions were important because they helped identify methods to address the problem statement stated earlier in the study. They were also crucial because they guided the study and ensured that it stayed within its intended scope.

After forming the objectives and research questions, this study proceeded with the literature review. In the literature review, it provided an insightful explanation about the Industrial Revolutions, including IR 1.0, IR 2.0, IR 3.0, IR 4.0, and IR 5.0. It not only introduced each Industrial Revolution but also discussed their impacts, the reasons the construction industry adopted each IR, and the limitations of each IR that drove construction industry to move toward the next stage. Furthermore, this study reviewed and referenced existing conceptual frameworks from other researchers related to the construction industry. The literature review also provided detailed explanations about the dependent variable (performance) and the independent variables (readiness and intention), which formed the basis of the new theoretical framework developed in this study.

Following the literature review, this study developed the research hypotheses. The hypotheses emerged from the theoretical framework and research model that linked the independent variables (readiness and intention) and dependence variable (performance). They were essential for guiding the design of the questionnaire. After developing the research hypotheses, the study continued with the methodology and work plan. The methodology specified the target audience (construction industry) and detailed the process for designing the questionnaire to align with the objectives.

At the same time, the study conducted pilot tests and reviewed the questionnaire design to gather feedback and make improvements. This process was repeated until the questionnaire design was complete and fully aligned with the study's purpose. In addition, once the questionnaire design was finalized and improved, this study proceeded with data collection. After collecting the data, the study used SPSS to conduct data screening and descriptive analysis. It applied inferential tests in PLS-SEM to ensure the reliability, validity, relationships, and impacts between the independent variables and the dependent variable. The study then conducted data analysis and tested the hypotheses using the results generated through PLS-SEM. Once the results and findings were obtained, the study continued to report writing. In the final phase, the report specifically presented the results and findings, discussed the impacts and relationships between the independent variables and the dependent variable, and concluded the study.

3.10 Questionnaire Design

Appendix A showed the design of the questionnaire used in this study. The questionnaire consists of two parts. The first part collected demographic information from the respondents. The second part assessed their knowledge and understanding of IR 5.0. The remaining parts contained questions related to the study's objectives. The second part focused on Objective 1, which aimed to determine the variables that affected the quantitative study on the performance of the construction industry in the IR 5.0 evolution. The next section addressed Objective 2, which investigated the relationship between readiness and intention toward construction industry's performance in IR 5.0. and explored the impact of construction industry' readiness and intention toward performance within the IR 5.0 environment.

3.11 Work Breakdown Structure

Outline Number	Task Name
1	**Quantitative study on performance of construction industry in Industrial Revolution 5.0**
1.1	**Introduction**
1.1.1	Define the general Introduction of this study
1.1.2	Define overview of the study
1.1.3	Define importance of the study
1.1.4	Define problem statement for the study
1.1.5	Define aim and objectives of the study
1.1.6	Define research question
1.1.7	Define hypothesis
1.1.8	Define scopes and limitation of the study
1.1.9	Define contribution of the study
1.1.10	Define impacts of the study
1.1.11	Define novelty of the study
1.2	**Literature Review**
1.2.1	Identify introduction of Industrial Revolution
1.2.2	**Industrial revolution 1.0**
1.2.2.1	Define introduction of industrial revolution 1.0
1.2.2.2	Define impacts of industrial revolution 1.0
1.2.2.3	Define adoption of construction industry to industrial revolution 1.0
1.2.2.4	Define limitations of industrial revolution 1.0 cause construction industry move toward industrial revolution 2.0
1.2.3	**Industrial revolution 2.0**
1.2.3.1	Define introduction of industrial revolution 2.0
1.2.3.2	Impacts of industrial revolution 2.0
1.2.3.3	Define adoption of construction industry to industrial revolution 2.0

1.2.3.4	Define limitations of industrial revolution 2.0 cause construction industry move toward industrial revolution 3.0
1.2.4	**Industrial revolution 3.0**
1.2.4.1	Define introduction of industrial revolution 3.0
1.2.4.2	Define impacts of industrial revolution 3.0
1.2.4.3	Define adoption of construction industry to industrial revolution 3.0
1.2.4.4	Define limitations of industrial revolution 3.0 cause construction industry move toward industrial revolution 4.0
1.2.5	**Industrial revolution 4.0**
1.2.5.1	Define introduction of industrial revolution 4.0
1.2.5.2	Define factors deriving the emergence of industrial revolution 4.0
1.2.5.3	Define the emergence of industrial revolution 4.0
1.2.5.4	Identify advantages of industrial revolution 4.0
1.2.5.5	Identify disadvantages of industrial revolution 4.0
1.2.5.6	Define impacts of industrial revolution on the construction industry
1.2.5.7	Define adoption of industrial revolution in construction industry
1.2.5.8	Define Limitations of Industrial Revolution 4.0 Driving the Shift to Industrial Revolution 5.0
1.2.6	**Determine differences between industrial revolution 4.0 and industrial revolution 5.0**
1.2.7	**Industrial revolution 5.0**
1.2.7.1	Define Introduction of industrial revolution 5.0
1.2.7.2	Define reasons for the Emergence of Industrial Revolution 5.0
1.2.7.3	Define evolution and Emergence of Industrial Revolution 5.0
1.2.7.4	Define advantages of industrial revolution 5.0
1.2.7.5	Disadvantages of industrial revolution 5.0

1.2.7.6	Define impacts of industrial revolution 5.0 in construction industry
1.2.7.7	Define adoption of industrial revolution in construction industry
1.2.7.8	Explain the reasons that apply industrial revolution 5.0
1.2.8	**Dependence Variable**
1.2.8.1	Explore different perspective of "performance"
1.2.8.2	Explain different perspective of "performance"
1.2.8.3	Identify the advantages of performance evaluation
1.2.8.4	Identify the disadvantages and limitation of performance evaluation
1.2.8.5	Identify the methods and techniques to evaluate construction industry's performance
1.2.8.6	**Explanation the framework of performance measurement in construction industry**
1.2.8.6.1	Explain balanced scorecard
1.2.8.6.2	Explain ERQM excellent model
1.2.8.6.3	Explain key performance indicator
1.2.8.6.4	Explain contract administration performance framework
1.2.8.6.5	Determine the component of performance
1.2.9	**Formulation of theoretical framework**
1.2.9.1	**Research different journal an article for the theoretical framework relate to the independence variable (readiness)**
1.2.9.1.1	Explain the theoretical framework : theory of reasoned action
1.2.9.1.2	Explain the theoretical framework : Unified theory of acceptance and use of technology (UTAUT)
1.2.9.2	**Research different journal and article for the theoretical framework relate to the independence variable (intention)**

1.2.9.2.1	Explain the theoretical framework : theory of organisational readiness of change
1.2.10	**Formulation of independence variables (readiness and intention)**
1.2.10.1	Conduct insightful explanation of independence variable (readiness)
1.2.10.2	Find journal and article that support the independence variable (readiness) as a factor affect construction performance
1.2.10.3	Conduct insightful explanation of independence variable (intention)
1.2.10.4	Find journal and article that support the independence variable (intention) as a factor affect construction performance
1.2.11	Define the relationship between independence variables (readiness and intention)
1.2.12	**Define the construction players' independence variable toward the performance industrial revolution 5.0**
1.2.12.1	Define impacts of construction players readiness toward the performance industrial revolution 5.0
1.2.12.2	Define impacts of construction players intention toward the performance industrial revolution 5.0
1.2.13	**Formulation of conceptual framework**
1.2.13.1	Develop Research Hypothesis
1.3	**Methodology and Plan**
1.3.1	Define the introduction of methodology and plan
1.3.2	**Explain two type of research design**
1.3.2.1	**Qualitative research**
1.3.2.1.1	Explore information of qualitative study
1.3.2.1.2	Explain insightful of qualitative research
1.3.2.2	**Quantitative research**
1.3.2.2.1	Explore information of quantitative study

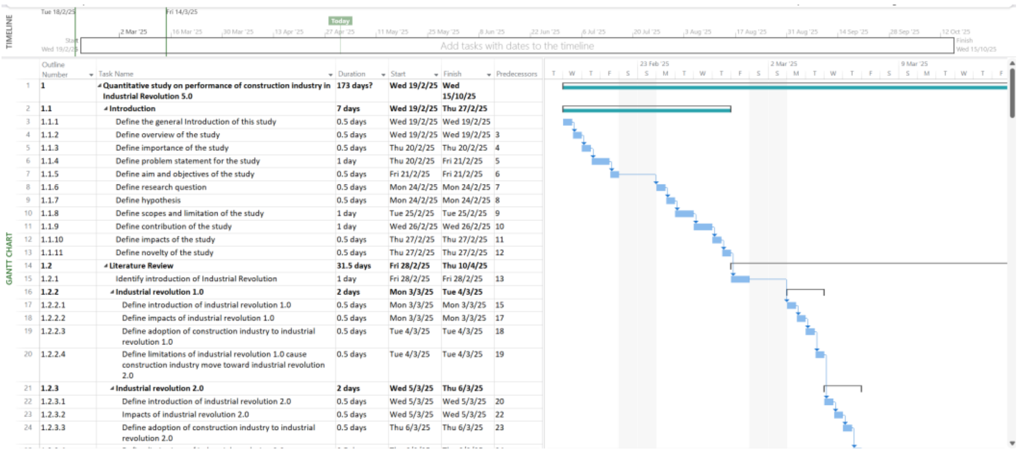
1.3.2.2.2	Explain insightful of quantitative research
1.3.3	**Compare the different between qualitative research and quantitative research**
1.3.4	**Data collection types**
1.3.4.1	Identify the use of primary data
1.3.4.2	Identify the use of secondary data
1.3.4.3	Finalize use of primary data
1.3.5	**Decide sampling size technique**
1.3.5.1	**Explore use of G*Power (sampling technique)**
1.3.5.1.1	Formula prove G*Power is useful and accuracy
1.3.5.1.2	Conduct manual calculation of using statistical formula prove G*Power's accuracy
1.3.5.1.3	Conduct Chi-Square Test for Goodness-for-Fit prove G*Power's accuracy
1.3.5.1.4	Conduct One-Way ANOVA (Analysis of Variance) prove G*Power's accuracy
1.3.5.1.5	Conduct linear regression prove G*Power's accuracy
1.3.6	Explore use of Krejcie and Morgan Formula for decide sampling size
1.3.7	**Decide sampling technique**
1.3.7.1	Identify the different type of sampling technique
1.3.7.2	Research the type of sampling technique
1.3.7.3	**Probability sampling**
1.3.7.3.1	Conduct research on type of probability sampling technique
1.3.7.3.2	Identify the use of different probability sampling technique
1.3.7.3.3	Decide the suitable probability sampling technique for the study
1.3.7.4	**Non-Probability sampling**
1.3.7.4.1	Conduct research on type of non-probability sampling technique

1.3.7.4.2	Identify the use of different non-probability sampling technique
1.3.7.4.3	Decide the suitable non-probability sampling technique for the study
1.3.7.5	**Research Instrument**
1.3.7.5.1	Research different type of research instrument (Test, focus group, interview and questionnaire)
1.3.7.5.2	Identify the use of different type research instrument (Test, focus group, interview and questionnaire)
1.3.7.5.3	Compare between different research instrument (Test, focus group, interview and questionnaire)
1.3.7.5.4	Decide the suitable research instrument for the study
1.3.8	Specify the target audience
1.3.9	**Conduct questionnaire design**
1.3.9.1	Find existing questionnaire sample that relate quantitative study about construction industry
1.3.9.2	Filter the suitable existing questionnaire design from other researcher
1.3.9.3	Adopt the suitable question to the study
1.3.9.4	Redesign the question relate to study's research question mention previous
1.3.9.5	**Instrument Test**
1.3.9.5.1	**Pre-Test**
1.3.9.5.1.1	Select the professional interviewee for pre-test
1.3.9.5.1.2	Request help from professional interviewee to attend pre-test
1.3.9.5.1.3	Provide questionnaire design to interviewee
1.3.9.5.1.4	Record comment from interviewee about the questionnaire design
1.3.9.5.1.5	Redesign the questionnaire design based on the comment
1.3.9.5.2	**Pilot Test**

1.3.9.5.2.1	Select a group of target audience (construction players)
1.3.9.5.2.2	Send questionnaire to the target audience (construction players)
1.3.9.5.2.3	Ask feedback from the target audience
1.3.9.5.2.4	Record the feedback about the questionnaire design
1.3.9.5.2.5	Redesign the questionnaire design based on the feedback
1.3.10	**Conduct data collection**
1.3.10.1	Send out the finalise questionnaire to target audience (construction players)
1.3.10.2	Follow out the questionnaire respondent
1.3.10.3	Filter the useful response and useless response
1.3.10.4	Confirm enough useful data
1.4	**Data Analysis**
1.4.1	**Statistical package for the social science**
1.4.1.1	Conduct Demographic analysis
1.4.1.2	Conduct Variable question analysis
1.4.2	**Partial Least Squares Structural Equation Modelling**
1.4.2.1	**Conduct measurement model**
1.4.2.1.1	Assess the indicator reliability
1.4.2.1.2	Assess the internal consistency reliability
1.4.2.1.3	Assess the convergent validity
1.4.2.1.4	Assess the discriminant validity
1.4.2.2	**Conduct structural assessment model**
1.4.2.2.1	Assess collinearity issues the structural model
1.4.2.2.2	Assess the significance and relevance of the structural model relationships
1.4.2.2.3	Assess the model's explanatory power
1.4.2.2.4	Assess the model's predictive power
1.4.2.2.5	Model comparisons

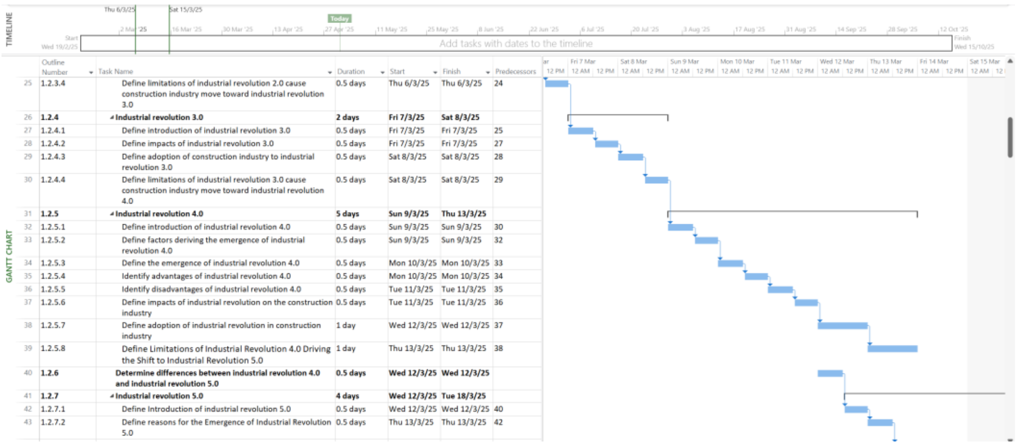
1.4.3	Test Hypothesis
1.5	**Result & Findings**
1.5.1	State the result
1.5.2	Confirm the result's accuracy
1.5.3	Confirm the result's validity
1.5.4	Compare result by the standard
1.5.5	Analysis result for each category
1.6	**Report Writing**
1.6.1	Explain the indicator that affect independence variables
1.6.2	Explain the independence variable affect the dependence variable
1.6.3	State the result of hypothesis 1
1.6.4	State the result of hypothesis 2
1.6.5	State the result of hypothesis 3
1.6.6	State the relationship between independence variables (readiness and intention)
1.6.7	State the impact between independence variables (readiness and intention) and dependence variables (performance)
1.6.8	Write summary of the study
1.6.9	Write the conclusion of the study

3.12 Gantt Chart



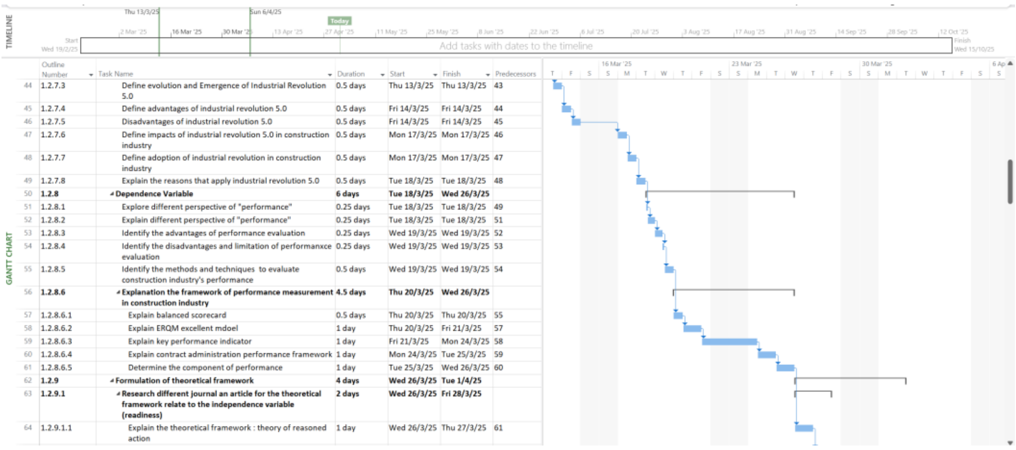
	Outline Number	Task Name	Duration	Start	Finish	Predecessors
1	**1**	**Quantitative study on performance of construction industry in Industrial Revolution 5.0**	**173 days?**	**Wed 19/2/25**	**Wed 15/10/25**	
2	**1.1**	**Introduction**	**7 days**	**Wed 19/2/25**	**Thu 27/2/25**	
3	1.1.1	Define the general Introduction of this study	0.5 days	Wed 19/2/25	Wed 19/2/25	
4	1.1.2	Define overview of the study	0.5 days	Wed 19/2/25	Wed 19/2/25	3
5	1.1.3	Define importance of the study	0.5 days	Thu 20/2/25	Thu 20/2/25	4
6	1.1.4	Define problem statement for the study	1 day	Thu 20/2/25	Fri 21/2/25	5
7	1.1.5	Define aim and objectives of the study	0.5 days	Fri 21/2/25	Fri 21/2/25	6
8	1.1.6	Define research question	0.5 days	Mon 24/2/25	Mon 24/2/25	7
9	1.1.7	Define hypothesis	0.5 days	Mon 24/2/25	Mon 24/2/25	8
10	1.1.8	Define scopes and limitation of the study	1 day	Tue 25/2/25	Tue 25/2/25	9
11	1.1.9	Define contribution of the study	1 day	Wed 26/2/25	Wed 26/2/25	10
12	1.1.10	Define impacts of the study	0.5 days	Thu 27/2/25	Thu 27/2/25	11
13	1.1.11	Define novelty of the study	0.5 days	Thu 27/2/25	Thu 27/2/25	12
14	**1.2**	**Literature Review**	**31.5 days**	**Fri 28/2/25**	**Thu 10/4/25**	
15	1.2.1	Identify introduction of Industrial Revolution	1 day	Fri 28/2/25	Fri 28/2/25	13
16	**1.2.2**	**Industrial revolution 1.0**	**2 days**	**Mon 3/3/25**	**Tue 4/3/25**	
17	1.2.2.1	Define introduction of industrial revolution 1.0	0.5 days	Mon 3/3/25	Mon 3/3/25	15
18	1.2.2.2	Define impacts of industrial revolution 1.0	0.5 days	Mon 3/3/25	Mon 3/3/25	17
19	1.2.2.3	Define adoption of construction industry to industrial revolution 1.0	0.5 days	Tue 4/3/25	Tue 4/3/25	18
20	1.2.2.4	Define limitations of industrial revolution 1.0 cause construction industry move toward industrial revolution 2.0	0.5 days	Tue 4/3/25	Tue 4/3/25	19
21	**1.2.3**	**Industrial revolution 2.0**	**2 days**	**Wed 5/3/25**	**Thu 6/3/25**	
22	1.2.3.1	Define introduction of industrial revolution 2.0	0.5 days	Wed 5/3/25	Wed 5/3/25	20
23	1.2.3.2	Impacts of industrial revolution 2.0	0.5 days	Wed 5/3/25	Wed 5/3/25	22
24	1.2.3.3	Define adoption of construction industry to industrial revolution 2.0	0.5 days	Thu 6/3/25	Thu 6/3/25	23

Figure 3.12: WBS Gantt Chart for Introduction and Literature Review phase (IR 1.0 and IR 2.0).



	Outline Number	Task Name	Duration	Start	Finish	Predecessors
25	1.2.3.4	Define limitations of industrial revolution 2.0 cause construction industry move toward industrial revolution 3.0	0.5 days	Thu 6/3/25	Thu 6/3/25	24
26	**1.2.4**	**Industrial revolution 3.0**	**2 days**	**Fri 7/3/25**	**Sat 8/3/25**	
27	1.2.4.1	Define introduction of industrial revolution 3.0	0.5 days	Fri 7/3/25	Fri 7/3/25	25
28	1.2.4.2	Define impacts of industrial revolution 3.0	0.5 days	Fri 7/3/25	Fri 7/3/25	27
29	1.2.4.3	Define adoption of construction industry to industrial revolution 3.0	0.5 days	Sat 8/3/25	Sat 8/3/25	28
30	1.2.4.4	Define limitations of industrial revolution 3.0 cause construction industry move toward industrial revolution 4.0	0.5 days	Sat 8/3/25	Sat 8/3/25	29
31	**1.2.5**	**Industrial revolution 4.0**	**5 days**	**Sun 9/3/25**	**Thu 13/3/25**	
32	1.2.5.1	Define introduction of industrial revolution 4.0	0.5 days	Sun 9/3/25	Sun 9/3/25	30
33	1.2.5.2	Define factors deriving the emergence of industrial revolution 4.0	0.5 days	Sun 9/3/25	Sun 9/3/25	32
34	1.2.5.3	Define the emergence of industrial revolution 4.0	0.5 days	Mon 10/3/25	Mon 10/3/25	33
35	1.2.5.4	Identify advantages of industrial revolution 4.0	0.5 days	Mon 10/3/25	Mon 10/3/25	34
36	1.2.5.5	Identify disadvantages of industrial revolution 4.0	0.5 days	Tue 11/3/25	Tue 11/3/25	35
37	1.2.5.6	Define impacts of industrial revolution on the construction industry	0.5 days	Tue 11/3/25	Tue 11/3/25	36
38	1.2.5.7	Define adoption of industrial revolution in construction industry	1 day	Wed 12/3/25	Wed 12/3/25	37
39	1.2.5.8	Define Limitations of Industrial Revolution 4.0 Driving the Shift to Industrial Revolution 5.0	1 day	Thu 13/3/25	Thu 13/3/25	38
40	**1.2.6**	**Determine differences between industrial revolution 4.0 and industrial revolution 5.0**	**0.5 days**	**Wed 12/3/25**	**Wed 12/3/25**	
41	**1.2.7**	**Industrial revolution 5.0**	**4 days**	**Wed 12/3/25**	**Tue 18/3/25**	
42	1.2.7.1	Define Introduction of industrial revolution 5.0	0.5 days	Wed 12/3/25	Wed 12/3/25	40
43	1.2.7.2	Define reasons for the Emergence of Industrial Revolution 5.0	0.5 days	Thu 13/3/25	Thu 13/3/25	42

Figure 3.13: WBS Gantt Chart for Literature Review phase (IR 3.0, IR 4.0 and IR 5.0).



