FACTORS FOR ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING APPLICATIONS IN THE PROJECT LIFECYCLE OF THE CONSTRUCTION INDUSTRY IN KLANG VALLEY MALAYSIA

CHONG CHEE HAO

A project report submitted in partial fulfilment of the requirements for the award of Master of Project Management

Lee Kong Chian Faculty of Engineering and Science
Universiti Tunku Abdul Rahman

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DECLARATION

I hereby declare that this project report is based on my original work except for citations and quotations which have 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.

Signature	:	
Name	:	CHONG CHEE HAO
ID No.	:	24UEB01833
Date	:	11 / 05 / 2026

APPROVAL FOR SUBMISSION

I certify that this project report entitled **"FACTORS FOR ARTIFICIAL INTELIGENCE AND MACHINE LEARNING APPLICATIONS IN THE PROJECT LIFECYCLE OF THE CONSTRUCTION INDUSTRY IN KLANG VALLEY MALAYSIA"** was prepared by **CHONG CHEE HAO** has met the required standard for submission in partial fulfilment of the requirements for the award of Master of Project Management at Universiti Tunku Abdul Rahman.

Approved by,

Signature	:	
Supervisor	:	Ts Dr Toh Tien Choon
Date	:	11 / 05 / 2026
Signature	:	
Co-Supervisor	:	Mr. Leong Chung Sum
Date	:	11 / 05 / 2026

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ABSTRACT

Malaysia government's Ministry of Work through, Construction Industry Development Board (CIDB) has implemented Construction 4.0 Strategic Plan (2021 – 2025) which is a blueprint for Malaysian construction industry to adapt Industrial Revolution 4.0 (IR 4.0) to overcome the schedule, cost overrun and productivity constraints. Although the plan was introduced since 2016, compared with other sector particularly manufacturing sector, construction industry lags very much behind in digitization in every phase of construction project lifecycle especially application of Artificial intelligence (AI) and machine learning (ML). Therefore, in this research paper aims to investigates the factors influencing AI and ML adoption in the construction project lifecycle in Klang Valley and evaluates their potential benefits in improving project lifecycle success. A quantitative approach was employed using questionnaire surveys based on Technology-Organisation-Environment (TOE) framework. The respondents are from all levels of construction practitioners which are registered with CIDB Malaysia. The data are analysed through mean ranking analysis (descriptive statistics) and factor analysis (Principal Component Analysis (PCA)) in IBM SPSS 27. The results indicate that technological factors, such as relative advantage, trialability, and perceived usefulness, are the primary drivers of adoption. Organisational and ecosystem supports act as enabling conditions but remain underdeveloped, while market-related factors have minimal influence, suggesting an early stage of digital transformation. In terms of benefits, AI and ML are mainly associated with improvements in time, cost, and quality performance, reflecting a productivity-driven adoption pattern. However, safety and environmental performance are less prioritised. The study further reveals that all benefits collectively contribute to overall project lifecycle success, highlighting a gap between short-term priorities and long-term value. A conceptual framework is proposed to support more holistic and sustainable adoption in the construction industry.

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ABBREVIATIONS

4IR	Forth Industrial Revolution
AI	Artificial Intelligence
BIM	Building Information Modelling
CIDB	Construction Industry Development Board
DOSM	Department of Statistics Malaysia
IT	Information Technology
ML	Machine Learning
PCA	Principal Component Analysis
TOE	Technological, Organisational, Environmental
KMO	Kaiser-Meyer-Olkin
$\chi 2$	Chi-square
SPSS	Statistical Package for Social Science

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CHAPTER 1

INTRODUCTION

1.1 General Introduction

The global population is growing exponentially over the years and according to Worldometer (2025), the global population has reached 8.2 to 8.3 billion with annual growth of about 0.8% to 0.9%. The world population is expected to reach around 8.5 billion in 2030 and 9.7 billion people by 2050 (United Nation, 2025). Therefore, it is crucial for our development to keep pace with the anticipated demand from such amount of population. Apart from the growing population, the requirement and technologies to be implemented into the development are getting more complex over the years. Many Malaysian construction practitioners find it challenging to meet such requirements due to infrastructure requirement complexity in a fast-pacing development while delivering higher quality standard. The challenges are often associated with low productivity, project delays, cost overruns, poor quality management, inefficient decision-making processes and inadequate of health and safety in health and safety outcome in the construction projects (Yap et al., 2022). The incompetent of construction to fulfil the predicted infrastructure requirements in the near future may be attributed to slow adoption of digitalization and excessive dependence on manual approaches (Bello et al., 2020).

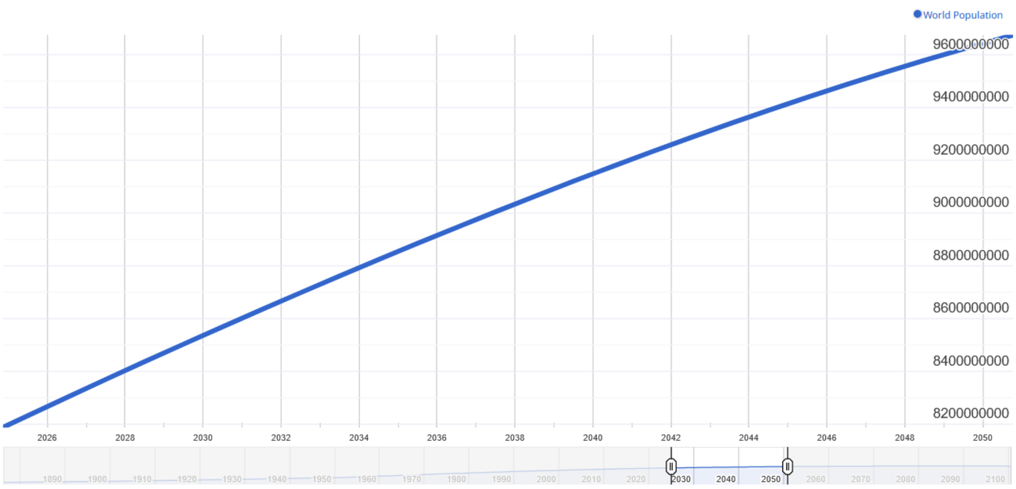

Figure 1.1: Expected World Population Growth from 2025 to 2050 (Worldometer, 2025)

To tackle the substantial growth in the construction sector, adoption of advanced technologies and equipment to support construction process to meet the anticipated demand has becoming vital in construction sector. Adoption of advanced technologies in construction industry will not only accelerate the output, but it will also facilitate the workflow process to deliver on time with higher quality standard. It implies that it will improves efficiency and productivity by enabling workers to manage tremendous amounts of works in a short period of time.

Introduction of Fourth Industrial Revolution (4IR) has marked a turning point in the construction industry to an era of digitalization and integration with advanced technology. This 4IR emphasises the integration of advanced technologies with all the intelligent automation and interconnected system to operate and exchange information with each other to make decision without intervention of human which will improve efficiency and accuracy (Folgado et al., 2024).

To maintain competitiveness in the global market, Malaysia government's Ministry of Works through, CIDB implemented Construction 4.0 Strategic Plan (2021 – 2025) in 2016 as a blueprint for Malaysia construction practitioners to respond to rapid changes of 4IR in construction industry. CIDB has determined twelve technologies that will further enhance efficiency and performance of construction industry which are:

- Building Information Modelling (BIM)
- Pre-fabrication and modular construction
- Autonomous construction
- Augmented reality and virtualisation
- Cloud and Realtime collaboration
- 3D scanning and photogrammetry
- Big data and predictive analysis
- Internet of things
- 3D printing and additive manufacturing
- Advanced building materials
- Blockchain
- Artificial intelligence (AI)

In this paper, the focus is on adoption of AI and ML in Malaysia construction industry. This is due to the fact of light that AI and ML are technological foundation in implementing full authentic digitalization in all field of engineering, manufacturing, construction and even management (Datta et al., 2024). AI enables computer to have human-like capabilities in analysing complex problems effectively and adaptively while, machine learning (ML) is part of integration of AI to develop own computer algorithms to acquire knowledge through historical data and make decision through statistical and computational methods (Kühl et al., 2022).