	Outline Number	Task Name	Duration	Start	Finish	Predecessors
44	1.2.7.3	Define evolution and Emergence of Industrial Revolution 5.0	0.5 days	Thu 13/3/25	Thu 13/3/25	43
45	1.2.7.4	Define advantages of industrial revolution 5.0	0.5 days	Fri 14/3/25	Fri 14/3/25	44
46	1.2.7.5	Disadvantages of industrial revolution 5.0	0.5 days	Fri 14/3/25	Fri 14/3/25	45
47	1.2.7.6	Define impacts of industrial revolution 5.0 in construction industry	0.5 days	Mon 17/3/25	Mon 17/3/25	46
48	1.2.7.7	Define adoption of industrial revolution in construction industry	0.5 days	Mon 17/3/25	Mon 17/3/25	47
49	1.2.7.8	Explain the reasons that apply industrial revolution 5.0	0.5 days	Tue 18/3/25	Tue 18/3/25	48
50	**1.2.8**	**Dependence Variable**	**6 days**	**Tue 18/3/25**	**Wed 26/3/25**	
51	1.2.8.1	Explore different perspective of "performance"	0.25 days	Tue 18/3/25	Tue 18/3/25	49
52	1.2.8.2	Explain different perspective of "performance"	0.25 days	Tue 18/3/25	Tue 18/3/25	51
53	1.2.8.3	Identify the advantages of performance evaluation	0.25 days	Wed 19/3/25	Wed 19/3/25	52
54	1.2.8.4	Identify the disadvantages and limitation of performanxce evaluation	0.25 days	Wed 19/3/25	Wed 19/3/25	53
55	1.2.8.5	Identify the methods and techniques to evaluate construction industry's performance	0.5 days	Wed 19/3/25	Wed 19/3/25	54
56	**1.2.8.6**	**Explanation the framework of performance measurement in construction industry**	**4.5 days**	**Thu 20/3/25**	**Wed 26/3/25**	
57	1.2.8.6.1	Explain balanced scorecard	0.5 days	Thu 20/3/25	Thu 20/3/25	55
58	1.2.8.6.2	Explain ERQM excellent mdoel	1 day	Thu 20/3/25	Fri 21/3/25	57
59	1.2.8.6.3	Explain key performance indicator	1 day	Fri 21/3/25	Mon 24/3/25	58
60	1.2.8.6.4	Explain contract administration performance framework	1 day	Mon 24/3/25	Tue 25/3/25	59
61	1.2.8.6.5	Determine the component of performance	1 day	Tue 25/3/25	Wed 26/3/25	60
62	**1.2.9**	**Formulation of theoretical framework**	**4 days**	**Wed 26/3/25**	**Tue 1/4/25**	
63	**1.2.9.1**	**Research different journal an article for the theoretical framework relate to the independence variable (readiness)**	**2 days**	**Wed 26/3/25**	**Fri 28/3/25**	
64	1.2.9.1.1	Explain the theoretical framework : theory of reasoned action	1 day	Wed 26/3/25	Thu 27/3/25	61

Figure 3.14: WBS Gantt Chart for Dependent Variable and Explanation of Theoretical Framework.

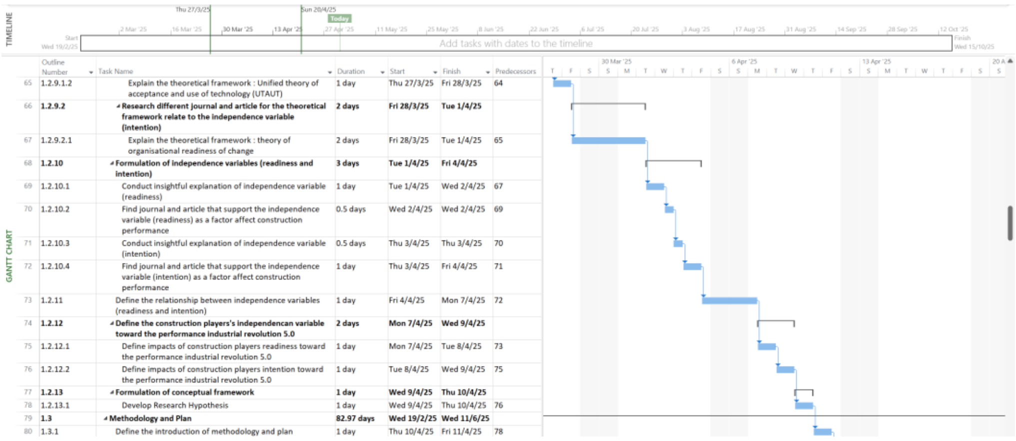


Figure 3.15: WBS Gantt Chart for Formulation of Independent Variable and Conceptual Framework.

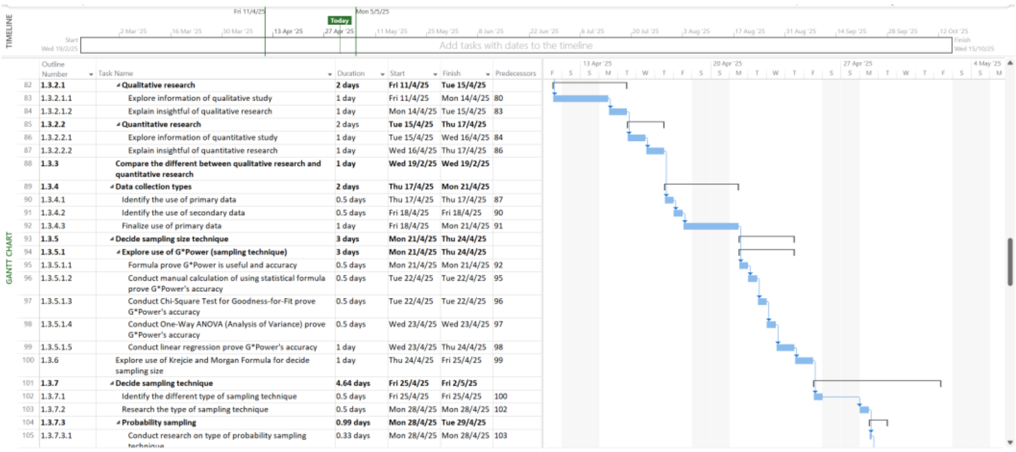


Figure 3.16: WBS Gantt Chart for Conducting Quantitative Research, Qualitative Research, Data Types, Explanation of G*Power, Decision of Sampling Technique, and Probability Sampling.

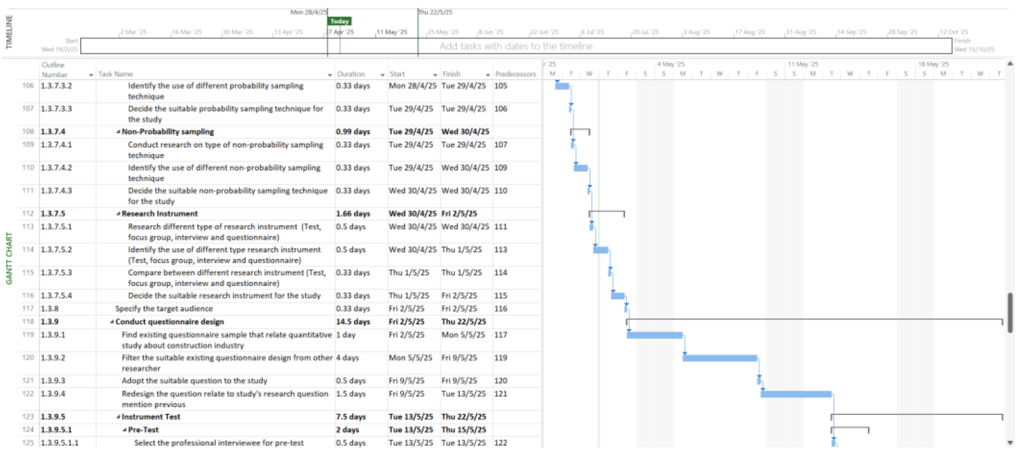


Figure 3.17: WBS Gantt Chart for Conducting Non-Probability Sampling, Research Instrument, Questionnaire Design, and Pre-Testing.

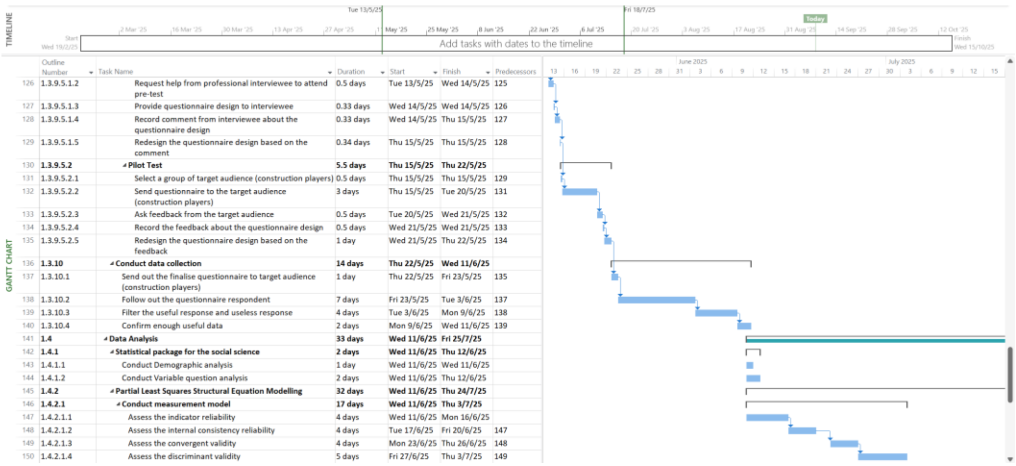


Figure 3.18: WBS Gantt Chart for Conducting Pilot-Test, Data Collection, and Data Analysis.

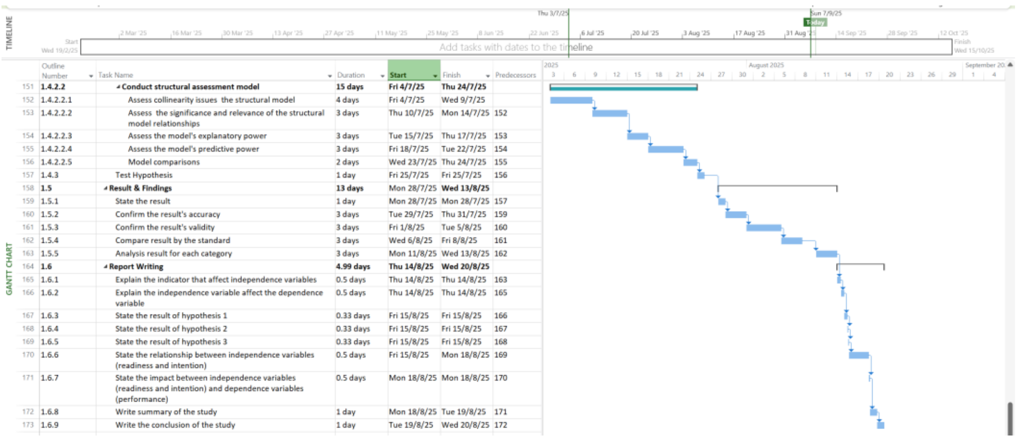


Figure 3.19: WBS Gantt Chart for Analysis of Results, Findings, and Report Writing.

3.13 Summary

This chapter presented the extensive methodological framework used to explore the connection between construction industry readiness, intention, and performance in the context of IR 5.0. It began with an overview of the research methodology, followed by a thorough explanation of the research design, which integrated both qualitative and quantitative methods to ensure methodological rigor. Data collection was conducted through both primary and secondary sources, with primary data collected via structured instruments such as tests, interviews, focus groups, and questionnaires. These instruments were constructed based on a meticulously designed measurement scale to effectively capture the constructs. The chapter further described the sampling strategy, including the determination of sample size, the techniques employed, and the overall sampling process to ensure that the sample accurately represented the target population within the construction industry. To confirm the reliability and validity of the data, various instrument testing procedures were employed, and the data were examined using SPSS. In addition, the study utilized PLS-SEM to evaluate both the measurement model and the structural model. The measurement model evaluation assessed the validity and reliability of the constructs, whereas the structural model assessment explored the hypothesized relationships among readiness, intention, and performance. By meticulously applying these methodologies, the chapter established a robust empirical basis for the ensuing data analysis and interpretation. Finally, the chapter also discussed the flow process of the study and presented the work breakdown structure to provide a clear and detailed timeline for how the study was completed.

Table 3.13: Summary of Research Methodology.

Research Design	Quantitative research was the main research design applied in this study.
Data Collection	The data collected in this study consisted of primary data.
Sampling technique	G*Power was employed as the primary method to determine the minimum required sample size.
Research instrument	The questionnaire served as the primary research instrument for this study.
Research instrument testing	Pilot and pre-tests were conducted in this study to verify the reliability of the questionnaire items and their alignment with the research hypotheses.
Data measurement	SPSS and PLS-SEM were used to analyse and measure the data in this study.

CHAPTER 4

RESULT AND DISCUSSION

4.1 Introduction

This study primarily focused on the performance of the construction industry in adopting IR 5.0. This chapter discussed the objectives of the study which were to investigate the relationship between construction industry' readiness and intention toward their performance and to explore the impact of these factors on overall construction industry performance. The data collection process played a critical role in helping the study evaluate and provide quantitative insights into how the readiness and intention influenced the construction industry's performance during this transition. The responses gathered allowed for a clearer understanding of the relationship between these variables and their contribution offered valuable findings that supported both construction industry and academic researchers in identifying key performance influencers under the IR 5.0 framework.

4.2 Screening of Data

Questionnaire offers an efficient and economical method for collecting data from a large segment of the population (Marchall, 2005). The questionnaire enabled this study to collect an efficient number of within a reasonable timeframe and limited financial resources. During the data collection period, the questionnaire was distributed via email to construction companies and sent through LinkedIn with construction industry working in or respondents related to the construction industry. Table 4.1 presented a summary of the number of responses sent out, responses received and non-responses during the data collection period from 23 June 2025 until 20 July 2025. Table 4.1 shows the total responses received during the first batch were 30 (31.25%) out of 96, with 66 (68.75%) being non-responses. In the second batch, 27 responses (22.69%) received out of 119, while 92 (77.31%) were non-responses. Next the third batch recorded 13 responses (5.04%) out of 258 and 245 (94.96%) were non-responses. In the fourth batch, 42 responses (33.33%) were received out of 126 and 84 (66.67%) were non-responses. During all four batches, reminder emails were sent to the companies 2-3 times per week, while new survey continued to be distributed to other companies and construction industry. After the data collection period ended, the responses were filtered to ensure only valid data were used for analysis

Table 4.1: Survey Response Summary.

Timeline	**Responses Sent Out**	**Response Received**	**Response Received Rate (%)**	**Non-responses**	**Non-response Rate**
First Batch (23/6 – 29/6)	96	30	31.25%	66	68.75%
Second Batch (30/6 – 6/7)	119	27	22.69%	92	77.31%
Third Batch (7/7 – 13/7)	258	13	5.04%	245	94.96%
Fourth Batch (14/7 – 20/7)	126	42	33.33%	84	66.67%

After the data collection period, Table 4.2 presented the total number of responses collected, which was 112 responses. After data screening, 101 responses were deemed valid and suitable for data analysis, while 11 responses were excluded due to being invalidity. According to Meade A and Craig S (2012), the survey responses were excluded due to signs of straight-lining, where participants consistently chose repetitive or sequential answer patterns, suggesting a lack of attention or disengagement, which compromises data quality. The excluded responses were removed because the respondents appeared to answer all questions using the same rating consistently, such as 1-1-1-1-1 or selecting 1-2-3-4-5 in sequence throughout the entire survey, indicating a lack of genuine engagement with the questionnaire. In conclusion, total 101 valid responses were used for data analysis, as show in Table 4.2.

Table 4.2: Summary of Data Collection Overview.

Cut-off Date	20 July 2025
Total Responses	112
Invalid Responses	11
Valid Responses	**101**

4.3 Pre-data Determination

4.3.1 Pre-test Result

A Pre-test was a preliminary trial of the questionnaire conducted with a small group of respondents to identify issues related to clarity, wording, and structure. It helped ensure that all questions were understandable and accurately captured the intended variables before the full-scale data collection began. This study conducted a pre-test involving 3 academics and 3 individuals from industry. The academic participants held positions such as Ts. Dr. and Head of Programme (Software Engineering), Assistant Professor, and Associate Professor. The industry participants included a Quantity Surveyor, a Technology Project Leader, and a Project Leader. Based on their feedback, a minor improvement was made to the questionnaire by revising the question "6. How big of the construction companies?" to "6. How big is the construction company?" to enhance clarity and grammatical accuracy. All other questions were found to be clear, relevant and free from issues.

4.3.2 Pilot Test Result

In the study, the pilot test was conducted to ensure that the performance of construction industry adopting the IR 5.0 revolution was accurately assessed. According to Livingston (2018), the degree to which random variables had no effect on test results was known as reliability. The independent variables in this study are the readiness of the construction industry to adopt the IR5.0 and the intention of construction industry to adopt the IR 5.0. Meanwhile, the dependent variable was the performance of the construction industry in adopting the IR 5.0. To assess the reliability of the measurement instruments, a reliability test was conducted using SPSS software to obtain Cronbach's Alpha. Table 4.3 presented the reliability test results for the variables of readiness, intention and performance. Based on Table 4.3, the Cronbach's Alpha values for the two independent variables IV_1, (Readiness) and IV_2 (Intention), and the dependent variable (Performance) were 0.836, 0.856, and 0.898 respectively. According to the commonly accepted reliability thresholds, a Cronbach's Alpha value above 0.8 indicates good internal consistency. Therefore, IV_1 (Readiness) demonstrates good reliability with a value of 0.836, while IV_2 (Intention) also showed good reliability with a value of 0.856. As shown in Table 4.3, both variables met the required standards for internal consistency, suggesting that the items used to measure these constructs were reliable. Similarly, the dependent variable, Performance, had a Cronbach's Alpha value of 0.898, which also fell within the range of good reliability. This indicated that the items used to measure performance were internally consistent and suitable for further analysis. These variables were analyzed through a reliability test, and the results were summarized in Table 4.3.

Table 4.3: Results of Reliability Test.

Variables	**Cronbach's Alpha**	**Strength of Association**	**Number of items**
Independent variables			
IV_1 - Readiness	0.836	Good	6
IV_2 - Intention	0.856	Good	6
Dependent variable			
DV - Performance	0.898	Good	6

4.4 Descriptive analysis

As previously mentioned, a total of 101 valid responses were obtained. Descriptive analysis was subsequently conducted based on the 101 valid responses. Descriptive analysis was a statistical method used to summarize and describe the main features of a dataset. According to (Kemp et al., 2017), descriptive analysis was a technique used to accurately detail the type and intensity of sensory attributes. Descriptive analysis helped this study present the data in a clear and understandable manner using measures such as frequency and percentage.

4.4.1 Descriptive Profile Analysis - Gender

Based on Figure 4.1, out of 101 responses, the highest number of responses came from male construction player, with 78 respondents (77.23 %), while lowest was from females' construction players which are 23 respondents (22.77 %). According to Wells et al. (2024), the long working hours, unpredictable schedules, and harsh work environment made construction roles less accessible to women, especially those balancing caregiving responsibilities. These factors were the reason why the number of female construction industry was lower than that of male construction industry. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

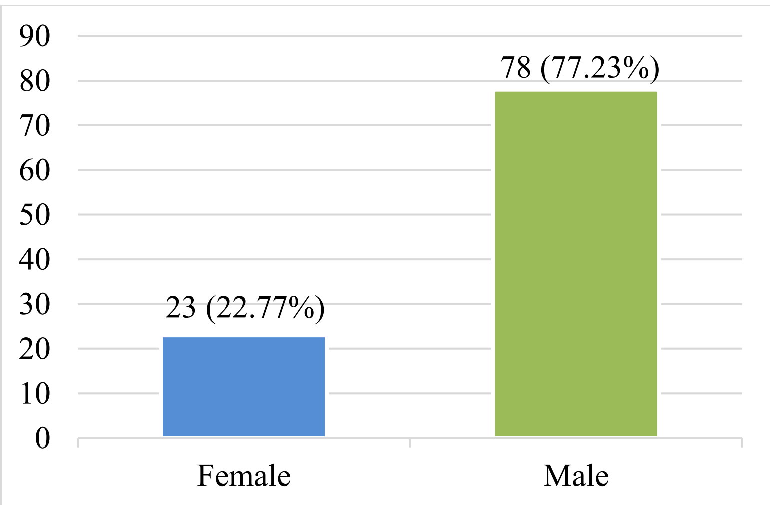


Figure 4.1: Descriptive Profile Analysis – Gender.

4.4.2 Descriptive Profile Analysis – Ethic Group

Based on Figure 4.2, out of 101 responses, 69 respondents were Chinese (68.32%), 27 Malay (26.73%), 5 Indian (4.95%) and 0 others. The highest number of responses came from Chinese respondents, likely due to historical dominance, strong networks, and greater access to resources. According to Peck-Ling et al. (2022), firms with higher Chinese ownership and board representation often dominated the construction industry. Indian participation was the lowest, as noted by Nur Sufiyah Binti Ismail (2021), due to concerns over job security, low wages, poor safety, and limited career opportunities. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

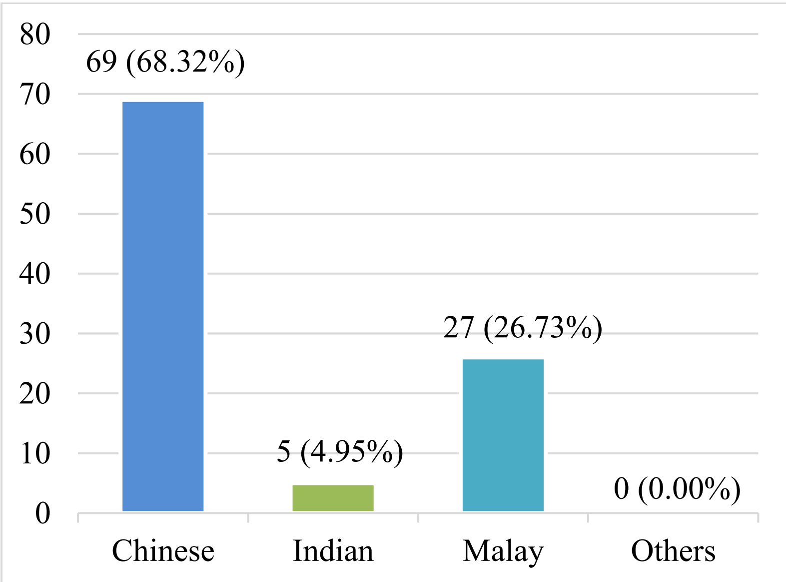


Figure 4.2: Descriptive Profile Analysis – Ethic Group.

4.4.3 Descriptive Profile Analysis – Age

Based on Figure 4.3, out of 101 responses, the highest number of respondents fell within the age group of 21–25 years, with a total of 22 responses (21.78%). This was followed by the 26–30 age group, with 19 responses (18.81%). In contrast, the lowest number of responses came from the age group above 65, with only 2 respondents. (1.98%) There were no respondents below the age of 20. This distribution suggests that most construction industry who participated in the survey were young adults, while older age groups were less represented. According to CIDB Malaysia (2020), Malaysia's construction workforce was increasingly younger due to digital advancements and education outreach. According to Ismail et al. (2021), the older individuals often avoid construction work dues to its physical demands and preference for less intensive roles. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

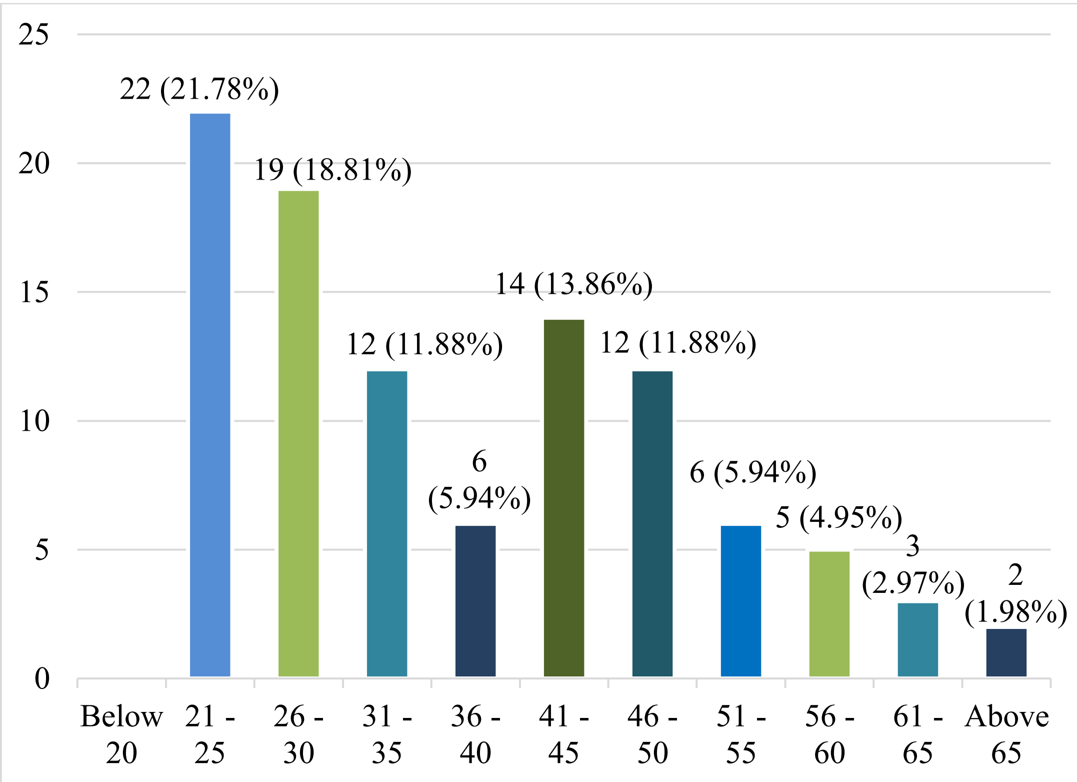


Figure 4.3: Descriptive Profile Analysis – Age.

4.4.4 Descriptive Profile Analysis – Highest Education

Based on Figure 4.4, out of 101 responses, the responses showed that secondary education with 5 respondents (4.95%) and pre-university with 2 respondents (1.98%) were the least common education levels among construction industry hold. Postgraduate diploma holders accounted for 6 respondents (5.94%), while bachelor's degree holders formed the largest group with 49 respondents (48.51%). Master's degree holders made up 22 responses (21.78%), followed by doctoral degree holders with 17 responses (16.83%). According to Mohd Fateh, Mohamed and Omar (2022), bachelor's degree holder was more common as key roles require tertiary education, while lower-skilled jobs suited for those with only secondary education were mostly filled by foreign labour. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

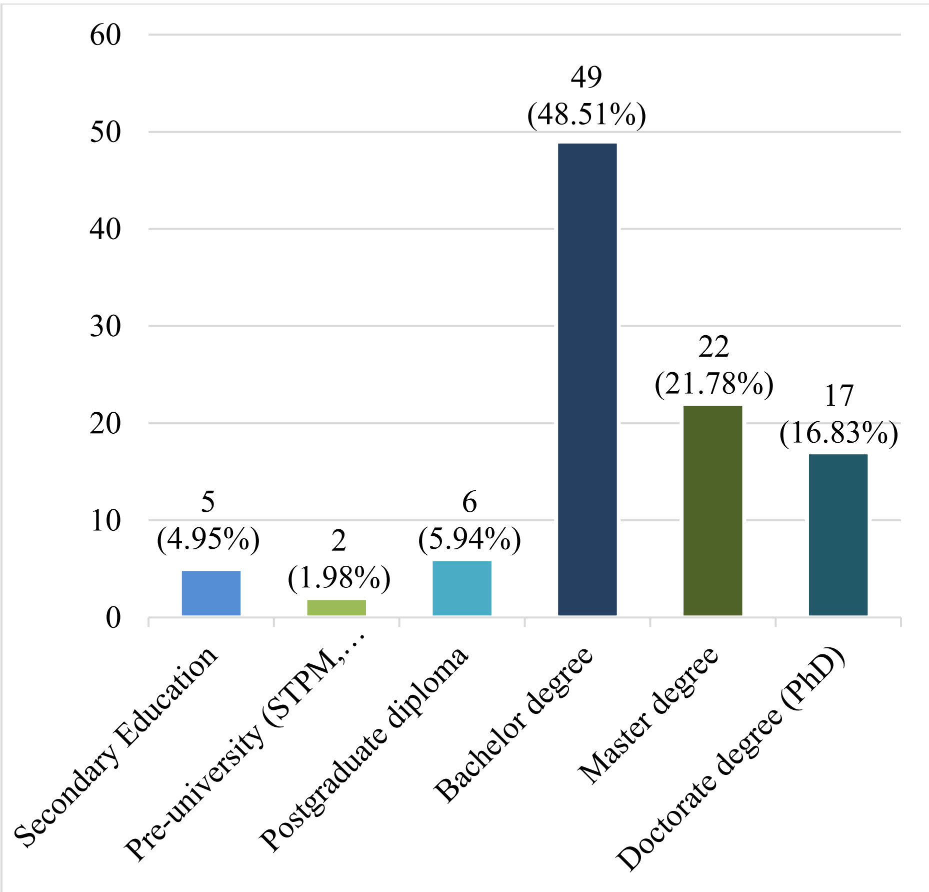


Figure 4.4: Descriptive Profile Analysis – Highest Education.

4.4.5 Descriptive Profile Analysis – Categories of Organization

Based on Figure 4.5, out of 101 responses, consultants recorded the highest number of responses at 36 (35.64%), followed by main contractors with 33 (32.67%), developers with 17 (16.83%) and subcontractors with the fewest at 15 (14.85%). According to Ismail (2006), Project Management Consultant (PMCs) became increasingly important in Malaysia, reflecting a growing demand for consultancy services. According to Rameezdeen and Gunarathna (2016) stated that main contractors often faced higher financial risks and project responsibilities, which may have contributed to their lower participation in the survey. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

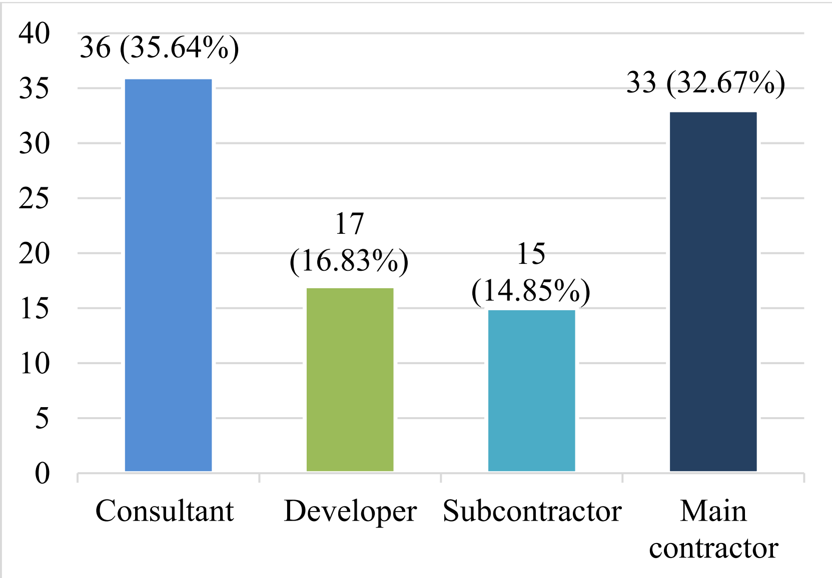


Figure 4.5: Descriptive Profile Analysis – Categories of Organization.

4.4.6 Descriptive Profile Analysis – Company Size

Based on Figure 4.6, out of 101 responses, most respondents were from small companies (10 – 49 workers), totaling 38 (37.62%), followed by large-sized companies (> 100 workers) with 32 (31.68%), medium-sized companies (50 – 99 workers) with 26 (25.74%), and the least from micro companies (1-9 workers) with 5 (4.95%). According to Hamid et al (2021), most construction firms employed 10 - 49 workers, aligned with CIDB's G1 – G3 classification, while micro firms were less common due to limited capital and operational scale. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

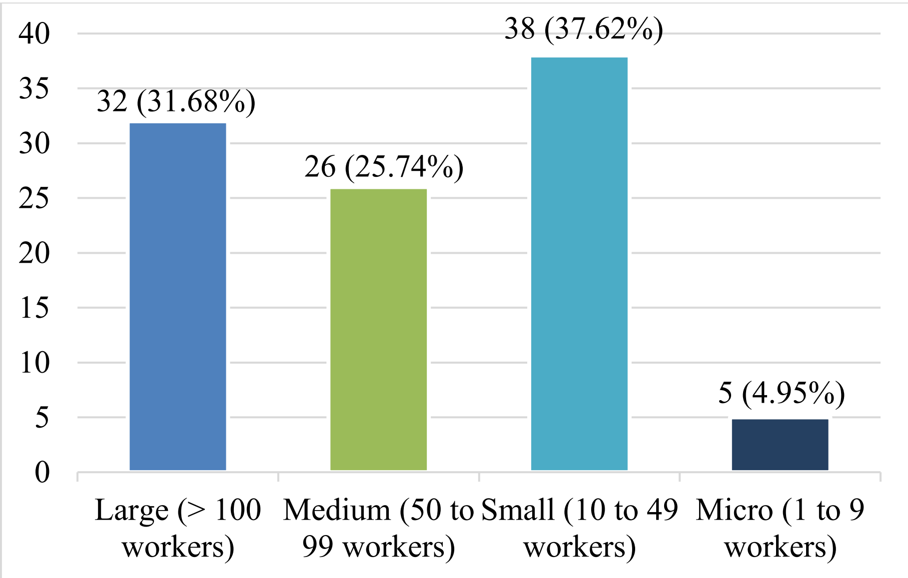


Figure 4.6: Descriptive Profile Analysis – Company Size.

4.4.7 Descriptive Profile Analysis – Role

Based on Figure 4.7, out of 101 respondents, most respondents held technician roles related to engineering or technology, totaling 82 (81.19%), while only 19 (18.81%) were in non-technician roles that were non-engineering or non-technology. According to Hassan, Noor and Mohammad (2021), technician roles were more common due to their support in site operations, lower entry barriers and higher demand. In contrast, non-technician roles were fewer as they required higher qualifications and had limited workforce availability. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

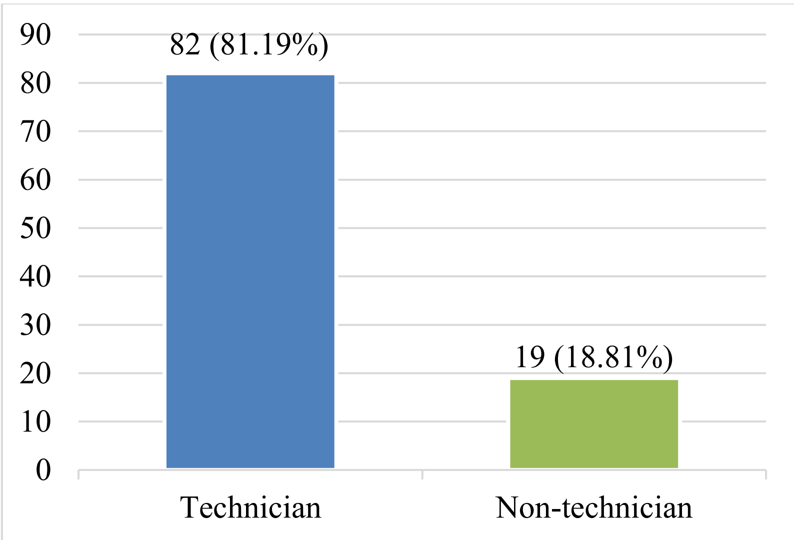


Figure 4.7: Descriptive Profile Analysis – Role.

4.4.8 Descriptive Profile Analysis – Position

Based on Figure 4.8, out of 101 respondents, most respondents held executive level, such as engineers or junior executives, totaling 36 (35.64%). This was followed by managerial level with 28 (27.72%), top management with 15 (14.85%), senior management with 13 (12.87%) and the fewest at supervisor level with only 9 (8.91%). According to CICS (2019), the supervisory tier was smaller and more narrowly focused than the broader executive tier (CIDB CICS, Level 3 vs Level 4). Organizational theory also supported that middle supervisory layers were fewer in number, serving primarily as operational links rather than decision-making hubs. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

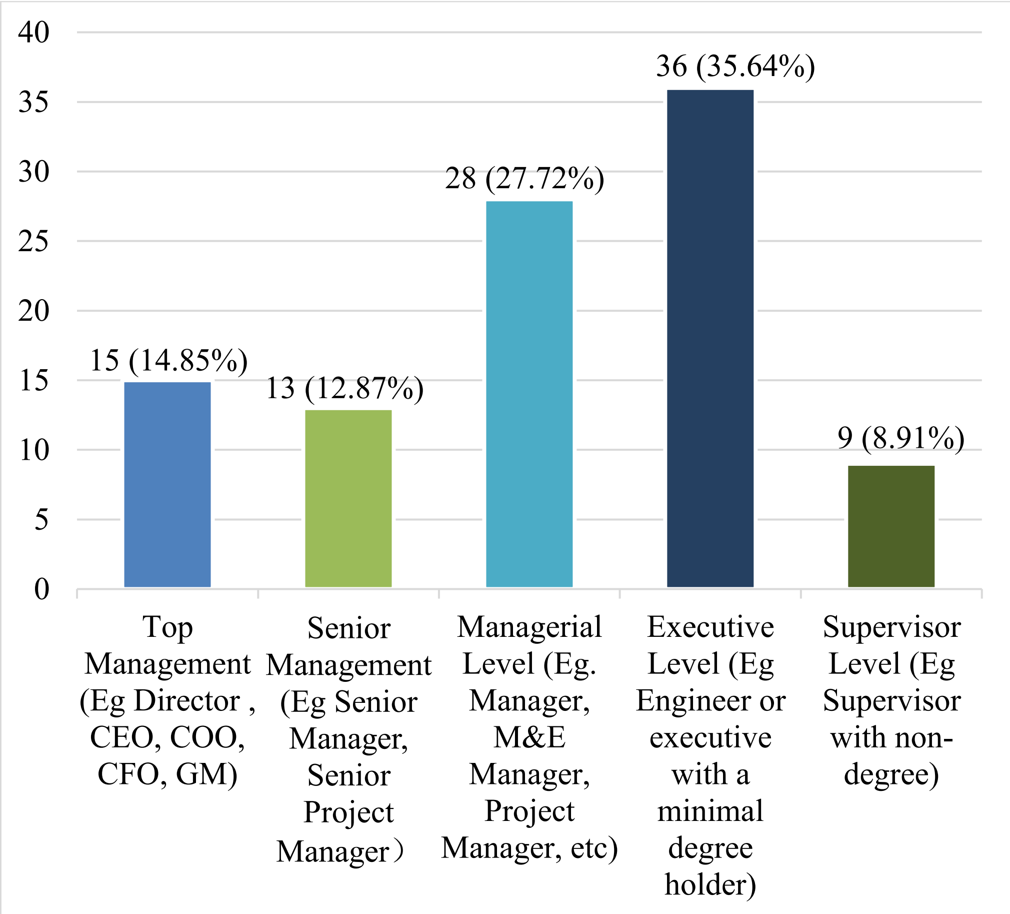


Figure 4.8: Descriptive Profile Analysis – Position.

4.4.9 Descriptive Profile Analysis – Work Experience

Based on Figure 4.9, out of 101 respondents, the majority of respondents had 1 – 5 years of work experience, with 32 respondents (31.68%). This was followed by those with 20 years of experience with 17 respondents (16.83%), Respondents with 16 – 20 years of work experiences followed closely which were 16 (15.84%). Those with 6 – 10 years and 11 – 15 years of experience, each totaling 14 respondents (13.86%), while the fewest had less than 1 year of experience, accounting for only with 8 respondents (7.92%). According to Oluseyi (2014), 1–5 years of experience was the most common (46.8%), indicating many respondents was early in their careers but had gained stable footing. In contrast, less than 1 year of experience was the least common (15.4%), likely due to early attrition and challenges in adapting to site demands. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

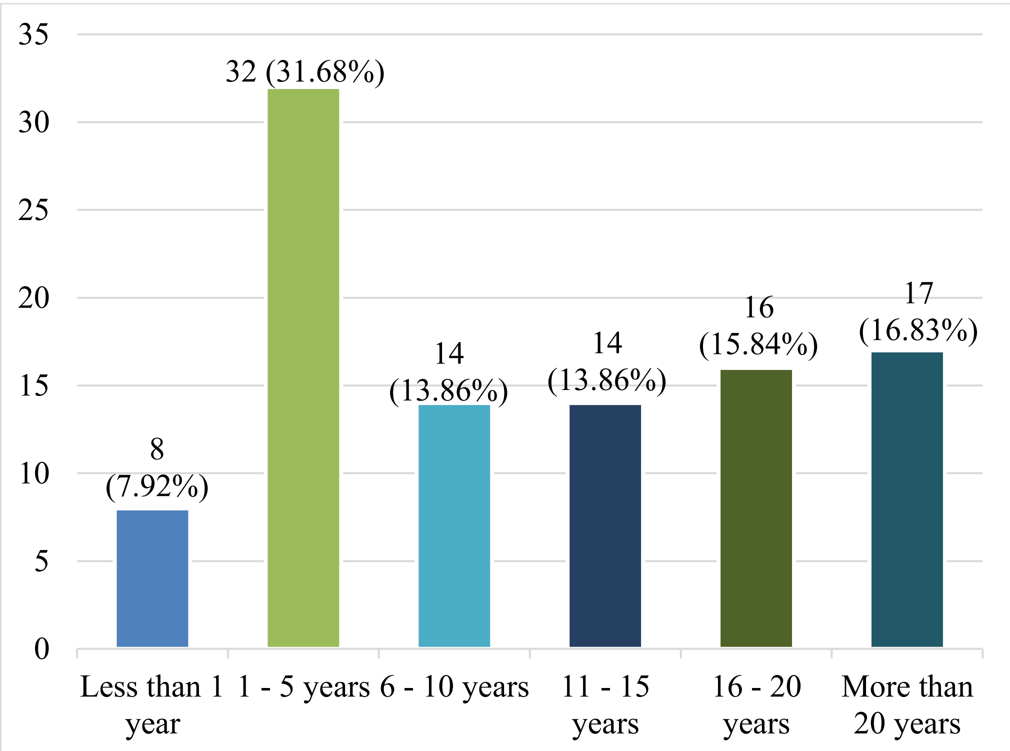


Figure 4.9: Descriptive Profile Analysis – Work Experience.

4.4.10 Descriptive Profile Analysis – Awareness of IR 5.0

Based on Figure 4.10, out of 101 respondents, most respondents heard of IR 5.0, with 70 respondents (69.31%), while only 31 respondents (30.69%) had not. According to Musarat et al. (2023b), the review showed IR 5.0 was still emerging in construction, but awareness had grown as professionals explored its human-centric and intelligent applications. This explained why awareness among construction industry was higher than those who had not heard of IR 5.0. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

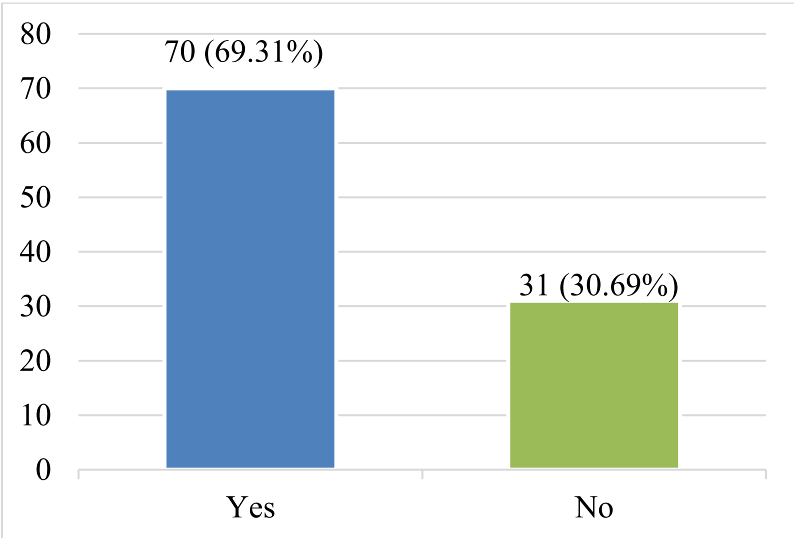


Figure 4.10: Descriptive Profile Analysis – Awareness of IR 5.0.

4.4.11 Descriptive Profile Analysis – Knowledge of IR 5.0

Based on Figure 4.11, out of 101 respondents, the majority of respondents reported a moderate familiarity with IR 5.0, totaling 38 respondents (37.62%). This was followed by both familiar and slightly familiar responses, with 24 respondents (23.76%). 13 respondents (12.87%) were completely unfamiliar with IR 5.0, while the fewest respondents, 5 (4.95%), were very familiar with IR 5.0. According to Musarat et al. (2023b), the review showed IR 5.0 was still emerging in construction, but awareness had grown as professionals explored its human-centric and intelligent applications. This explained why awareness among construction players was higher than those who had heard of IR 5.0. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

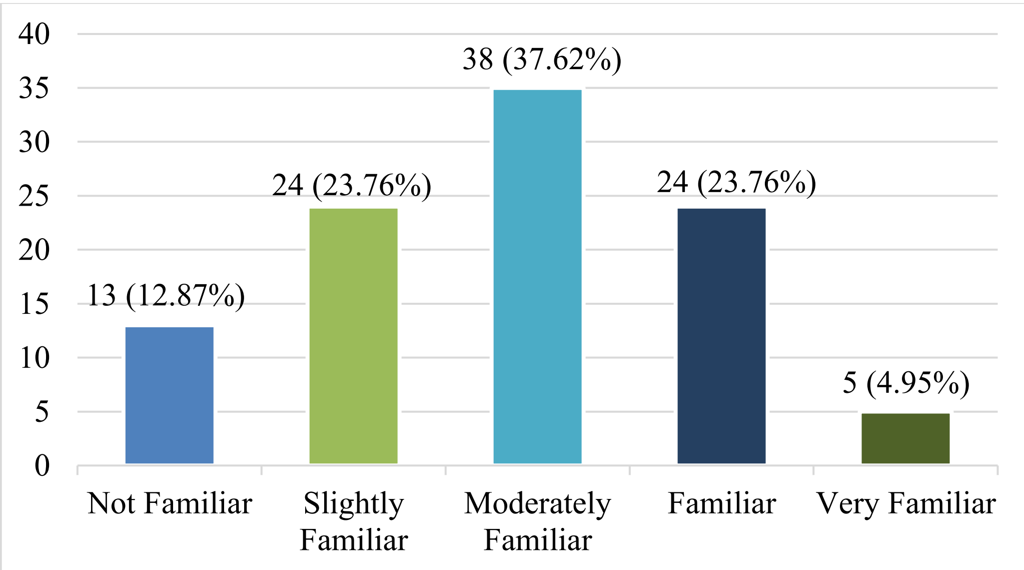


Figure 4.11: Descriptive Profile Analysis – Knowledge of IR 5.0.

4.4.12 Descriptive Analysis (Performance) – Q1: Applying Construction IR 5.0 technologies improves my work efficiency.

Based on Figure 4.12, out of 101 respondents, respondents' views about applying construction IR 5.0 technologies improve their work efficiency showed that the highest number agreed with 40 respondents (39.60%). This was followed by a neutral stance from 34 respondents (33.66%). A total of 12 respondents (11.88%) strongly agreed, while 8 respondents (7.92%) disagreed, and the fewest construction industry, 7 respondents (6.93%), strongly disagreed. The majority of the 40 (30.60%) respondents were found to agree, compared to 7 (6.93%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

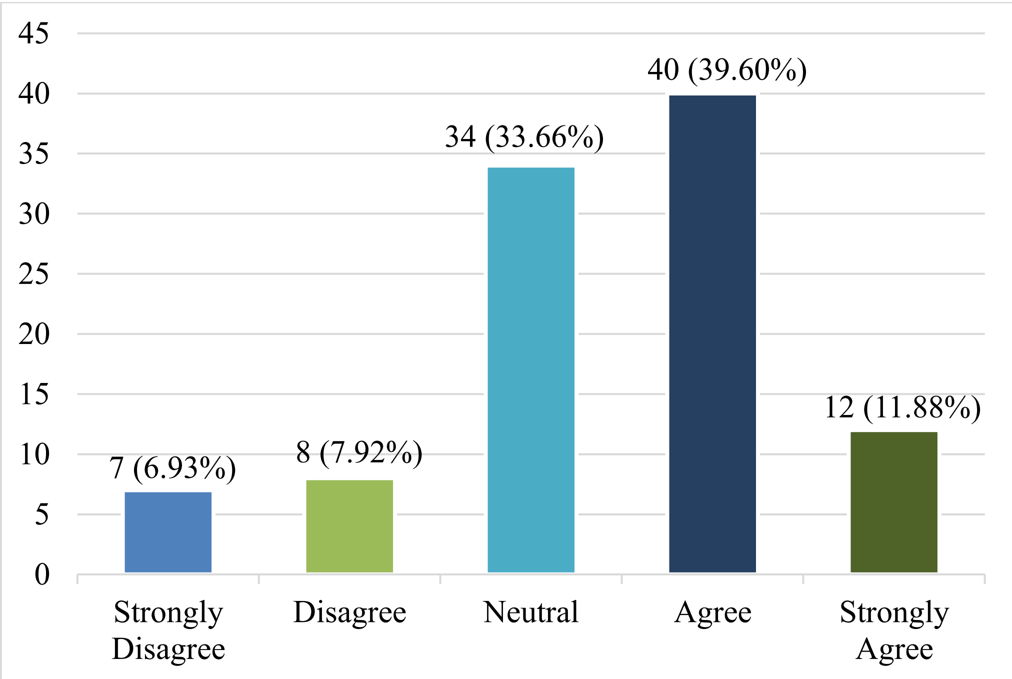


Figure 4.12: Descriptive Analysis (Performance) – Q1: Applying Construction IR 5.0 technologies improves my work efficiency.

4.4.13 Descriptive Analysis (Performance) – Q2: Using IR 5.0 practices reduces errors and rework in my daily tasks.

Based on Figure 4.13, out of 101 respondents, the majority of 41 respondents (40.59%) agreed that using IR 5.0 practices reduced errors and rework in their daily tasks, followed by 30 respondents (29.70%) who held on a neutral view. A total of 14 respondents (13.86%) strongly agreed with the statement, while 9 respondents (8.91%) disagreed. Strong disagreement was the least common response, selected by only 7 respondents (6.93%). The majority of the 41 (40.59%) respondents were found to agree, compared to 7 (6.93%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

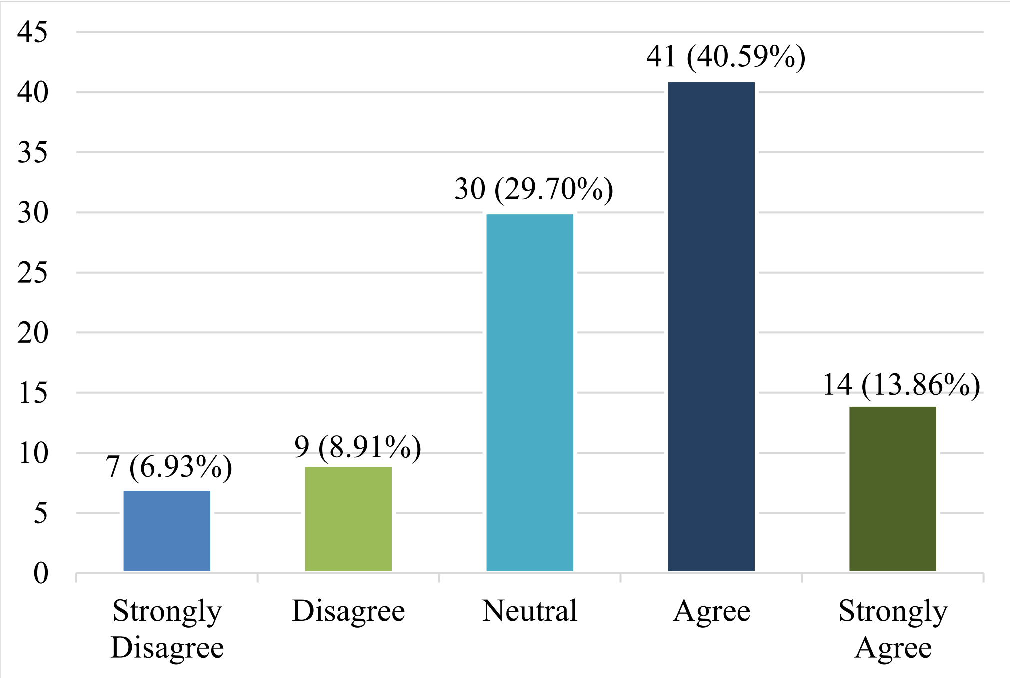


Figure 4.13: Descriptive Analysis (Performance) – Q2: Using IR 5.0 practices reduces errors and rework in my daily tasks.

4.4.14 Descriptive Analysis (Performance) – Q3: IR 5.0 helps me complete projects faster than traditional methods.

Based on Figure 4.14, out of 101 respondents, the majority of 46 respondents (45.54%) agreed that IR 5.0 had helped them complete projects faster than traditional methods, followed by 23 respondents (22.77%) who held on a neutral view. A total of 17 respondents (16.83%) strongly agreed with the statement, while 10 respondents (9.90%) disagreed. Strong disagreement was the least common response, selected by only 5 respondents (4.95%). The majority of the 46 (45.54%) respondents were found to agree, compared to the 5 (4.95%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

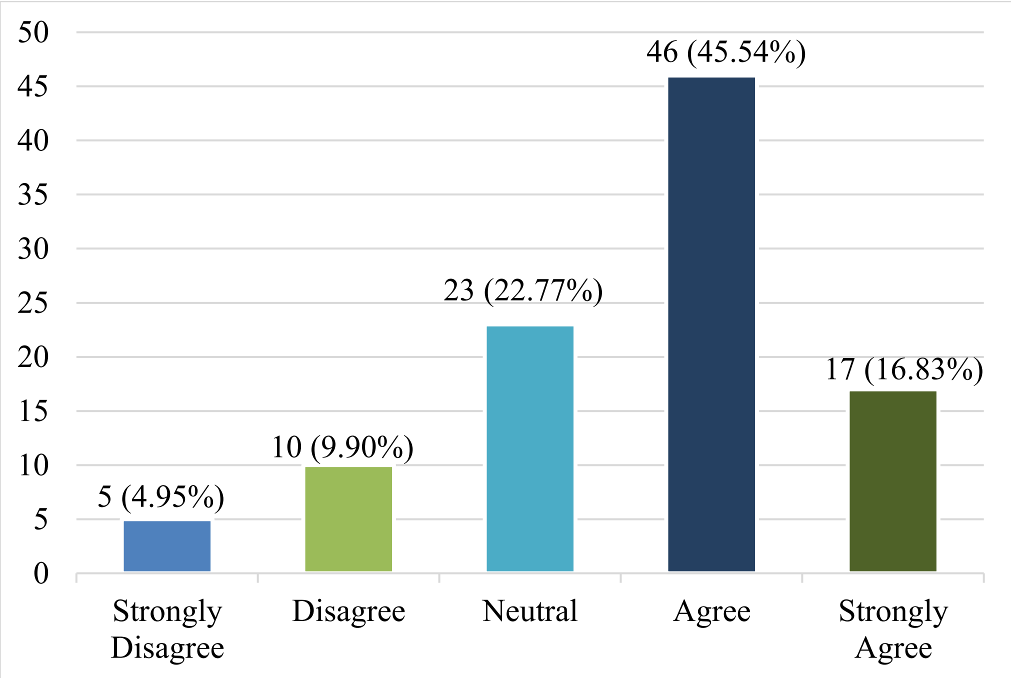


Figure 4.14: Descriptive Analysis (Performance) – Q3: IR 5.0 helps me complete projects faster than traditional methods.

4.4.15 Descriptive Analysis (Performance) – Q4: Integration of human-centric technologies enhances my decision-making quality.

Based on Figure 4.15, out of 101 respondents, the majority of 44 respondents (43.56%) agreed that the integration of human-centric technologies enhanced their decision-making quality, followed by 25 respondents (24.75%) who held a neutral view. A total of 18 respondents (17.82%) strongly agreed with the statement, while 8 respondents (7.92%) disagreed. Strong disagreement was the least common response, selected by only 6 respondents (5.94%). The majority of the 44 (43.56%) respondents were found to agree, compared to the 6 (5.94%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

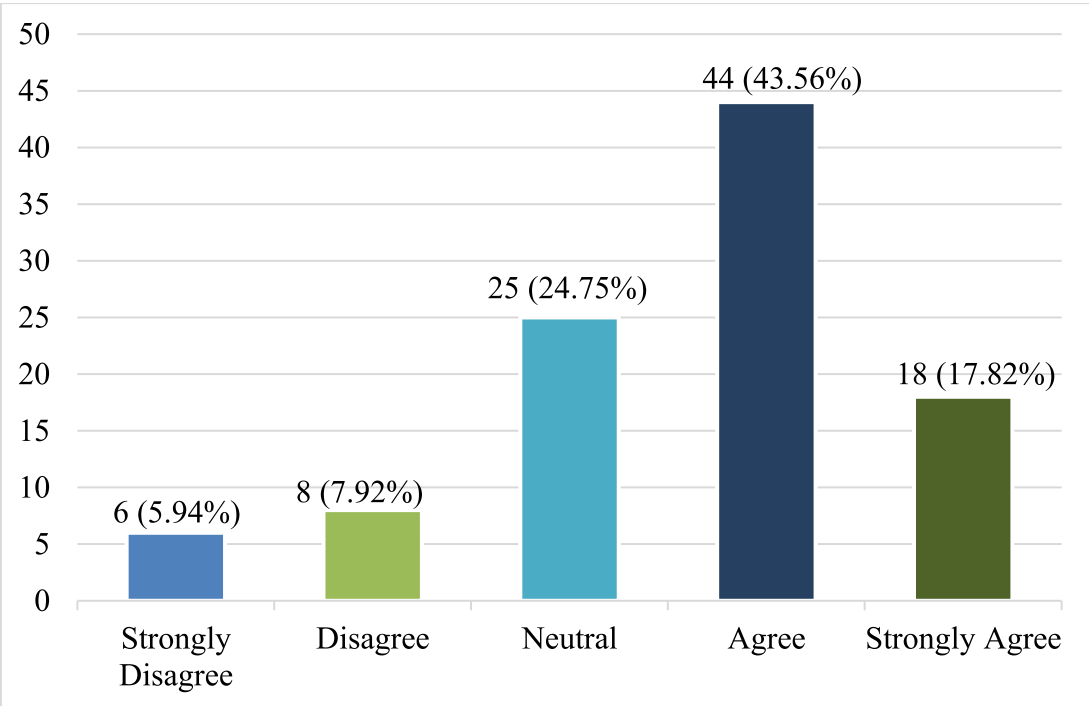


Figure 4.15: Descriptive Analysis (Performance) – Q4: Integration of human-centric technologies enhances my decision-making quality.

4.4.16 Descriptive Analysis (Performance) – Q5: Applying IR 5.0 increases the overall quality of my engineering outputs.

Based on Figure 4.16, out of 101 respondents, the majority of 46 respondents (45.54%) agreed that applying IR 5.0 increased the overall quality of their engineering outputs, followed by 21 respondents (20.79%) who held a neutral view. A total of 19 respondents (18.81%) strongly agreed with the statement, while 11 respondents (10.89%) disagreed. Strong disagreement was the least common response, selected by only 5 respondents (4.95%). The majority of the 46 (45.54%) respondents were found to agree, compared to 5 (4.95%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

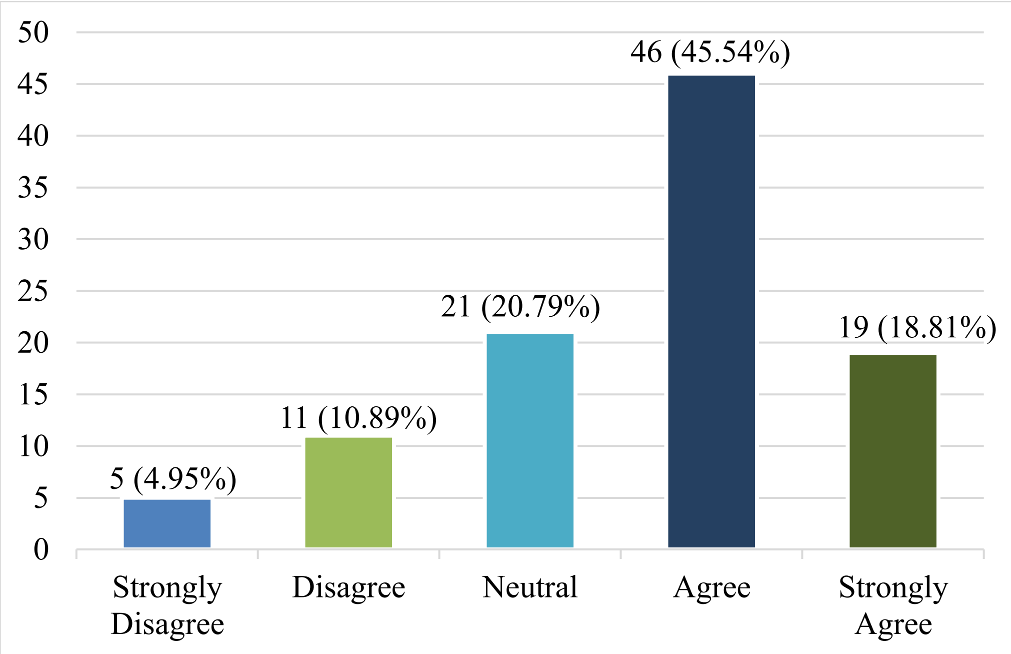


Figure 4.16: Descriptive Analysis (Performance) – Q5: Applying IR 5.0 increases the overall quality of my engineering outputs.

4.4.17 Descriptive Analysis (Performance) – Q6: Using IR 5.0 concepts improves collaboration and communication with my team.

Based on Figure 4.17, out of 101 respondents, the majority of 35 respondents (34.65%) agreed that using IR 5.0 concepts improved collaboration and communication with their team, followed by 29 respondents (28.71%) who held a neutral view. A total of 16 respondents (15.84%) strongly agreed with the statement, while 17 respondents (16.83%) disagreed. Strong disagreement was the least common response, selected by only 4 respondents (3.96%). The majority of the 35 (34.65%) respondents were found to agree, compared to 4 (3.96%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

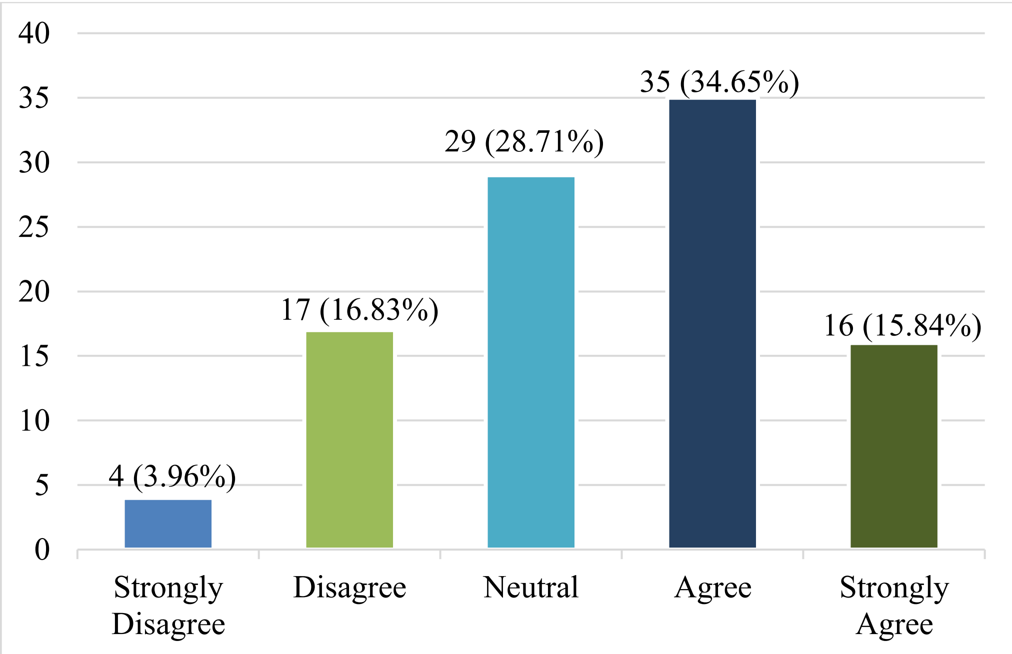


Figure 4.17: Descriptive Analysis (Performance) – Q6: Using IR 5.0 concepts improves collaboration and communication with my team.

4.4.18 Descriptive Analysis (Readiness) – Q1: I am ready to adopt new technology associated with Construction IR 5.0 in my daily work.

Based on Figure 4.18, out of 101 respondents, the majority of 37 respondents (36.63%) agreed they were ready to adopt new technology associated with construction IR 5.0 in their daily work, followed by 29 respondents (28.71%) who held a neutral view. A total of 17 respondents (16.83%) strongly agreed with the statement, while 11 respondents (10.89%) disagreed. Strong disagreement was the least common response, selected by only 7 respondents (6.93%). The majority of the 37 (36.63%) respondents were found to agree, compared to 7 (6.93%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

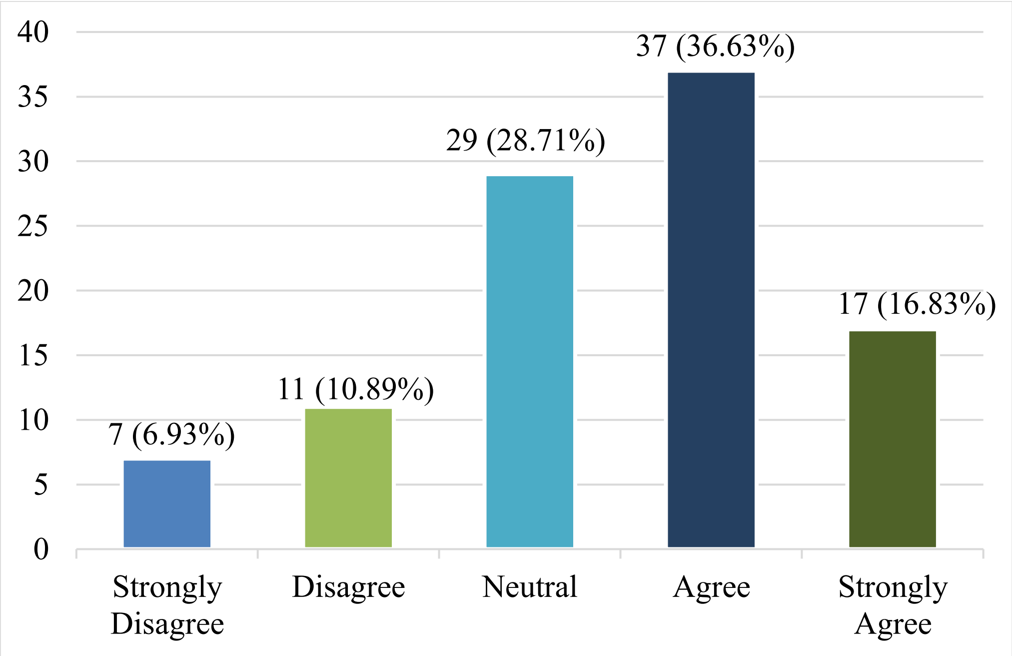


Figure 4.18: Descriptive Analysis (Readiness) – Q1: I am ready to adopt new technology associated with Construction IR 5.0 in my daily work.

4.4.19 Descriptive Analysis (Readiness) – Q2: I feel prepared to work alongside intelligent machines and AI tools on construction projects.

Based on Figure 4.19, out of 101 respondents, the majority of 37 respondents (36.63%) agreed they were felt prepared to work alongside intelligent machines and AI tools on construction projects, followed by 22 respondents (21.78%) who held a neutral view and strongly agreed. A total of 17 respondents (16.83%) disagreed. Strong disagreement was the least common response, selected by only 3 respondents (2.97%). The majority of the 37 (36.63%) respondents were found to agree, compared to 3 (2.97%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

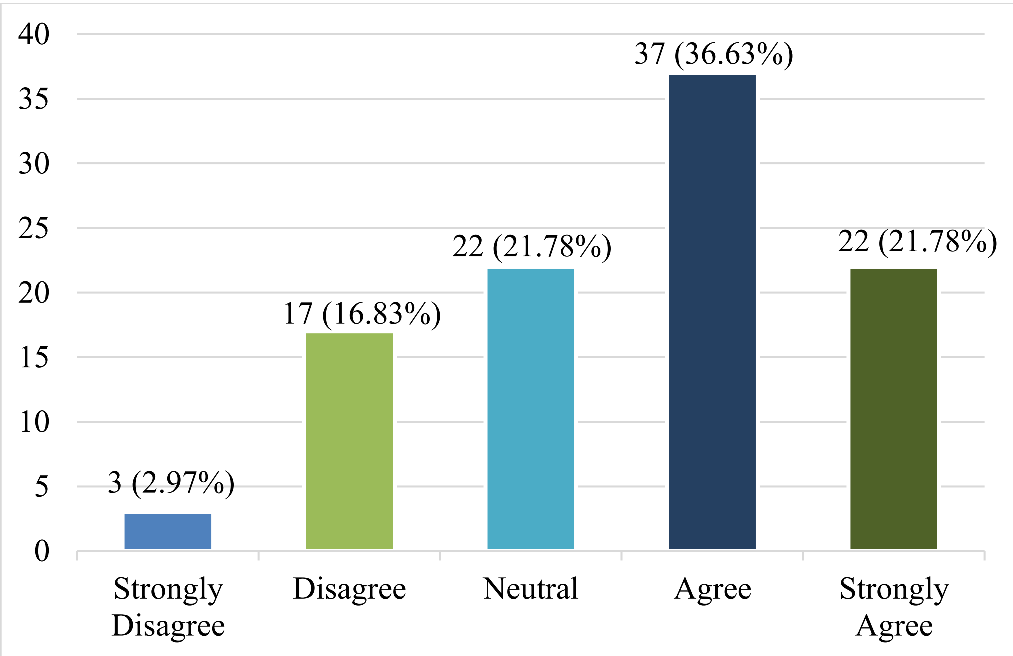


Figure 4.19: Descriptive Analysis (Readiness) – Q2: I feel prepared to work alongside intelligent machines and AI tools on construction projects.

4.4.20 Descriptive Analysis (Readiness) – Q3: I have the necessary skills to implements IR 5.0 principles effectively in construction.

Based on Figure 4.20, out of 101 respondents, the majority of 39 respondents (38.61%) agreed they had the necessary skills to implement IR 5.0 principles effectively in construction, followed by 33 respondents (32.67%) who held a neutral view. A total of 13 respondents (12.87%) strongly agreed with the statement, while 11 respondents (10.89%) disagreed. Strong disagreement was the least common response, selected by only 5 respondents (4.95%). The majority of the 39 (38.61%) respondents were found to agree, compared to the 5 (4.95%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

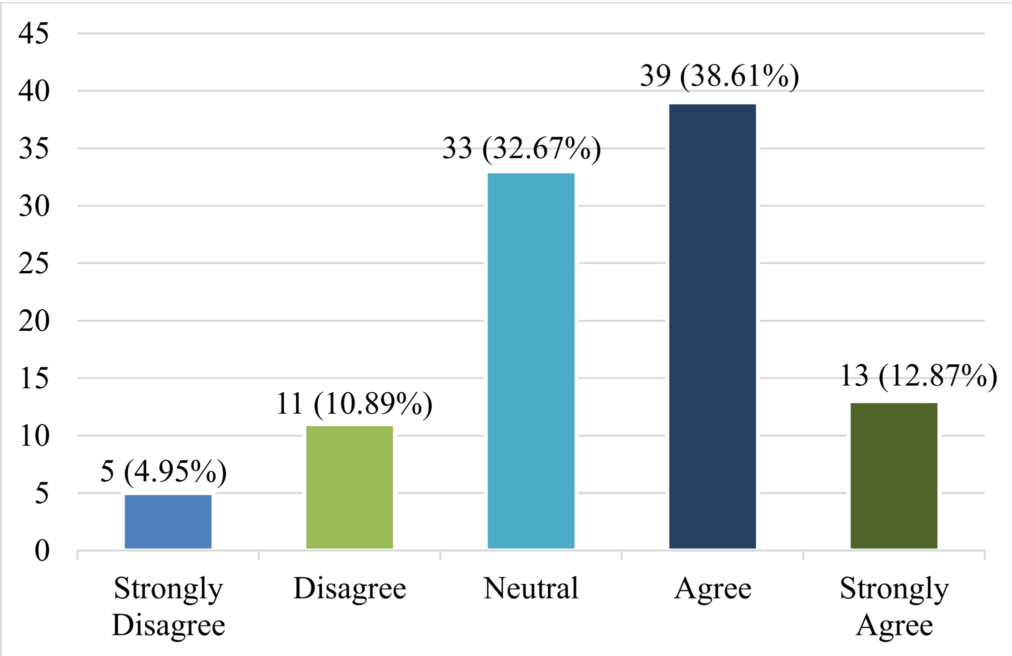


Figure 4.20: Descriptive Analysis (Readiness) – Q3: I have the necessary skills to implements IR 5.0 principles effectively in construction.

4.4.21 Descriptive Analysis (Readiness) – Q4: I am mentally and professionally ready to embrace the changes introduced by construction IR 5.0.

Based on Figure 4.21, out of 101 respondents, the majority of 48 respondents (47.52%) agreed they were mentally and professionally ready to embrace the changes introduced by construction IR 5.0, followed by 23 respondents (22.77%) who held a neutral view. A total of 15 respondents (14.85%) strongly agreed with the statement, while 13 respondents (12.87%) disagreed. Strong disagreement was the least common response, selected by only 2 respondents (1.98%). The majority of the 48 (47.52%) respondents were found to agree, compared to 2 (1.98%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

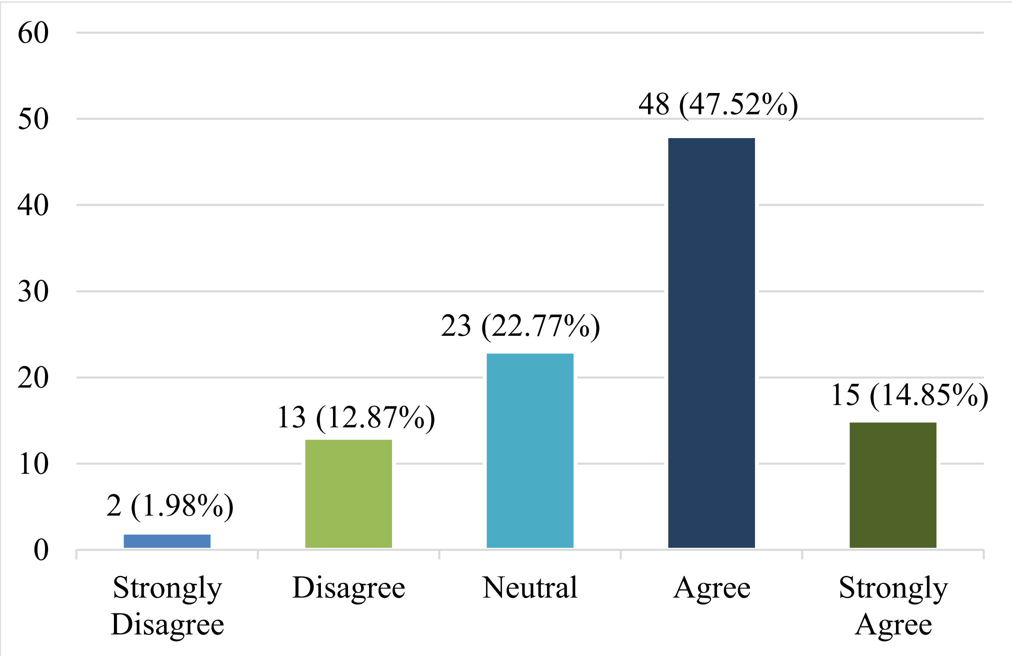


Figure 4.21: Descriptive Analysis (Readiness) – Q4: I am mentally and professionally ready to embrace the changes introduced by construction IR 5.0.

4.4.22 Descriptive Analysis (Readiness) – Q5: I have access to sufficient resources and support to apply IR 5.0 in my tasks.

Based on Figure 4.22, out of 101 respondents, the majority of 39 respondents (38.61%) agreed they had access to sufficient resources and support to apply IR 5.0 in their tasks, followed by 28 respondents (27.72%) who held a neutral view. A total of 18 respondents (17.82%) disagreed with the statement, while 11 respondents (10.89%) strongly agreed. Strong disagreement was the least common response, selected by only 5 respondents (4.95%). The majority of the 39 (38.61%) respondents were found to agree, compared to 5 (4.95%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

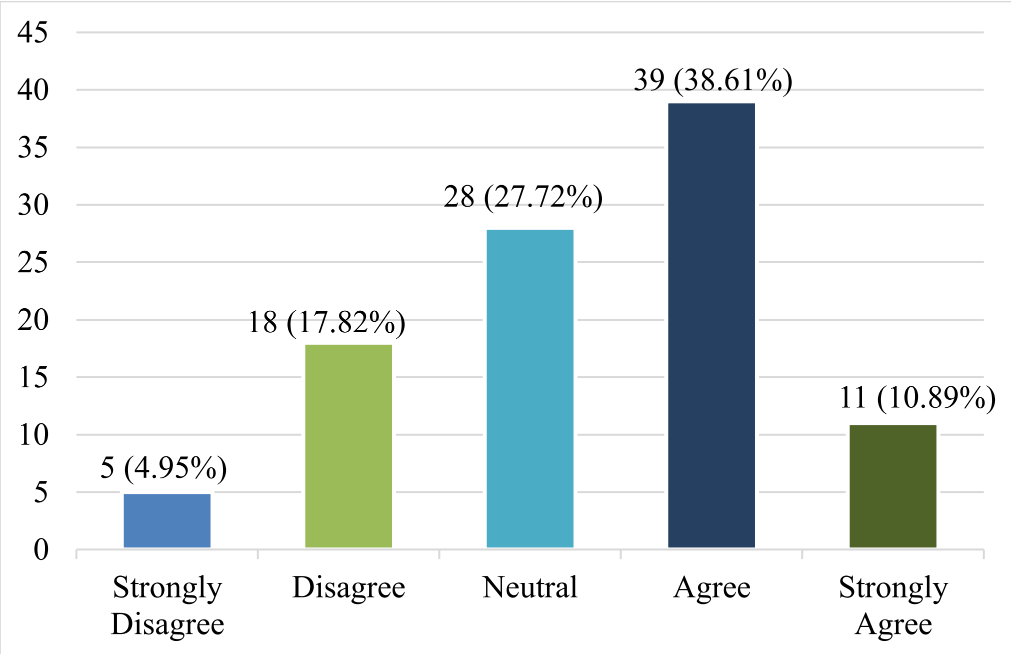


Figure 4.22: Descriptive Analysis (Readiness) – Q5: I have access to sufficient resources and support to apply IR 5.0 in my tasks.

4.4.23 Descriptive Analysis (Readiness) – Q6: I am confident in my ability to manage challenges that may arise from implementing IR 5.0 technologies in construction.

Based on Figure 4.23, out of 101 respondents, the majority of 36 respondents (35.64%) agreed they had confidence in their ability to manage challenges that might have arise from implementing IR 5.0 technologies in construction, followed by 30 respondents (29.70%) who held a neutral view. A total of 20 respondents (19.80%) strongly agreed with the statement, while 11 respondents (10.89%) disagreed. Strong disagreement was the least common response, selected by only 4 respondents (3.96%). The majority of the 36 (35.64%) respondents were found to agree, compared to the 4 (3.96%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

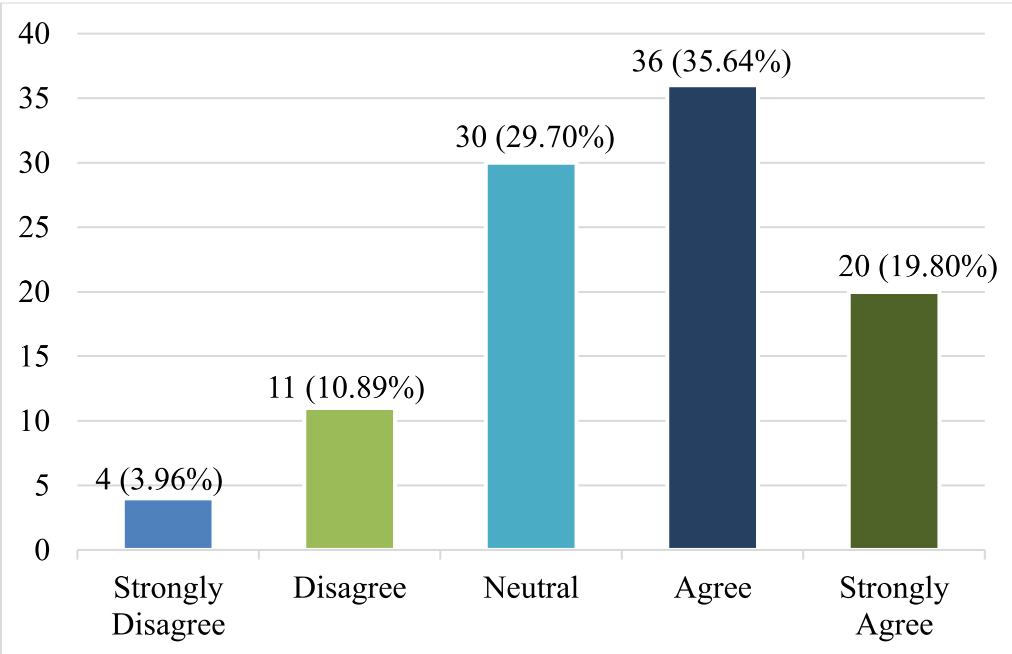


Figure 4.23: Descriptive Analysis (Readiness) – Q6: I am confident in my ability to manage challenges that may arise from implementing IR 5.0 technologies in construction.

4.4.24 Descriptive Analysis (Intention) – Q1: I intend to incorporate IR 5.0 technologies in my daily construction tasks.

Based on Figure 4.24, out of 101 respondents, the majority of 39 respondents (38.61%) agreed they intended to incorporate IR 5.0 technologies in their daily construction tasks, followed by 26 respondents (25.74%) who held a neutral view. A total of 21 respondents (20.79%) strongly agreed with the statement, while 11 respondents (10.89%) disagreed. Strong disagreement was the least common response, selected by only 4 respondents (3.96%). The majority of the 36 (35.64%) respondents were found to agree, compared to the 4 (3.96%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

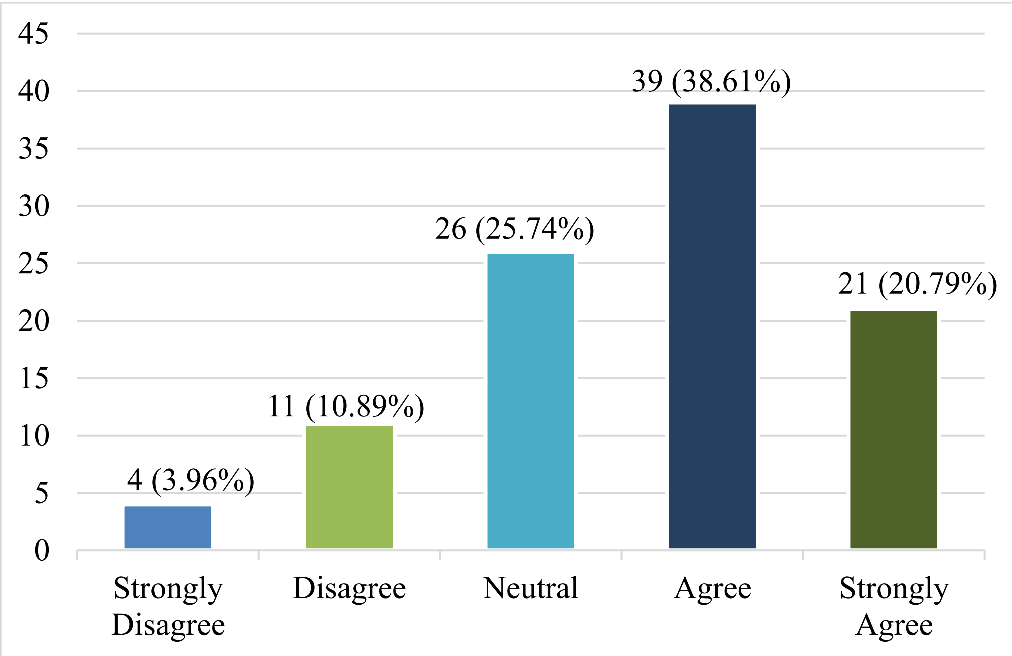


Figure 4.24: Descriptive Analysis (Intention) – Q1: I intend to incorporate IR 5.0 technologies in my daily construction tasks.

4.4.25 Descriptive Analysis (Intention) – Q2: I plan to actively learn more about construction IR 5.0 and its applications.

Based on Figure 4.25, out of 101 respondents, the majority of 39 respondents (38.61%) agreed they planned to actively learn more about construction IR 5.0 and its applications, followed by 22 respondents (21.78%) who held a neutral view. A total of 25 respondents (24.75%) strongly agreed with the statement, while 13 respondents (12.87%) disagreed. Strong disagreement was the least common response, selected by only 2 respondents (1.98%). The majority of the 39 (38.61%) respondents were found to agree, compared to the 2 (1.98%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

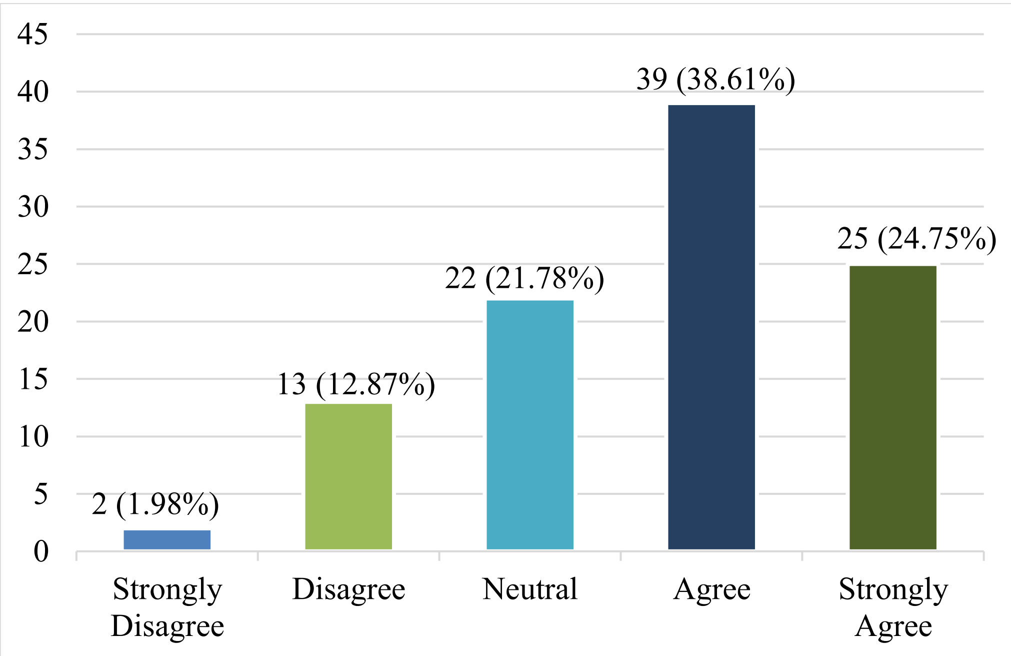


Figure 4.25: Descriptive Analysis (Intention) – Q2: I plan to actively learn more about construction IR 5.0 and its applications.

4.4.26 Descriptive Analysis (Intention) – Q3: I aim to use human-centric technologies in upcoming projects.

Based on Figure 4.26, out of 101 respondents, the majority of 47 respondents (46.53%) agreed they had aimed to use human-centric technologies in upcoming projects, followed by 23 respondents (22.77%) who held a neutral view. A total of 16 respondents (15.84%) strongly agreed with the statement, while 11 respondents (10.89%) disagreed. Strong disagreement was the least common response, selected by only 4 respondents (3.96%). The majority of the 47 (46.53%) respondents were found to agree, compared to the 4 (3.96%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

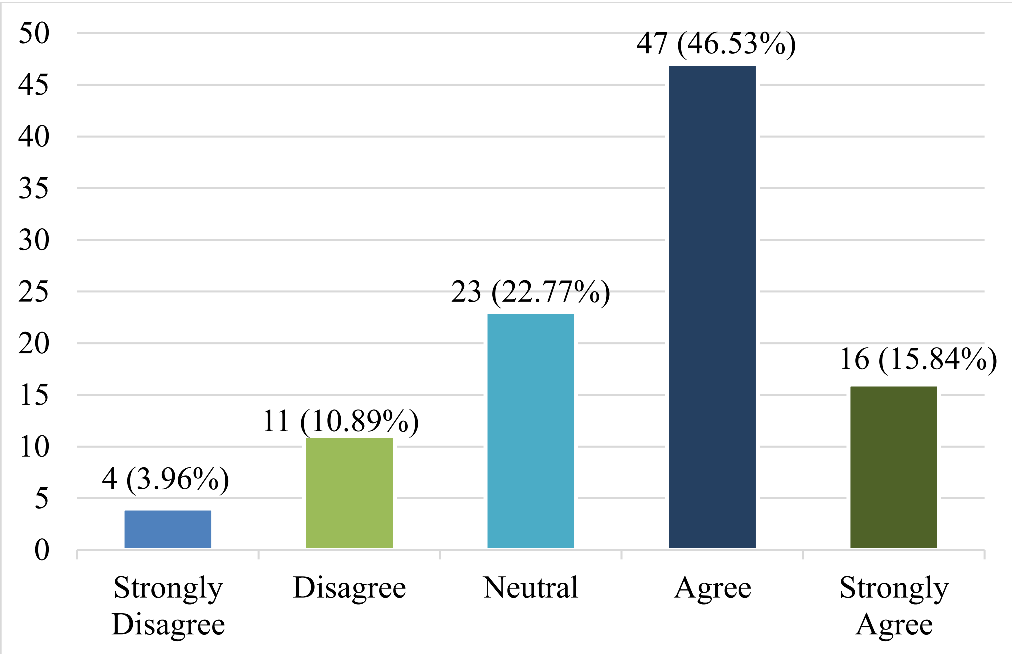


Figure 4.26: Descriptive Analysis (Intention) – Q3: I aim to use human-centric technologies in upcoming projects.

4.4.27 Descriptive Analysis (Intention) – Q4: I am committed to adopting new tools and method aligned with IR 5.0.

Based on Figure 4.27, out of 101 respondents, the majority of 46 respondents (45.54%) agreed they were committed to adopting new tools and methods aligned with IR 5.0, followed by 21 respondents (20.79%) who held a neutral view. A total of 17 respondents (16.83%) strongly agreed with the statement, while 12 respondents (11.88%) disagreed. Strong disagreement was the least common response, selected by only 5 respondents (4.95%). The majority of the 46 (45.54%) respondents were found to agree, compared to the 5 (4.95%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

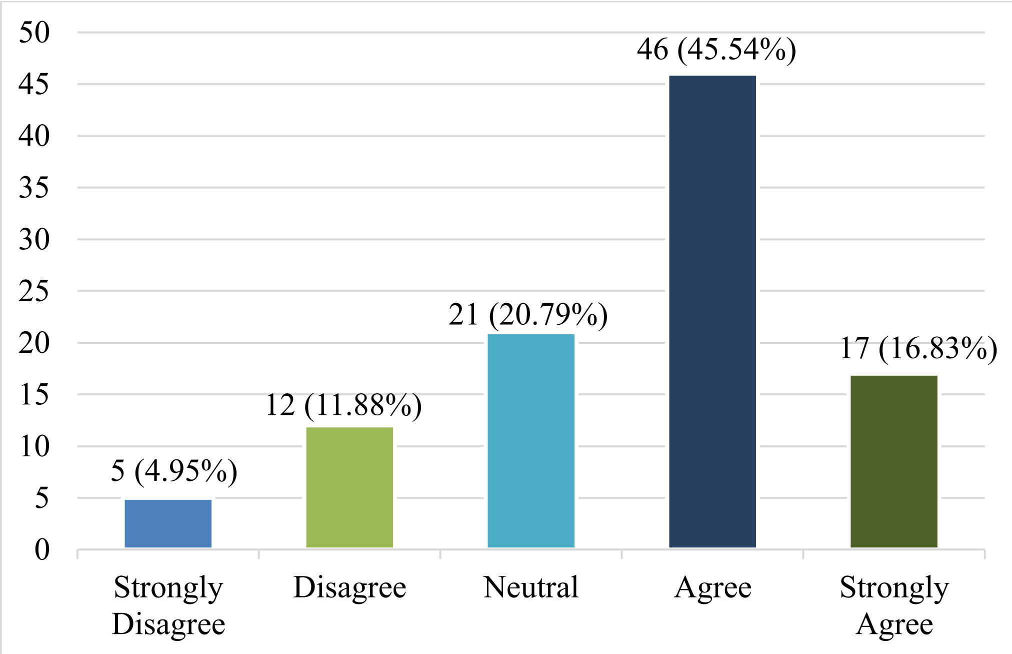


Figure 4.27: Descriptive Analysis (Intention) – Q4: I am committed to adopting new tools and method aligned with IR 5.0.

4.4.28 Descriptive Analysis (Intention) – Q5: I intend to collaborate closely with AI and automation systems in my work.

Based on Figure 4.28, out of 101 respondents, the majority of 38 respondents (37.62%) agreed they tended to collaborate closely with AI and automation systems in their work, followed by 27 respondents (26.73%) who held a neutral view and another 27 respondents (26.73%) who strongly agreed with the statement. A total of 5 respondents (4.95%) disagreed. Strong disagreement was the least common response, selected by only 4 respondents (3.96%). The majority of the 38 (37.62%) respondents were found to agree, compared to the 4 (3.96%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

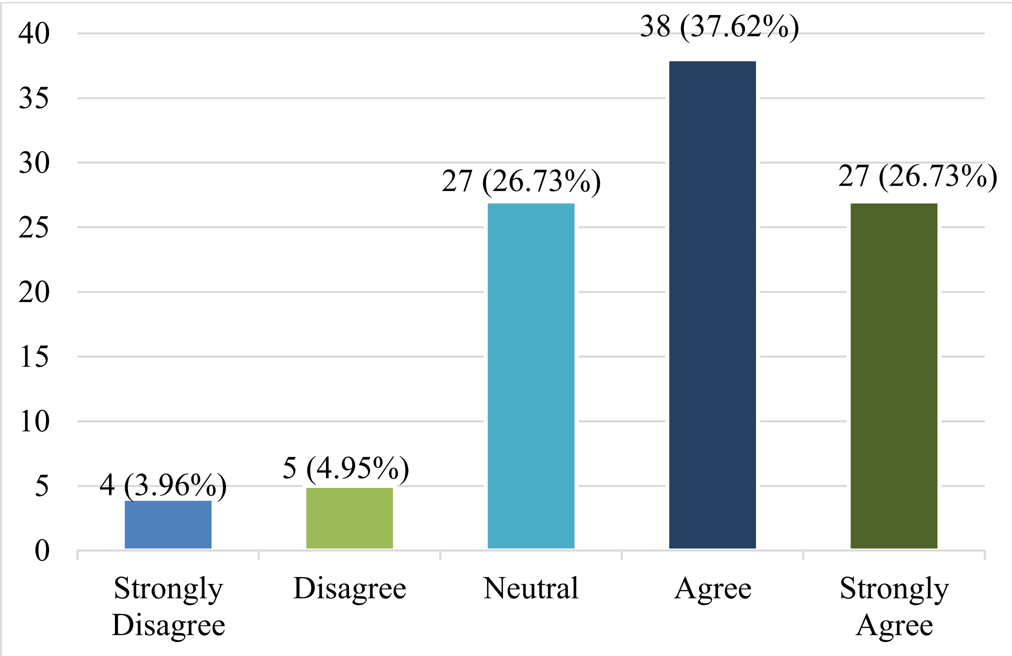


Figure 4.28: Descriptive Analysis (Intention) – Q5: I intend to collaborate closely with AI and automation systems in my work.

4.4.29 Descriptive Analysis (Intention) – Q6: I plan to recommend the use of IR 5.0 technologies within my team or organisations.

Based on Figure 4.29, out of 101 respondents, the majority of 38 respondents (37.62%) agreed they planned to recommend the use of IR 5.0 technologies within their teams or organizations, followed by 25 respondents (24.75%) who held a neutral view and another 20 respondents (19.80%) who strongly agreed with the statement. A total of 14 respondents (13.86%) disagreed. Strong disagreement was the least common response, selected by only 4 respondents (3.96%). The majority of the 38 (37.62%) respondents were found to agree, compared to the 4 (3.96%) disagreed category. According to Frederick J Gravetter and Larry B. Wallnau (2016), descriptive statistics were used to organize and simplify data so that patterns and tendencies in responses could be easily observed.

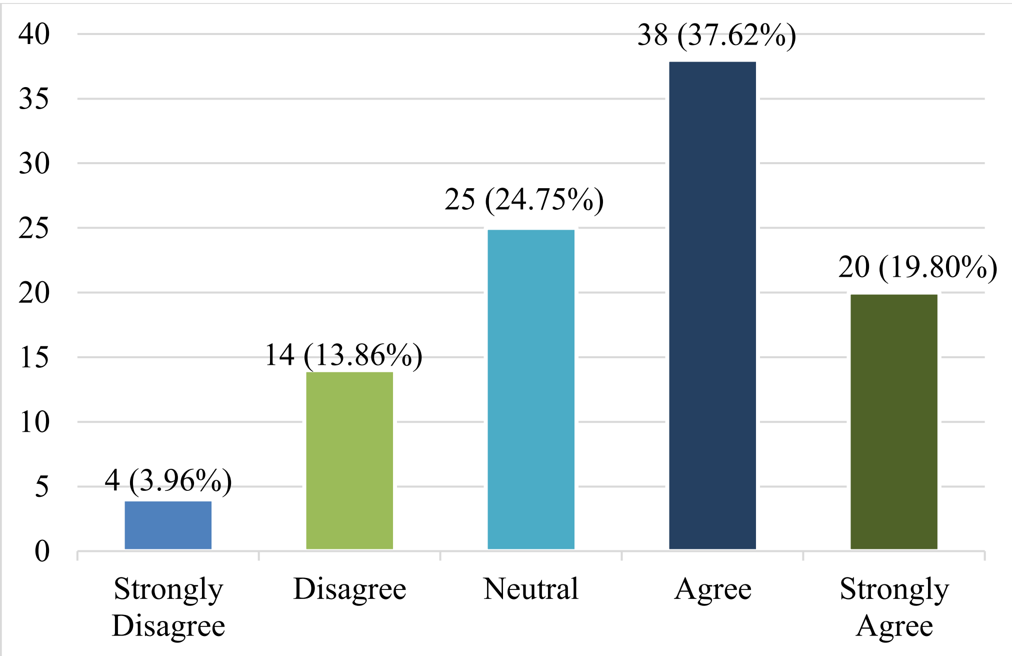


Figure 4.29: Descriptive Analysis (Intention) – Q6: I plan to recommend the use of IR 5.0 technologies within my team or organisations.

4.5 Reliability Measurement

Reliability measurement was primarily used to ensure the consistency or stability of a questionnaire over time. According to Cohen (1988), reliability refers to how consistency or dependably a measurement tool performed, and reliability importance in evaluating psychometric properties and conducting power analysis. In this section, a total of 101 responses were used to conduct an internal consistency reliability test, which aimed to measure how well the indicators within each scale correlated with one other. The test was performed using Cronbach's Alpha (α).

Based on Table 4.4, the reliability test result for the performance variable (DV) was 0.929, which fall under the "Excellent" category, indicating that the performance's indicators measuring construction performance were highly consistent. The reliability test for the readiness variable (IV_1) was 0.888, which placed it in the "Good" category and showed that the readiness' indicators measuring readiness were consistent with one another. Meanwhile, the intention variable (IV_2) recorded a reliability result of 0.907, which was also categorized as "Excellent", demonstrating that the intention's indicators measuring intention were strongly aligned. Overall, these results prove that variable reliability was strong and consistent across all three constructs (Performance, Readiness and Intention). According to Taber (2018), Cronbach's Alpha (α) value between 0.70 and 0.80 indicated acceptable reliability. Values between 0.80 and 0.90 were considered good, and values above 0.90 demonstrate excellent internal consistency.

Table 4.4: Summary of Reliability Analysis for Performance, Readiness, and Intention Constructs.

Construct	**Cronbach's Alpha (α)**	**Strength of Association**	**Number of indicators**
Independent variables			
IV_1 - Readiness	0.888	Good	6
IV_2 - Intention	0.907	Excellent	6
Dependent variable			
DV - Performance	0.929	Excellent	6

4.6 Reflective Measurement Model Assessment

A reflective measurement model assessment was conducted to ensure that the survey items (indicators) used in the study were reliable and valid. This was a crucial step in quantitative study, as it ensured that the constructs of performance, readiness and intention were accurately measured before proceeding with the structural model assessment procedure. The first step in the reflective measurement model assessment was to assess the indicator reliability.

4.6.1 Assess the Indicator Reliability

According to TomassMHultt (2021), indicator reliability involves evaluating the degree to which each indicator accounted for the variance in its underlying construct, which reflects the indicator's dependability. Figure 4.30 illustrated the structural diagram of performance, readiness and intention constructs, with the indicator reliability value (outer loadings (λ)) shown in decimal format.

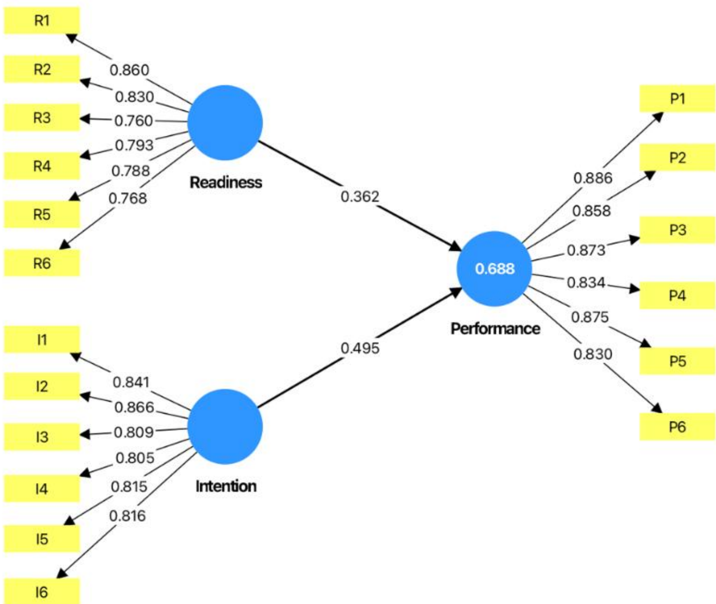


Figure 4.30: Indicator Reliability Based on Outer Loadings for Readiness, Intention and Performance.

All indicators had acceptable outer loading (λ) with value exceeding 0.708. According to Hair et al. (2022), that indicator reliability was assessed by examining the outer loadings (λ), where values exceeding 0.708. Figure 4.30

showed that the outer loadings (λ) for the performance indicators P1, P2, P3, P4, P5, and P6 were 0.886, 0.858, 0.873, 0.834, 0.875 and 0.830 respectively. Moreover, readiness indicators R1, R2, R3, R4, R5, R6 had outer loadings (λ) of 0.860, 0.830, 0.760, 0.793, 0.788 and 0.768, all of which exceeded the recommended threshold of 0.708. In addition, the intention indicators I1, I2, I3, I4, I5 and I6 showed outer loadings (λ) of 0.841, 0.866, 0.809, 0.805, 0.815, and 0.816. All result exceeded the 0.708 benchmark, indicating that each indicator demonstrated high indicator reliability. This shows that more than 50% of variance in each indicator was explained by its construct, confirming that the indicators consistently and accurately measured readiness, intention and performance for construction industry.

4.6.2 Assess the Internal Consistency Reliability

Internal consistency reliability was measured using both Cronbach's alpha and composite reliability (CR). According to Sarstedt, Ringle, and Hair (2021), a CR (rho_a) value exceeding 0.70 indicated strong internal consistency reliability. Based on Table 4.5, the Cronbach's Alpha (α) for the performance construct was 0.929, readiness was 0.888 and intention was 0.907. The Cronbach's Alpha (α) value for performance and intention fell under "Excellent" category, indicating that the survey items are highly consistent in measuring the same construct. The readiness construct's Cronbach's Alpha (α) value fell under the "Good" category, suggesting that the items in the scale were consistently measuring the same construct with minimal measurement error. Based on Table 4.5, the CR (rho_a) values for the performance and intention constructs were 0.930 and 0.910, respectively, indicating very high internal consistency. Similarly, the readiness construct recorded a CR (rho_a) value of 0.898, demonstrating strong internal consistency. These results suggest that the items for all three constructs were strongly linked and worked consistently to measure their respective constructs. According to Hair et al. (2024), CR (rho_a) values exceeding 0.70 indicate acceptable internal consistency, with values above 0.90 reflecting very high reliability for the construction industry performance.

Table 4.5: Internal Consistency Reliability Measures for Performance, Readiness and Intention Constructs.

Construct	**Cronbach's Alpha (α)**	**Composite reliability (rho_a)**
Performance	0.929	0.930
Readiness	0.888	0.898
Intention	0.907	0.910

4.6.3 Assess the Convergent Validity

According to Hair et al. (2024), an AVE value above 0.50 suggests that the construct explains more than half of the variance of its indicators. Based on Table 4.6, the AVE values for performance, readiness, and intention were 0.739, 0.641, and 0.682, respectively. The construction industry performance construct demonstrated very strong convergent validity, represent that its items effectively measured the construct, while the construction industry readiness and intention construct showed good convergent validity, represented that their items adequately represented their respective constructs. At least 50% of the variance in the indicators was explained by each construct (Hair et al, 2022).

Table 4.6: Convergent Validity Measures for Performance, Readiness and Intention Constructs.

Construct	**Average variance extracted (AVE)**
Performance	0.739
Readiness	0.641
Intention	0.682

4.6.4 Assess the Discriminant validity (Fornell-Lacker Criterion)

4.6.4.1 Fornell-Lacker Criterion

According to Hei et al. (2024), discriminant validity referred to the degree to which one construct was different from another, ensuring that each captured phenomena not represented by other variables in the model. Based on Table 4.7, the AVE value for intention was 0.826, followed by the correlation between performance and intention, which was 0.810, and the square root of the AVE for performance, which was 0.860. In addition, the correlation between construction industry readiness and construction industry intention was 0.868, between construction industry readiness and construction industry performance was 0.792, and the square root of the AVE for readiness was 0.801. The bold values represented the square root of the AVE for each construct. According to Hair et al. (2022), these values were expected to be higher than all other values in their respective rows and columns to confirm discriminant validity. However, the correlation between readiness and intention (0.868) exceeded the square root of the AVE for readiness (0.801), indicating a lack of discriminant validity between the two constructs. This implied that readiness and intention were perceived as highly similar and were not clearly distinguished by respondents. Therefore, the initial results did not fully satisfy the Fornell-Larcker criterion, particularly for the readiness construct, suggesting conceptual overlap with the intention construct (Henseler et al., 2015).

Table 4.7: Fornell-Larcker Discriminant Validity.

Constructs	**Intention**	**Performance**	**Readiness**
Intention	**0.826**		
Performance	0.810	**0.860**	
Readiness	0.868	0.792	**0.801**

4.6.4.2 Heterotrait-Monotrait Ratio of Correlations (HTMT)

According to Henseler, Ringle, and Sarstedt (2015), HTMT evaluated how strongly indicators from different constructs correlated with each other (heterotrait-heteromethod correlations) relative to the correlations among indicators within the same construct (monotrait-heteromethod). A high HTMT value suggested that the two constructs were not sufficiently distinct, indicating potential issues with discriminant validity. Based on Table 4.8, the HTMT value between performance and intention was 0.878, followed by readiness and intention at 0.964, and readiness and performance at 0.862. This indicated that the relationships between readiness and performance for construction industry, as well as between intention and performance for the construction industry, contained significant differences. The HTMT value between readiness and intention exceeded the recommended threshold of 0.90, indicating a potential issue with discriminant validity. This implied that readiness and intention were not substantially different from each other. According to Henseler, Ringle, and Sarstedt (2015), HTMT values above 0.90 suggest that the constructs may not be sufficiently distinct, implying conceptual overlap. Therefore, the initial model failed to establish discriminant validity between readiness and intention.

Table 4.8: Discriminant Validity Assessment Using the Heterotrait-Monotrait Ratio.

Constructs	**Intention**	**Performance**	**Readiness**
Intention			
Performance	0.878		
Readiness	**0.964**	0.862	

As a result, items R1, R4, and R6 were removed, as shown in Figure 4.31. R1 (‘I am ready to adopt new technology associated with Construction IR 5.0 in my daily work’) described a current willingness to act, which overlapped with the concept of intention. R4 (‘I am mentally and professionally ready to embrace the changes introduced by construction IR 5.0’) was removed because it reflected psychological willingness and readiness to take action, aligning closely with intention and causing overlap in the HTMT and Fornell–Larcker tests. In addition, R6 (‘I am confident in my ability to manage challenges that may arise from implementing IR 5.0 technologies in construction’) was removed because it expressed self-efficacy and future-oriented confidence, which could be interpreted as a form of intention. According to Hair et al. (2022), these items represented motivational or attitudinal aspects, conceptually overlapping with the intention construct. The remaining items, R2, R3, and R5, focused on practical readiness, such as skills, access to resources, and AI tool preparedness, thereby improving discriminant validity and maintaining construct clarity.

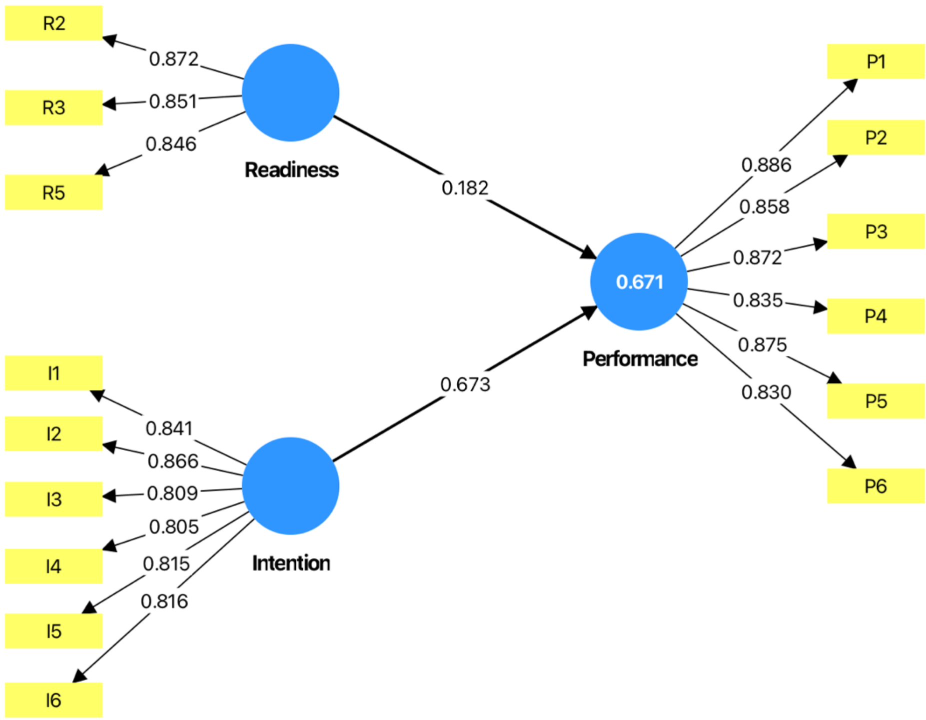


Figure 4.31: Structural Model Diagram of Performance, Readiness, and Intention Constructs (After remove R1, R4, and R6).

Figure 4.31 showed that after removing the items R1, R2 and R6, the outer loadings for the performance indicators P1, P2, P3, P4, P5, and P6 were 0.886, 0.858, 0.872, 0.835, 0.875 and 0.830 respectively. Moreover, readiness indicators R2, R3, and R5 had outer loadings of 0.872, 0.851, and 0.846, all of which exceeded the recommended threshold of 0.708. In addition, the intention indicator I1, I2, I3, I4, I5 and I6 showed outer loadings of 0.841, 0.866, 0.809, 0.805, 0.815, and 0.816. All result exceeded the 0.708 benchmark, indicating that each indicator demonstrated high indicator reliability.

Based on Table 4.9, the Cronbach's Alpha value for the performance construct was 0.929, readiness was 0.819 and intention was 0.907. The Cronbach's Alpha value for performance and intention fell under "Excellent" category, indicating that the survey items are highly consistent in measuring the same construct. The readiness construct's Cronbach's Alpha value fell under the "Good" category, suggesting that the items in the scale were consistently measuring the same construct with minimal measurement error. Based on Table 4.9, the composite reliability (rho_a) value for the performance and intention constructs were 0.929 and 0.910 respectively, indicating that both constructs exhibited very high internal consistency. The readiness construct's composite reliability (rho_a) value was which was 0.827, which indicated strong internal consistency.

Table 4.9: Internal Consistency Reliability Measures for Performance, Readiness and Intention Constructs (After Removing R1, R4 and R6).

Construct	**Cronbach Alpha (α)**	**Composite reliability (rho_a)**
Performance	0.929	0.929
Readiness	0.819	0.827
Intention	0.907	0.910

Based on Table 4.10, the AVE values for performance, readiness and intention were 0.739, 0.734 and 0.682 respectively, indicated good convergent validity. At least 50% of the variance in the indicators was explained by each construct (Hair et al, 2022).

Table 4.10: Convergent Validity Measures for Performance, Readiness and Intention Constructs (After Removing R1, R4 and R6).

Construct	**Average variance extracted (AVE)**
Performance	0.739
Readiness	0.734
Intention	0.682

Based on Table 4.11, before removing any indicators, the AVE value for intention was 0.826, followed by the correlation between performance and intention, which was 0.810, and the square root of the AVE for performance, which was 0.860. In addition, the correlation between readiness and intention was 0.753, between readiness and performance was 0.689, and the square root of the AVE for readiness was 0.857. The bold values represented the square root of the AVE for each construct. According to Hair et al. (2022), the square root of the AVE for each construct was expected to be higher than all correlations with other constructs in the corresponding rows and columns to confirm discriminant validity. In this case, the correlation between readiness and intention (0.753) was lower than the square root of the AVE for readiness (0.857), indicating that discriminant validity was achieved for these constructs. Therefore, the initial results satisfied the Fornell–Larcker criterion for the readiness construct and did not indicate conceptual overlap with the intention construct (Henseler et al., 2015).

Table 4.11: Fornell-Larcker Discriminant Validity (After Removing R1, R4 and R6).

Construct	**Intention**	**Performance**	**Readiness**
Intention	**0.826**		
Performance	0.810	**0.860**	
Readiness	0.753	0.689	**0.857**

Based on Table 4.12, the HTMT value between intention and performance was 0.878, between readiness and intention was 0.871, and between performance and readiness was 0.785 after remove R1, R4 and R6. All values were below the threshold of 0.90, indicating that discriminant validity had been established. These results confirmed that each construct measured a unique concept and did not overlap excessively with other constructs in the model. These results justified that each construct measured a unique concept and did not overlap excessively with other constructs in the model. This implied that readiness and intention were substantially different from each other.

Table 4.12: Discriminant Validity Assessment Using the Heterotrait-Monotrait Ratio (After Removing R1, R4 and R6).

Construct	**Intention**	**Performance**	**Readiness**
Intention			
Performance	0.878		
Readiness	0.871	0.785	

4.7 Structural Assessment Model

4.7.1 Assess Collinbearity Issues the Structural Model

Collinearity assessment was conducted to examine whether the independent constructs in the structural model were highly correlated, which could bias the estimation of path coefficients. The VIF value between intention and performance, as well as between readiness and performance was 2.309, as shown in Table 4.13. Based on Table 3.5, the VIF value fell under "Ideal" category because they were below 3.0, indicating no collinearity concerns among the constructs. This showed that each predictor provided unique information in predicting performance, and both constructs could independently predict performance. According to Hair et al. (2022), VIF value below 3.0 suggest that collinearity was not a concern in PLS-SEM structural models.

Table 4.13: Collinearity Statistics (VIF) for Structural Model.

Constructs	**VIF Value**
Intention -> Performance	2.309
Readiness -> Performance	2.309

4.7.2 Assess the Significant and Relevant of the Structural Model Relationships

Based on Table 4.14, the β value between readiness and performance was 0.182, which represented small positive effect. This suggested that changes in the readiness construct had only a minor impact on performance; if readiness increased, performance would increase slightly. According to Cohen (1988) and Hair et al. (2022), β values of 0.10, 0.30, and 0.50 represented small, moderate, and strong effects respectively. Furthermore, the t-value (t) and p-value (p) for the relationship between readiness and performance were 1.318 and 0.187, respectively, indicating that it was not significant at the 1% level. The t-value indicated that the relationship was weak and could easily be negligible or absent in other samples and the p-value indicated that if there were no true relationship between readiness and performance, the observed effect could occur due to random chance with an 18.7% probability, meaning that readiness did not meaningfully influence performance. According to Hair et al. (2022), a t-value had to be greater than 2.58 to be considered significant at the 1% level, and p-value had to be smaller than 0.01 to achieve the same threshold. Since both conditions were not met, the structural model analysis revealed that readiness did not have a significant relationship on performance. Therefore, hypothesis H_{2a} was not supported. Moreover, the effect size (f^2) between readiness and performance was 0.044, indicating a small effect. This showed that readiness had a minor impact on performance, and the effect was not statistically significant; therefore, hypothesis H_{3a}, which proposed that readiness influences performance, was not supported.

Based on Table 4.14, the β value between intention and performance was 0.673, which represented strong positive effect. This suggested that changes in the intention construct had a substantial impact on performance. if intention increased, performance would increase a lot. Furthermore, the t-value (t) and p-value (p) between intention and performance was 5.116 and 0.000, which was significant at 1% level. The t-value (t) indicated that the relationship was strong and unlikely to be negligible or absent in other samples and the p-value (p) indicated that if there were a true relationship between intention and performance, the observed effect could not occur due to random chance (0% probability), meaning that intention meaningfully influenced performance. According to Hair et al. (2022), a t-value (t) had to be greater than 2.58 to be considered significant at the 1% level, and p-value (p) had to be smaller than 0.01 to achieve the same threshold. Since both conditions were met, the structural model analysis revealed that intention have a significant effect on performance. Therefore, hypothesis H_{2b} was supported. Moreover, the effect size (f^2) between intention and performance was 0.595, indicating a large effect. This demonstrated that intention had a substantial impact on performance, and the effect was statistically significant; therefore, hypothesis H_{3b} , which proposed that intention influences performance, was supported.

Table 4.14: Hypothesis Testing Results for Structural Model Path Coefficients.

Hypothesis	**Path**	$\boldsymbol{\beta(O)}$	**t-value (t)**	**p-value (p)**	**Effect Size (f^2)**	**Supported**
H_{2a} / H_{3a}	Readiness -> Performance	0.182	1.318	0.187	0.044	No
H_{2b} / H_{3b}	Intention -> Performance	0.673	5.116	0.000	0.595	Yes

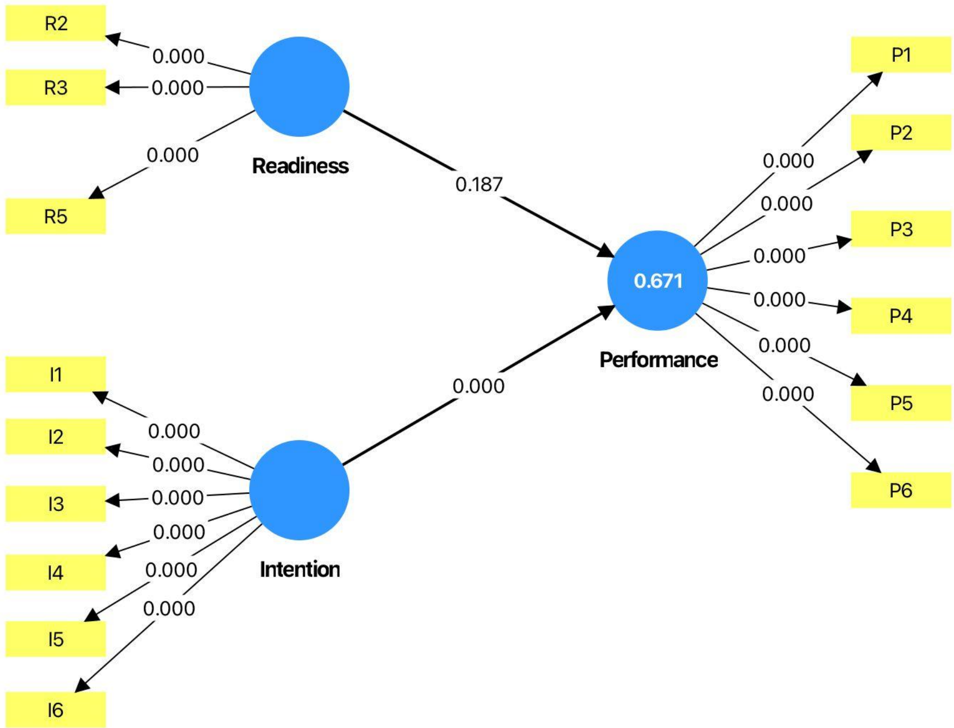


Figure 4.32: Hypothesis Testing Results for Structural Model Path Coefficients.

4.7.3 Assess the Model's Explanatory Power (R^2)

The coefficient of determination (R^2) for performance was 0.671, while the adjusted R^2 was 0.664, as shown in Table 4.15. This indicated that 67.1% of the variance in performance was explained by readiness and intention, as referred to in Figure 4.33. According to Hair et al. (2022), this R^2 value was considered moderate to substantial, suggesting that the model had a good level of explanatory power.

Table 4.15: Coefficient of Determination (R^2 and Adjusted R^2) for Performance.

Construct	R^2	Adjusted R^2	Interpretation
Performance	0.671	0.664	Moderate to Substantial

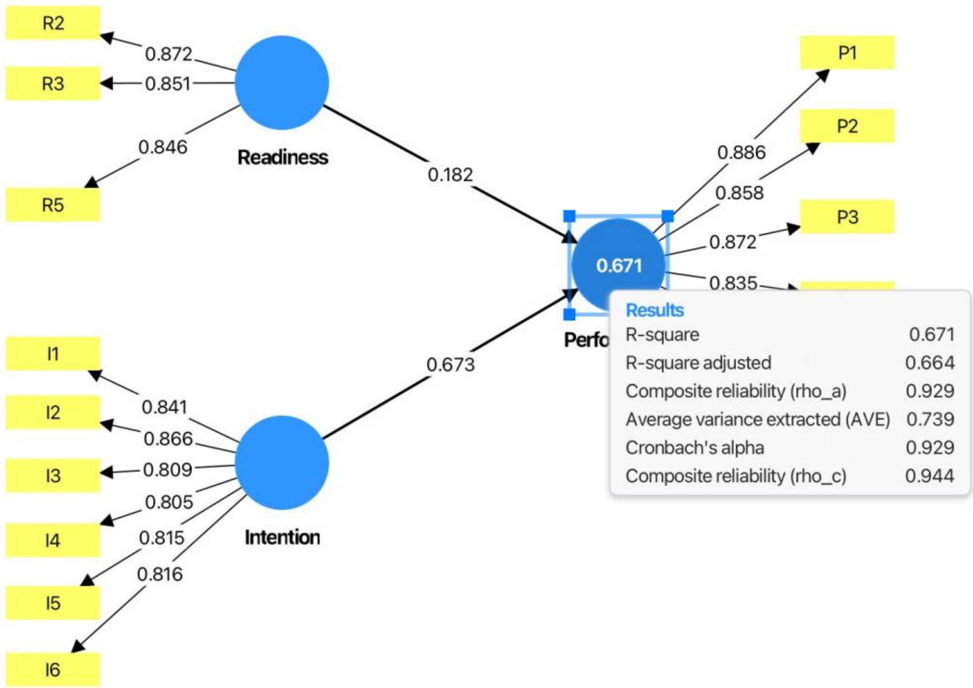


Figure 4.33: Coefficient of Determination (R^2 and Adjusted R^2) for Performance.

4.7.4 Assess the Model's Predictive Power

Based on Table 4.16, the Q^2_predict values of P1, P2, P3, P4, P5, and P6 were 0.468, 0.446, 0.471, 0.478, 0.487, and 0.432 respectively, and all values were greater than 0. This indicated that the model had sufficient predictive relevance. According to Hair et al. (2022), a Q^2_predict value greater than 0 indicated predictive relevance for the corresponding endogenous construct, while a value of 0 or below suggested no predictive relevance. In addition, when the prediction errors of PLS-SEM were compared against the Linear Model Root Mean Squared Error (LM_RMSE), the RMSE values of P1 ($0.756 < 0.791$), P3 ($0.761 < 0.807$), P4 ($0.769 < 0.799$), and P6 ($0.810 < 0.839$) were smaller, showing that PLS-SEM provided better predictive accuracy for these indicators. However, for P2 ($0.795 > 0.779$) and P5 ($0.762 > 0.759$), the linear model (LM) showed slightly better predictive performance.

The PLS-SEM_MAE values for P1, P2, P3, P4, P5, and P6 were 0.596, 0.650, 0.600, 0.611, 0.635, and 0.675 respectively. These results showed the average size of the prediction errors for each performance indicator. Among them, P1 and P3 had the lowest MAE values (0.596 and 0.600), indicating that the model predicted these indicators with higher accuracy. P2, P5, and P6 recorded comparatively higher MAE values, with P6 (0.675) being the highest, suggesting that the model had more difficulty in accurately predicting this indicator. Overall, the MAE values were reasonably small, which suggested that the model achieved an acceptable level of predictive accuracy across all indicators (Hair et al., 2022).

Table 4.16: PLS-SEM Predictive Power Assessment (PLS vs Linear Model).

Indicator	**Q^2_predict**	**PLS-SEM_RMSE**	**PLS-SEM_MAE**	**LM_RMSE**
P1	0.468	0.756	0.596	0.791
P2	0.446	**0.795**	0.650	**0.779**
P3	0.471	0.761	0.600	0.807
P4	0.478	0.769	0.611	0.799
P5	0.487	**0.762**	0.635	**0.759**
P6	0.432	0.810	0.675	0.839

4.7.5 Model Comparisons

The predictive power of the model was assessed using the Q^2_predict, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) values. As shown in Table 4.16, all Q^2_predict values were greater than 0, indicating that the PLS-SEM model had predictive relevance for all items (e.g., P2 = 0.446, P5 = 0.487). For Indicator P2, the Partial Least Squares Structural Equation Modeling Root Mean Squared Error (PLS-SEM_RMSE) (0.795) was higher than the Linear Model (LM) RMSE (0.779), and the Partial Least Squares Structural Equation Modeling Mean Absolute Error (PLS-SEM_MAE) (0.650) was also lower than the LM_RMSE (0.779). This result suggested that while the PLS model showed predictive relevance, the LM model offered slightly better predictive accuracy for this indicator. For Indicator P5, the PLS-SEM RMSE (0.762) was also higher than the LM_RMSE (0.759). Likewise, the PLS-SEM MAE (0.635) was lower than the LM_RMSE (0.759). These results again implied that the LM performed marginally better in predictive accuracy for this item. Despite some indicators showing better performance in the LM model, the overall Q^2_predict results confirmed that the PLS-SEM model still held acceptable predictive power and could be relied upon for structural model assessment.

4.8 Findings in Relation to Research Objectives, Questions, and Hypotheses

Based on the Theory of Reasoned Action (TRA), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Theory of Organizational Readiness for Change (TORC), the conceptual framework establishes that readiness and intention significantly influence construction performance. The findings of this study support this theoretical foundation by demonstrating that construction industry with readiness and intention are positioned to affect performance in the context of the IR 5.0 evolution. Accordingly, the results fulfil Objective 1, which was to determine the variables influencing construction performance in the IR 5.0 era. They also provide a direct answer to Research Question 1, which sought to identify the variables affecting the performance of the construction industry during this technological transition. The evidence confirms that readiness and intention are the key variables affect construction performance. Therefore, the findings validate the proposed hypothesis 1, which stated that readiness and intention were the critical factors affecting the performance of the construction industry in the IR 5.0 context.

Moreover, the study fulfilled Objective 2, which was to investigate the relationship between readiness and intention and construction industry performance in the IR 5.0 context. This objective was addressed through RQ_{2a}: What is the relationship between readiness and construction industry performance in IR 5.0? and RQ_{2b}: What is the relationship between intention and construction industry performance in IR 5.0? Correspondingly, the hypotheses were formulated as follows: H_{2a} proposed that there is a significant relationship between readiness and construction industry performance in IR 5.0, while H_{2b} proposed that there is a significant relationship between intention and construction industry performance in IR 5.0. The findings indicated that H_{2a} was rejected, as the path coefficient (β) was 0.182, the t-value was 1.318 ($t < 2.58$) and the p-value was 0.187 ($p < 0.01$) indicating no statistically significant relationship between readiness and construction industry performance. In contrast, $H_{2b}$was supported, as the path coefficient (β) was 0.673, the t-value was 5.116 ($t > 2.58$), and the p-value was 0.000 ($p > 0.01$), confirming a statistically significant relationship between intention and construction industry performance.

The study also fulfilled Objective 3, which was to examine the impact of readiness and intention on construction industry performance in the IR 5.0 context. This was addressed through RQ_{3a}: What is the impact of construction industry readiness on performance in IR 5.0? and RQ_{3b}: What is the impact of construction industry intention on performance in IR 5.0? The corresponding hypotheses, H_{3a} and H_{3b}, proposed that readiness and intention would each have a significant impact on performance. The findings revealed that H_{3a} was rejected, as readiness did not demonstrate a significant impact on construction performance. The structural model showed a path coefficient (β) of 0.182, indicating that a one-unit increase in readiness would result in only a 0.182-unit increase in performance, which was minimal. The p-value of 0.187 ($p > 0.01$) and the effect size (f^2) was 0.044, further confirming a small contribution of readiness to performance. Conversely, H_{3b} was supported, as intention exhibited a strong impact on construction performance, with a path coefficient (β) of 0.673, suggesting that a one-unit increase in intention led to a 0.673-unit increase in performance. The p-value of 0.000 ($p < 0.01$) and a large effect size (f^2 = 0.595) confirmed that intention had a substantial and meaningful contribution to performance outcomes. These results demonstrated that while readiness alone had a minor effect, strong intention within the construction industry significantly enhanced performance in the IR 5.0 era.

CHAPTER 5
CONCLUSION AND RECOMMANDATIONS

5.1 Introduction

In this chapter, an overview of the research study was presented, accompanied by an insightful explanation of the data collected through the questionnaire survey to evaluate the performance of the construction industry in the context of IR 5.0 evolution. The chapter also discussed the recommendations derived from the research findings. Finally, the conclusion addressed the research objectives by highlighting the key insights and implications of the study.

5.2 Conclusions

The first objective of the study was to determine the variables that affected the performance of the construction industry in the IR 5.0 evolution. Based on the conceptual model, it was proven that readiness and intention were the key factors influencing the performance of the construction industry in adapting to IR 5.0. The results, supported by previous articles and theories, indicated that both readiness and intention played a role in shaping performance. The conceptual model was further validated through the Theory of Organisational Readiness for Change, the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Theory of Reasoned Action (TRA).

The second objective was to investigate the relationship between readiness and intention towards performance in IR 5.0, while the third objective was to explore the impact of readiness and intention on performance. Based on the structural model assessment, the findings revealed that the relationship between readiness and performance was not significant at the 1% level. Specifically, the t-value and p-value between readiness and performance were 1.318 and 0.187 respectively, which confirmed the lack of statistical significance. In contrast, the relationship between intention and performance was found to be significant. The analysis demonstrated that the β value between intention and performance was 0.763, representing a strong positive effect. Furthermore, the t-value and p-value for intention and performance were 5.116 and 0.000 respectively, confirming a statistically significant relationship. This indicated that intention had a substantial effect on the performance of the construction industry in the IR 5.0 evolution, while readiness did not exhibit a significant direct impact.

5.3 Recommendations

This study highlighted the significance of intention in influencing the performance of the construction industry in the context of IR 5.0, while readiness did not show a statistically significant direct effect. Based on these findings, future research was recommended to expand the conceptual model by including additional variables such as leadership support, organizational culture, digital infrastructure, and employee competencies to provide a more comprehensive understanding of performance drivers. Longitudinal studies were also suggested to examine how readiness and intention evolved over time as the industry gradually adapted to IR 5.0 technologies. Furthermore, the adoption of mixed-method approaches, such as combining surveys with interviews or case studies, was encouraged to provide richer insights into the factors shaping industry performance. Expanding the research to different regions or countries would also allow for meaningful comparisons across diverse economic, cultural, and policy environments. From a theoretical perspective, future studies were encouraged to refine and extend established frameworks such as the Theory of Organisational Readiness for Change, UTAUT, and the Theory of Reasoned Action, ensuring their relevance in the emerging landscape of IR 5.0 adoption in the construction industry.

For the construction industry, the findings of this study underscored the crucial role of intention in driving performance improvements under IR 5.0 adoption. Construction firms were therefore encouraged to focus on strengthening organizational commitment by embedding digital transformation into their strategic objectives and fostering a culture that valued innovation. Top management played a key role in motivating employees by clearly communicating the long-term benefits of IR 5.0 technologies such as artificial intelligence, robotics, and smart systems. Although readiness was not statistically significant in this study, enhancing readiness remained essential in practice, as initiatives like training programs, workshops, and change management strategies could build workforce confidence and reduce resistance to technological change. Moreover, collaboration with technology providers and industry partners was recommended to accelerate the integration of digital solutions while reducing implementation costs. Policymakers and regulatory bodies were also advised to establish supportive frameworks and incentives, while firms themselves were encouraged to allocate dedicated resources for innovation and digital adoption. By strengthening both intention and readiness, the construction industry was better positioned to leverage the opportunities of IR 5.0 and sustain long-term performance.

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APPENDICES

Appendix A Questionnaire Design

UNIVERSITI TUNKU ABDUL RAHMAN (UTAR)

Lee Kong Chian Faculty of Engineering and Science

Bachelor of Software Engineering (Hons)

Dear respondents,

We are the undergraduate students of Master of Civil Engineering (Hons) and Bachelor of Software Engineering (Hons) at Universiti Tunku Abdul Rahman (UTAR). We are currently conducting a combined research involving a study on the Industry 5.0 in Construction: A Quantitative Approach"

The purpose of this survey is to gather data regarding the **understanding of construction industry moving** towards **Industry 5.0 (IR 5.0)** revolution. The findings will contribute to understanding the perspectives of construction industry towards the integration of IR 5.0 technologies and practices in their daily operations.

What is Industry 5.0?

Industry 5.0 represents the next phase of industrial evolution where **human creativity and critical thinking are integrated with advanced technologies** such as Artificial Intelligence (AI), robotics, the Internet of Things (IoT), and big data. Unlike Industry 4.0, which focuses on automation and digitalization, **IR 5.0 emphasizes human-machine collaboration, personalization, and sustainable innovation**.

This Google Form contains **two sections**:

A) **Demographic Information** – Collects basic respondent details for classification.

B) **IR 5.0 Adoption Factors** – Examines key variables influencing the adoption of Industry 5.0 in the construction sector.

Your participation is **greatly appreciated** and will provide valuable insights into the industry's preparedness for this technological transformation. All responses will be kept confidential and used solely for academic research purposes.

Note: This survey is only for individuals currently working in or involved with the construction industry. Please do not proceed if you are not from this field.
Thank you for your time and contribution.

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Personal Data Protection Statement

Before proceeding, please carefully read the following statement and provide your consent.

This is a Privacy Notice and shall govern UTAR in dealing with protection of personal data. To protect personal data, the Notice may be changed from time to time.Personal Data Protection Act 2010 ("PDPA") came into force on 15 November 2013, therefore Universiti Tunku Abdul Rahman ("UTAR") is hereby bound to make notice and require consent in relation to collection, recording, storage, usage and retention of personal data.

1. This is a Privacy Notice and shall govern UTAR in dealing with protection of personal data. To protect personal data, the Notice may be changed from time to time.

2. Personal Data Protection Act 2010 ("PDPA") came into force on 15 November 2013, therefore Universiti Tunku Abdul Rahman ("UTAR") is hereby bound to make notice and require consent in relation to collection, recording, storage, usage and retention of personal data.

A. **What is personal data**

Personal data refers to any information which may directly or indirectly identify a person which could include sensitive personal data and expression of opinion. Among others it includes:

i. Name
ii. Identity card
iii. Place of Birth
iv. Address
v. Examination Result
vi. Education History
vii. Employment History
viii. Medical History
ix. Blood type

x. Race

xi. Religion

xii. Photo

B. **<u>Sources of personal data</u>**

In processing relevant services, UTAR may obtain personal data from various sources such as:

i. Your self

a. from your application forwarded to us. By submitting any application to us, you are hereby confirmed that you had obtained necessary consent for the information to be declared in the application.

b. There could be capturing of images or audios e.g. CCTV for safety and/or recording purposes. A notice will be displayed to the effect.

ii. Third parties

c. UTAR affiliates in competition or survey or research or programmes.

d. your participation with other entities.

e. your guardian, legal representative or guarantor.

f. there may be cross reference of your personal data for loan application or credit reference.

g. previous education institutions or employers.

iii. Websites

h. your IP address is automatically login into our server. Generally, we do not link your IP address to identify each link unless in case of serious breach.

i. you may adjust your browser to disable 'cookies' to prevent storage of certain information in your system.

C. **Purpose of personal data:**

In servicing our obligations, the purposes for which your personal data may be used are inclusive but not limited to:

i. For assessment of any application to UTAR

ii. For processing any benefits and services

iii. For communication purposes

iv. For advertorial and news

v. For general administration and record purposes

vi. For enhancing the value of education

vii. For educational and related purposes consequential to UTAR

viii. For replying any responds to complaints and enquiries

ix. For the purpose of our corporate governance

x. For consideration as a guarantor for UTAR staff/ student applying for his/her scholarship/ study loan

D. **Disclosure of personal data:**

i. UTAR is under legal obligation to secure and protect confidential information including but not limited to personal data prior and after PDPA and it is our continuous and existing policy to do so.

ii. In order to be effective in providing continuous service, certain disclosure needs to be exercised. Your personal data may be transferred and/or disclosed to third party and/or UTAR collaborative partners including but not limited to the respective and appointed outsourcing agents for purpose of fulfilling our obligations to you in respect of the purposes and all such other purposes that are related to the purposes and also in providing integrated services, maintaining and storing records.

iii. In processing your welfare and/or providing our services, it is very important to transmit or share personal information to third parties, including but not limited to:

a. insurance company for processing insurance claims

b. financial institutions for payment of financial rewards eg scholarship, loan, allowance, salary
c. entities/affiliates for any loan/scholarship award or recognition and education-related activities
d. your authorized third parties
e. your guardian or legal representative or guarantor
f. credit rating agency for credit reference in loan related application
g. enforcement regulatory and governmental agencies or by any order of court or to meet obligations to authorities

iv. Your data may be shared when required by laws and when disclosure is necessary to comply with applicable laws.

E. **Retention of personal data**

Any personal information shall be retained by UTAR in order to serve the above purposes and as required by relevant laws and shall be destroyed and/or deleted in accordance with our retention policy applicable for us in the event such information is no longer required.

F. **Our strict privacy policy**

i. UTAR is committed in ensuring the confidentiality, protection, security and accuracy of your personal information made available to us and it has been our ongoing strict policy to ensure that your personal information is accurate, complete, not misleading and updated. UTAR would also ensure that your personal data shall not be used for political and commercial purposes.

ii. UTAR takes a high stand that protection of personal rights is well-established long before the introduction of PDPA. PDPA now serves as an apparent Act to protect and a defined tool to provide transparency and give public awareness in how personal data is dealt.

iii. Subject to relevant applicable laws, sensitive personal data shall only be disclosed upon your express consent from your self.

G. **Access to your personal data**

You may access and update your personal data by writing to us at rgo@utar.edu.my (Attention: Ms Loh Siaw Yien). We may require further details or confirmations if necessary.

H. **Consent is fundamental**

By submitting or providing your personal data to UTAR, you had consented and agreed for your personal data to be used in accordance to the terms and conditions in the Notice and our relevant policy.

I. **Withdrawal of consent**

i. You may withdraw consent at any time by writing to us. We may require further details or confirmations if necessary.

ii. If you do not consent or subsequently withdraw your consent to the processing and disclosure of your personal data, UTAR will not be able to fulfill our obligations or to contact you or to reward or to assist you in respect of the purposes and/or for any other purposes related to the purpose.

J. **Dual Version**

The Privacy Notice shall be in English and Malay. In the event of inconsistency, English version shall prevail.

Updated on 22 June 2023

Acknowledgement of Privacy Notice

I had read and understood the Privacy Notice provided above, and I hereby acknowledge and consent to the collection, use, storage, and disclosure of my personal data by Universiti Tunku Abdul Rahman (UTAR) in accordance with the Personal Data Protection Act 2010 (PDPA) and the terms stated.

Do you consent to the collection and use of your personal data as described in the Privacy Notice?

Yes (   )

No (   )

<u>Section A : Demographic Information</u>

Aims to capture background details of the respondent for analytical segmentation.

1. Gender

    Male (   )   Female (   )

2. Ethic Group

    Malay (   ) Chinese (   ) Indian (   ) Others ______

3. Age

    Below 20 (   )

    21 – 25 (   )

    26 – 30 (   )

    31 – 35 (   )

    36 – 40 (   )

    41 – 45 (   )

    46 – 50 (   )

    51 – 55 (   )

    56 – 60 (   )

    61 – 65 (   )

4. Highest Education Level

    Secondary education ( )

    Pre-university (STPM, Matriculation, Foundation) ( )

    Postgraduate diploma ( )

    Bachelor degree ( )

    Master degree ( )

    Doctorate degree (PhD) ( )

5. Category of the organization

    Main contractor ( )

    Subcontractor ( )

    Developer ( )

    Consultant (eg, M&E, C&S, Architectural , Quantity Surveyor ,etc) ( )

6. How big of the construction companies?

    Large (> 100 workers) ( )

    Medium (50 to 99 workers) ( )

    Small (10 to 49 workers) ( )

    Micro (1 to 9 workers) ( )

7. Role

    Technician (relate to engineering or technology) ( )

    Non-technician (Non-engineering or non-technology) ( )

8. Position

    Top Management (Eg Director, CEO, COO, CFO, GM)
    ( )

    Senior Management (Eg Senior Manager, Senior Project Manager)
    ( )

    Managerial Level (Eg Manager, M&E Manager, Project manager, etc)
    ( )

    Executive Level (Eg Engineer or executive with a minimal degree holder)

( )

Supervisor Level (Eg Supervisor with non-degree) ( )

9. Work Experience

Less than 1 year ( )

1 – 5 years ( )

6 – 10 years ( )

11 – 15 years ( )

16 – 20 years ( )

More than 20 years ( )

10. Had you ever heard about : Industry 5.0; Human-centric Industry.

Yes ( ) No ( )

11. Rate your current knowledge about the IR 5.0.

NF (Not familiar)	LF (Low familiar)	MF (Moderate familiar)	F (Familiar)	VF (Very familiar)
1	2	3	4	5

[1 = Strongly Disagree (SD), 2 = Disagree (D), 3 = Neutral (N), 4 = Agree (A), 5 = Strongly Agree (SA)]

Section B: Impacts of IR 5.0 Adoption on Construction Industry Performance

Investigates how the integration of IR 5.0 influences a person's productivity, efficiency, and innovation in construction.

	SD	D	N	A	SA
Applying Construction IR 5.0 technologies improves my work efficiency.	1	2	3	4	5
Using IR 5.0 practices reduces errors and rework in my daily tasks.	1	2	3	4	5
IR 5.0 helps me complete projects faster than traditional methods.	1	2	3	4	5
Integration of human-centric technologies enhances my decision-making quality.	1	2	3	4	5
Applying IR 5.0 increases the overall quality of my engineering outputs.	1	2	3	4	5
Using IR 5.0 concepts improves collaboration and communication with my team.	1	2	3	4	5

Section B : Readiness of Construction Industry to Adopt IR 5.0

Examines the preparedness of construction professionals and organizations to implement IR 5.0.

	SD	D	N	A	SA
I am ready to adopt new technology associated with Construction IR 5.0 in my daily work.	1	2	3	4	5
I feel prepared to work alongside intelligent machines and AI tools on construction projects.	1	2	3	4	5
I had the necessary skills to implements IR 5.0 principles effectively in construction.	1	2	3	4	5
I am mentally and professionally ready to embrace the changes introduced by construction IR 5.0.	1	2	3	4	5
I had access to sufficient resources and support to apply IR 5.0 in my tasks.	1	2	3	4	5
I am confident in my ability to manage challenges that may arise from implementing IR 5.0 technologies in construction.	1	2	3	4	5

<u>Section B : Intention to Adopt IR 5.0 in the Construction Industry</u>

Evaluates the willingness and likelihood of construction professionals to embrace IR 5.0 in future practices.

	SD	D	N	A	SA
I intend to incorporate IR 5.0 technologies in my daily construction tasks.	1	2	3	4	5
I plan to actively learn more about construction IR 5.0 and its applications.	1	2	3	4	5
I aim to use human-centric technologies in upcoming projects.	1	2	3	4	5
I am committed to adopting new tools and method aligned with IR 5.0.	1	2	3	4	5
I intend to collaborate closely with AI and automation systems in my work.	1	2	3	4	5
I plan to recommend the use of IR 5.0 technologies within my team or organisations.	1	2	3	4	5

Appendix B Pre-test Dr Lai (Academic)

Title: The Performance of Construction Industry in IR 5.0 evolution: Using Conceptual Model Approach

Instructions for Reviewers:

- Please read each question.
- Tick ✓ if the question is clear and appropriate.
- Cross ✗ if the question needs improvement.
- Optionally, write comments or suggestions for improvement in the last column.

Section A : Demographic Information

No	Question	Response	✓ / ✗	Comment
1.	Gender	Male / Female	✓	
2.	Ethic Group	Malay / Chinese / Indian / Others	✓	
3.	Age	Below 20 / 21 – 25 / 26 -30 / 31 – 35 / 36 – 40 / 41 – 45 / 46 – 50 / 51 – 55 / 56 – 60 / 61 – 65 / 65 above	✓	
4.	Highest Education level	Secondary education / Pre-university (STPM, Matriculation, Foundation) / Postgraduate diploma / Bachelor degree / Master degree/ Doctorate degree (PhD)	✓	

5.	Category of the organization	Main contractor / Subcontractor / Developer / Consultant (Eg M&E, C&S, Architectural, Quantity Surveyor, etc)	✓	
6.	How big of the construction companies?	Large (> 100 workers) / Medium (50 to 99 workers) / Small (10 to 49 workers) / Micro (1 to 9 workers)	✓	
7.	Role	Technician (Relate to engineering or technology) / Non-technician (Non-engineering or non-technology)	✓	
8.	Position	Top Management (Eg director, CEO, COO, CFO, GM) / Senior Management (Eg Senior Management, Senior Project Manager) / Managerial Level (Eg Manager, M&E Manager, Project Manager,etc)	✓	
9.	Work experience	Less than 1 year / 1 – 5 years / 6 - 10 years / 11 – 15 years /	✓	

		16 – 20 years / More than 20 years		
10	Have you ever heard about : Industry IR 5.0 ; Human-Centric Industry	Yes / No	✓	
11	Rate your current knowledge about the IR 5.0	Likert Scale (Not familiar – very familiar)	✓	

Section B : Impact of IR 5.0 Adoption on Construction Industry Performance

No	Question	Response	✓ / ✗	Comment
1.	Applying Construction IR 5.0 technologies improves my work efficiency.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
2.	Using IR 5.0 practice reduces errors and rework in my daily tasks.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
3.	IR 5.0 helps me complete projects faster than traditional methods.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
4.	Integration of human-centric technologies enhance my decision-making quality.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
5.	Applying IR 5.0 increases the overall quality of my engineering outputs.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
6.	Using IR 5.0 concepts improves collaboration and communication with my team.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	

Section B : Readiness of Construction Players to Adopt IR 5.0

No	Question	Response	✓ / ✗	Comment
1.	I am ready to adopt new technology associated with Construction IR 5.0 in my daily work.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
2.	I feel prepared to work alongside intelligent machines and AI tools on construction projects.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
3.	I have the necessary skills to implements IR 5.0 principles effectively in construction.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
4.	I am mentally and professionally ready to embrace the changes introduced by construction IR 5.0.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
5.	I have access to sufficient resources and support to apply IR 5.0 in my tasks.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
6.	I am confident in my ability to manage challenges that may arise from implementing IR 5.0 technologies in construction.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	

Section B : Intention of Construction Players to Adopt IR 5.0

No	Question	Response	✓ / ✗	Comment
1.	I intend to incorporate IR 5.0 technologies in my daily construction tasks.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
2.	I plan to actively learn more about construction IR 5.0 and its applications.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
3.	I aim to use human-centric technologies in upcoming projects.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
4.	I am committed to adopting new tools and method aligned with IR 5.0.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
5.	I intend to collaborate closely with AI and automation systems in my work.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	
6.	I plan to recommend the use of IR 5.0 technologies within my team or organisations.	Linkert scale (Strongly Disagree – Strongly Agree)	✓	

I hereby confirm that I have reviewed the questionnaire titled:

"Survey of Construction Industry in IR 5.0 Revolution: Using Conceptual Model"

I have provided my feedback based on clarity, relevance, structure, and appropriateness of the questions for the intended target respondents.

I understand that my feedback will be used solely for the purpose of improving the quality and effectiveness of the research instrument.

Full Name ______Lai Yen Lung____________

Position ___Assoc. Professor____________

Organization ___Universiti Tunkuu Abdul Rahman___

Signature ____

Date ________30/6/2025__________________

Appendix C Pre-test Dr Lee (Academic)

Title: Survey of Construction Industry in IR 5.0 Revolution: Using Conceptual Model

Instructions for Reviewers:

- Please read each question.
- Tick ✓ if the question is clear and appropriate.
- Cross ✗ if the question needs improvement.
- Optionally, write comments or suggestions for improvement in the last column.

Section A : Demographic Information

No	Question	Response	✓ / ✗	Comment
1	Gender	Male / Female	✓	
2	Ethic Group	Malay / Chinese / Indian / Others	✓	
3	Age	Below 20 / 21 – 25 / 26 -30 / 31 – 35 / 36 – 40 / 41 – 45 / 46 – 50 / 51 – 55 / 56 – 60 / 61 – 65 / 65 above	✓	
4	Highest Education level	Secondary education / Pre-university (STPM, Matriculation, Foundation) / Postgraduate diploma / Bachelor degree / Master degree/ Doctorate degree (PhD)	✓	

5	Category of the organization	Main contractor / Subcontractor / Developer / Consultant (Eg M&E, C&S, Architectural, Quantity Surveyor, etc)	✓	
6	How big of the construction companies?	Large (> 100 workers) / Medium (50 to 99 workers) / Small (10 to 49 workers) / Micro (1 to 9 workers)	✓	
7	Role	Technician (Relate to engineering or technology) / Non-technician (Non-engineering or non-technology)	✓	
8	Position	Top Management (Eg director, CEO, COO, CFO, GM) / Senior Management (Eg Senior Management, Senior Project Manager) / Managerial Level (Eg Manager, M&E Manager, Project Manager,etc)	✓	
9	Work experience	Less than 1 year / 1 – 5 years / 6 - 10 years / 11 – 15 years / 16 – 20 years / More than 20 years	✓	

11	Have you ever heard about : Industry IR 5.0 ; Human-Centric Industry	Yes / No	✓	
12.	Rate your current knowledge about the IR 5.0	Likert Scale (Not familiar – very familiar)	✓	

Section B : Impact of IR 5.0 Adoption on Construction Industry Performance

No	Question	Response	✓ / ✗	Comment
1	Applying Construction IR 5.0 technologies improves my work efficiency.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	Using IR 5.0 practice reduces errors and rework in my daily tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	IR 5.0 helps me complete projects faster than traditional methods.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	Integration of human-centric technologies enhance my decision-making quality.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	Applying IR 5.0 increases the overall quality of my engineering outputs.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	Using IR 5.0 concepts improves collaboration and communication with my team.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

Section B : Readiness of Construction Players to Adopt IR 5.0

No	Question	Response	✓ / ✗	Comment
1	I am ready to adopt new technology associated with Construction IR 5.0 in my daily work.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	I feel prepared to work alongside intelligent machines and AI tools on construction projects.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	I have the necessary skills to implements IR 5.0 principles effectively in construction.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	I am mentally and professionally ready to embrace the changes introduced by construction IR 5.0.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	I have access to sufficient resources and support to apply IR 5.0 in my tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	I am confident in my ability to manage challenges that may arise from implementing IR 5.0 technologies in construction.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

Section B : Intention of Construction Players to Adopt IR 5.0

No	Question	Response	✓ / ✗	Comment
1	I intend to incorporate IR 5.0 technologies in my daily construction tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	I plan to actively learn more about construction IR 5.0 and its applications.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	I aim to use human-centric technologies in upcoming projects.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	I am committed to adopting new tools and method aligned with IR 5.0.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	I intend to collaborate closely with AI and automation systems in my work.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	I plan to recommend the use of IR 5.0 technologies within my team or organisations.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

I hereby confirm that I have reviewed the questionnaire titled:

"Survey of Construction Industry in IR 5.0 Revolution: Using Conceptual Model"

I have provided my feedback based on clarity, relevance, structure, and appropriateness of the questions for the intended target respondents.

I understand that my feedback will be used solely for the purpose of improving the quality and effectiveness of the research instrument.

Full Name Ts Dr Lee Chen Kang

Position Assistant Professor

Organization Universiti Tunku Abdul Rahman

Signature Lee Chen Kang

Date 26/6/2025

Appendix D Pre-test Ms Beh (Academic)

Title: Survey of Construction Industry in IR 5.0 Revolution: Using Conceptual Model

Instructions for Reviewers:

- Please read each question.
- Tick ✓ if the question is clear and appropriate.
- Cross ✗ if the question needs improvement.
- Optionally, write comments or suggestions for improvement in the last column.

Section A : Demographic Information

No	Question	Response	✓ / ✗	Comment
1	Gender	Male / Female	✓	-
2	Ethic Group	Malay / Chinese / Indian / Others	✓	-
3	Age	Below 20 / 21 – 25 / 26 -30 / 31 – 35 / 36 – 40 / 41 – 45 / 46 – 50 / 51 – 55 / 56 – 60 / 61 – 65 / 65 above	✓	-
4	Highest Education level	Secondary education / Pre-university (STPM, Matriculation, Foundation) / Postgraduate diploma / Bachelor degree / Master degree/ Doctorate degree (PhD)	✓	-

5	Category of the organization	Main contractor / Subcontractor / Developer / Consultant (Eg M&E, C&S, Architectural, Quantity Surveyor, etc)	✓	-
6	How big of the construction companies?	Large (> 100 workers) / Medium (50 to 99 workers) / Small (10 to 49 workers) / Micro (1 to 9 workers)	✓	-
7	Role	Technician (Relate to engineering or technology) / Non-technician (Non-engineering or non-technology)	✓	-
8	Position	Top Management (Eg director, CEO, COO, CFO, GM) / Senior Management (Eg Senior Management, Senior Project Manager) / Managerial Level (Eg Manager, M&E Manager, Project Manager,etc)	✓	-
9	Work experience	Less than 1 year / 1 – 5 years / 6 - 10 years / 11 – 15 years / 16 – 20 years /	✓	-

		More than 20 years		
10	Have you ever heard about : Industry IR 5.0 ; Human-Centric Industry	Yes / No	✓	-
11	Rate your current knowledge about the IR 5.0	Likert Scale (Not familiar – very familiar)	✓	-

Section B : Impact of IR 5.0 Adoption on Construction Industry Performance

No	Question	Response	✓ / ✗	Comment
1	Applying Construction IR 5.0 technologies improves my work efficiency.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	Using IR 5.0 practice reduces errors and rework in my daily tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	IR 5.0 helps me complete projects faster than traditional methods.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	Integration of human-centric technologies enhance my decision-making quality.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	Applying IR 5.0 increases the overall quality of my engineering outputs.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	Using IR 5.0 concepts improves collaboration and communication with my team.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

Section B : Readiness of Construction Players to Adopt IR 5.0

No	Question	Response	✓ / ✗	Comment
1	I am ready to adopt new technology associated with Construction IR 5.0 in my daily work.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	I feel prepared to work alongside intelligent machines and AI tools on construction projects.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	I have the necessary skills to implements IR 5.0 principles effectively in construction.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	I am mentally and professionally ready to embrace the changes introduced by construction IR 5.0.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	I have access to sufficient resources and support to apply IR 5.0 in my tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	I am confident in my ability to manage challenges that may arise from implementing IR 5.0 technologies in construction.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

Section B : Intention of Construction Players to Adopt IR 5.0

No	Question	Response	✓ / ✗	Comment
1	I intend to incorporate IR 5.0 technologies in my daily construction tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	I plan to actively learn more about construction IR 5.0 and its applications.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	I aim to use human-centric technologies in upcoming projects.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	I am committed to adopting new tools and method aligned with IR 5.0.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	I intend to collaborate closely with AI and automation systems in my work.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	I plan to recommend the use of IR 5.0 technologies within my team or organisations.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

I hereby confirm that I have reviewed the questionnaire titled:

"Survey of Construction Industry in IR 5.0 Revolution: Using Conceptual Model"

I have provided my feedback based on clarity, relevance, structure, and appropriateness of the questions for the intended target respondents.

I understand that my feedback will be used solely for the purpose of improving the quality and effectiveness of the research instrument.

Full Name Michelle Beh________________________

Position Lecturer__________________________

Organization UTAR__________________________

Signature __________________________

Date 1 July 2025__________________________

Appendix E Pre-test Mr Chee Hong (Industry)

Title: Survey of Construction Industry in IR 5.0 Revolution: Using Conceptual Model

Instructions for Reviewers:

- Please read each question.
- Tick ✓ if the question is clear and appropriate.
- Cross ✗ if the question needs improvement.
- Optionally, write comments or suggestions for improvement in the last column.

Section A : Demographic Information

No	Question	Response	✓ / ✗	Comment
1	Gender	Male / Female	✓	
2	Ethic Group	Malay / Chinese / Indian / Others	✓	
3	Age	Below 20 / 21 – 25 / 26 -30 / 31 – 35 / 36 – 40 / 41 – 45 / 46 – 50 / 51 – 55 / 56 – 60 / 61 – 65 / 65 above	✓	
4	Highest Education level	Secondary education / Pre-university (STPM, Matriculation, Foundation) / Postgraduate diploma / Bachelor degree / Master degree/ Doctorate degree (PhD)	✓	

5	Category of the organization	Main contractor / Subcontractor / Developer / Consultant (Eg M&E, C&S, Architectural, Quantity Surveyor, etc)	✓	
6	How big of the construction companies?	Large (> 100 workers) / Medium (50 to 99 workers) / Small (10 to 49 workers) / Micro (1 to 9 workers)	✗	Suggest rephrase question to "How big is the construction company?"
7	Role	Technician (Relate to engineering or technology) / Non-technician (Non-engineering or non-technology)	✓	
8	Position	Top Management (Eg director, CEO, COO, CFO, GM) / Senior Management (Eg Senior Management, Senior Project Manager) / Managerial Level (Eg Manager, M&E Manager, Project Manager,etc)	✓	
9	Work experience	Less than 1 year / 1 – 5 years / 6 - 10 years / 11 – 15 years / 16 – 20 years /	✓	

		More than 20 years		
10	Have you ever heard about : Industry IR 5.0 ; Human-Centric Industry	Yes / No	✓	
11	Rate your current knowledge about the IR 5.0	Likert Scale (Not familiar – very familiar)	✓	

Section B : Impact of IR 5.0 Adoption on Construction Industry Performance

No	Question	Response	✓ / ✗	Comment
1	Applying Construction IR 5.0 technologies improves my work efficiency.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	Using IR 5.0 practice reduces errors and rework in my daily tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	IR 5.0 helps me complete projects faster than traditional methods.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	Integration of human-centric technologies enhance my decision-making quality.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	Applying IR 5.0 increases the overall quality of my engineering outputs.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	Using IR 5.0 concepts improves collaboration and communication with my team.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

Section B : Readiness of Construction Players to Adopt IR 5.0

No	Question	Response	✓ / ✗	Comment
1	I am ready to adopt new technology associated with Construction IR 5.0 in my daily work.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	I feel prepared to work alongside intelligent machines and AI tools on construction projects.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	I have the necessary skills to implements IR 5.0 principles effectively in construction.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	I am mentally and professionally ready to embrace the changes introduced by construction IR 5.0.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	I have access to sufficient resources and support to apply IR 5.0 in my tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	I am confident in my ability to manage challenges that may arise from implementing IR 5.0 technologies in construction.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

Section B : Intention of Construction Players to Adopt IR 5.0

No	Question	Response	✓ / ✗	Comment
1	I intend to incorporate IR 5.0 technologies in my daily construction tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	I plan to actively learn more about construction IR 5.0 and its applications.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	I aim to use human-centric technologies in upcoming projects.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	I am committed to adopting new tools and method aligned with IR 5.0.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	I intend to collaborate closely with AI and automation systems in my work.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	I plan to recommend the use of IR 5.0 technologies within my team or organisations.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

I hereby confirm that I have reviewed the questionnaire titled:

"Survey of Construction Industry in IR 5.0 Revolution: Using Conceptual Model"

I have provided my feedback based on clarity, relevance, structure, and appropriateness of the questions for the intended target respondents.

I understand that my feedback will be used solely for the purpose of improving the quality and effectiveness of the research instrument.

Full Name Loong Chee Hong

Position Tech Lead

Organization TIME

Signature *CheeHong*

Date 26/06/2025

Appendix F Pre-test Mr Vincent (Industry)

Title: Survey of Construction Industry in IR 5.0 Revolution: Using Conceptual Model

Instructions for Reviewers:

- Please read each question.
- Tick ✓ if the question is clear and appropriate.
- Cross ✗ if the question needs improvement.
- Optionally, write comments or suggestions for improvement in the last column.

Section A : Demographic Information

No	Question	Response	✓ / ✗	Comment
1	Gender	Male / Female	✓	
2	Ethic Group	Malay / Chinese / Indian / Others	✓	
3	Age	Below 20 / 21 – 25 / 26 -30 / 31 – 35 / 36 – 40 / 41 – 45 / 46 – 50 / 51 – 55 / 56 – 60 / 61 – 65 / 65 above	✓	
4	Highest Education level	Secondary education / Pre-university (STPM, Matriculation, Foundation) / Postgraduate diploma / Bachelor degree / Master degree/ Doctorate degree (PhD)	✓	

5	Category of the organization	Main contractor / Subcontractor / Developer / Consultant (Eg M&E, C&S, Architectural, Quantity Surveyor, etc)	✓	
6	How big of the construction companies?	Large (> 100 workers) / Medium (50 to 99 workers) / Small (10 to 49 workers) / Micro (1 to 9 workers)	✓	
7	Role	Technician (Relate to engineering or technology) / Non-technician (Non-engineering or non-technology)	✓	
8	Position	Top Management (Eg director, CEO, COO, CFO, GM) / Senior Management (Eg Senior Management, Senior Project Manager) / Managerial Level (Eg Manager, M&E Manager, Project Manager,etc)	✓	
9	Work experience	Less than 1 year / 1 – 5 years / 6 - 10 years / 11 – 15 years / 16 – 20 years / More than 20 years	✓	

10	Have you ever heard about : Industry IR 5.0 ; Human-Centric Industry	Yes / No	✓	
11	Rate your current knowledge about the IR 5.0	Likert Scale (Not familiar – very familiar)	✓	

Section B : Impact of IR 5.0 Adoption on Construction Industry Performance

No	Question	Response	✓ / ✗	Comment
1	Applying Construction IR 5.0 technologies improves my work efficiency.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	Using IR 5.0 practice reduces errors and rework in my daily tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	IR 5.0 helps me complete projects faster than traditional methods.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	Integration of human-centric technologies enhance my decision-making quality.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	Applying IR 5.0 increases the overall quality of my engineering outputs.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	Using IR 5.0 concepts improves collaboration and communication with my team.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

Section B : Readiness of Construction Players to Adopt IR 5.0

No	Question	Response	✓ / ✗	Comment
1	I am ready to adopt new technology associated with Construction IR 5.0 in my daily work.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	I feel prepared to work alongside intelligent machines and AI tools on construction projects.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	I have the necessary skills to implements IR 5.0 principles effectively in construction.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	I am mentally and professionally ready to embrace the changes introduced by construction IR 5.0.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	I have access to sufficient resources and support to apply IR 5.0 in my tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	I am confident in my ability to manage challenges that may arise from implementing IR 5.0 technologies in construction.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

Section B : Intention of Construction Players to Adopt IR 5.0

No	Question	Response	✓ / ✗	Comment
1	I intend to incorporate IR 5.0 technologies in my daily construction tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	I plan to actively learn more about construction IR 5.0 and its applications.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	I aim to use human-centric technologies in upcoming projects.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	I am committed to adopting new tools and method aligned with IR 5.0.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	I intend to collaborate closely with AI and automation systems in my work.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	I plan to recommend the use of IR 5.0 technologies within my team or organisations.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

I hereby confirm that I have reviewed the questionnaire titled:

"Survey of Construction Industry in IR 5.0 Revolution: Using Conceptual Model"

I have provided my feedback based on clarity, relevance, structure, and appropriateness of the questions for the intended target respondents.

I understand that my feedback will be used solely for the purpose of improving the quality and effectiveness of the research instrument.

Full Name Vincent Chai Min Shen

Position Senior Consultant – Project Implementation

Organization Cardzone Sdn Bhd

Signature Vincent

Date 26/6/2025

Appendix G Pre-test Mr Ryan (Industry)

Title: Survey of Construction Industry in IR 5.0 Revolution: Using Conceptual Model

Instructions for Reviewers:

- Please read each question.
- Tick ✓ if the question is clear and appropriate.
- Cross ✗ if the question needs improvement.
- Optionally, write comments or suggestions for improvement in the last column.

Section A : Demographic Information

No	Question	Response	✓ / ✗	Comment
1	Gender	Male / Female	✓	
2	Ethic Group	Malay / Chinese / Indian / Others	✓	
3	Age	Below 20 / 21 – 25 / 26 -30 / 31 – 35 / 36 – 40 / 41 – 45 / 46 – 50 / 51 – 55 / 56 – 60 / 61 – 65 / 65 above	✓	
4	Highest Education level	Secondary education / Pre-university (STPM, Matriculation, Foundation) / Postgraduate diploma / Bachelor degree / Master degree/ Doctorate degree (PhD)	✓	

5	Category of the organization	Main contractor / Subcontractor / Developer / Consultant (Eg M&E, C&S, Architectural, Quantity Surveyor, etc)	✓	
6	How big of the construction companies?	Large (> 100 workers) / Medium (50 to 99 workers) / Small (10 to 49 workers) / Micro (1 to 9 workers)	✓	
7	Role	Technician (Relate to engineering or technology) / Non-technician (Non-engineering or non-technology)	✓	
8	Position	Top Management (Eg director, CEO, COO, CFO, GM) / Senior Management (Eg Senior Management, Senior Project Manager) / Managerial Level (Eg Manager, M&E Manager, Project Manager,etc)	✓	
9	Work experience	Less than 1 year / 1 – 5 years / 6 - 10 years / 11 – 15 years / 16 – 20 years /	✓	

		More than 20 years		
10	Have you ever heard about : Industry IR 5.0 ; Human-Centric Industry	Yes / No	✓	
11	Rate your current knowledge about the IR 5.0	Likert Scale (Not familiar – very familiar)	✓	

Section B : Impact of IR 5.0 Adoption on Construction Industry Performance

No	Question	Response	✓ / ✗	Comment
1	Applying Construction IR 5.0 technologies improves my work efficiency.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	Using IR 5.0 practice reduces errors and rework in my daily tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	IR 5.0 helps me complete projects faster than traditional methods.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	Integration of human-centric technologies enhance my decision-making quality.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	Applying IR 5.0 increases the overall quality of my engineering outputs.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	Using IR 5.0 concepts improves collaboration and communication with my team.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

Section B : Readiness of Construction Players to Adopt IR 5.0

No	Question	Response	✓ / ✗	Comment
1	I am ready to adopt new technology associated with Construction IR 5.0 in my daily work.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	I feel prepared to work alongside intelligent machines and AI tools on construction projects.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	I have the necessary skills to implements IR 5.0 principles effectively in construction.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	I am mentally and professionally ready to embrace the changes introduced by construction IR 5.0.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	I have access to sufficient resources and support to apply IR 5.0 in my tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	I am confident in my ability to manage challenges that may arise from implementing IR 5.0 technologies in construction.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

Section B : Intention of Construction Players to Adopt IR 5.0

No	Question	Response	✓ / ✗	Comment
1	I intend to incorporate IR 5.0 technologies in my daily construction tasks.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
2	I plan to actively learn more about construction IR 5.0 and its applications.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
3	I aim to use human-centric technologies in upcoming projects.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
4	I am committed to adopting new tools and method aligned with IR 5.0.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
5	I intend to collaborate closely with AI and automation systems in my work.	Likert scale (Strongly Disagree – Strongly Agree)	✓	
6	I plan to recommend the use of IR 5.0 technologies within my team or organisations.	Likert scale (Strongly Disagree – Strongly Agree)	✓	

I hereby confirm that I have reviewed the questionnaire titled:

"Survey of Construction Industry in IR 5.0 Revolution: Using Conceptual Model"

I have provided my feedback based on clarity, relevance, structure, and appropriateness of the questions for the intended target respondents.

I understand that my feedback will be used solely for the purpose of improving the quality and effectiveness of the research instrument.

Full Name Ryan Khoo

Position Quantity Surveyor

Organization Northern Solar Sdn Bhd

Signature

Date 26/6/2025