1.2 Importance of the Study

Recent studies on the Malaysian construction industry have predominantly focused on traditional operational issues such as construction site safety and construction waste management (Ting & Yahaya, 2024). Although research on emerging technologies has gradually increased, studies specifically examining the adoption factors of AI and ML across the construction project lifecycle in Malaysia remain limited (Khudzari et al., 2024). There are very few of studies investigate the factors of advanced technologies such as AI and ML applications in construction industry before it could incorporate with the construction 4.0 strategic plan which is initiated by Malaysia government through CIDB and preference of machinery and equipment by construction practitioners in Malaysia. Therefore, it is important to determine the factor of AI and ML application in the project lifecycle of the construction industry in Malaysia. This paper would not only contribute to the academic discourse but also provide practical insight for the Malaysia construction industry, thereby playing vital role in shaping Malaysia’s construction future in adopting AI and ML in the day-to-day operation.

1.3 Problem Statement

According to CIDB (2024), AI applications in Malaysia’s construction industry is in the verge of technological revolution. It was found that AI in global construction industry worths 519.63 million United State Dollar (USD) in 2021 and expected to skyrocket to 3,554.22 million USD in 2027, boosting a

Compound Annual Growth Rate (CAGR) of 37.78% (CIDB, 2024). Despite impressive global numbers reported, the uptake of AI in Malaysia construction industry still remains slow and modest. Malaysia government has also initiated a program, called Construction 4.0 Strategic Plan in 2021 to provide a blueprint for Malaysia construction practitioners to adopt the advanced technologies to incorporate with era of 4IR.

However, Malaysia construction practitioners are reluctant to change their traditional method in construction practices which are manual labour and old-school machineries (CIDB, 2020). These traditional methods are prone to have human errors and known as low productivity method (Chan et al., 2017). This trend will lead to our construction industry falls behind neighbour countries in this competitive era.

Hence, it is important to investigate the factor for AI and ML which are the technologies foundation in implementing 4IR in project lifecycle of construction industry in Klang Valley, Malaysia and identify the perceived performance effects of AI and ML applications in project lifecycle of construction industry for achieving construction industry project lifecycle success.

1.4 Research Questions

Based on the problem statement, the research questions could be found as follows:

i) What are the factors for artificial intelligence and machine learning applications in the project lifecycle of the construction industry?

ii) What are the perceived performance effects of artificial intelligence and machine learning in the project lifecycle of the construction industry for improved construction industry project lifecycle success?

1.5 Research Aim

This research aims to critically investigate the factors and the perceived performance effects of AI and ML applications across the construction project lifecycle in Klang Valley, Malaysia. Ultimately, to propose a framework for achieving improve construction industry project lifecycle success through AI and ML applications in the project lifecycle of the construction industry as influenced by technological, organisational and environmental dimensions.

1.6 Research Objectives

Based on the research questions found, the research objectives are set as below:

i) To investigate the factors for artificial intelligence and machine learning applications in the project lifecycle of the construction industry.

ii) To investigate the perceived performance effects of artificial intelligence and machine learning in the project lifecycle of the construction industry for improved construction industry project lifecycle success.

1.7 Research Scope

This study examines the factors influencing the adoption of AI and ML, as well as their perceived performance effects across the construction project lifecycle in Klang Valley, Malaysia. A quantitative research approach is employed through a structured questionnaire survey administered via Google Forms to CIDB-registered construction practitioners. The collected data enables the identification and evaluation of critical technological, organisational, and environmental factors that influence AI and ML adoption within the Malaysian construction industry, as well as the perceived performance effects of these technologies on project performance throughout the construction lifecycle. Based on the findings, a conceptual framework will be developed to support the effective implementation of AI and ML applications within the Malaysian construction sector.

1.8 Chapter Organisation

This research is structured into five chapters to ensure a systematic and comprehensive presentation of the study.

Chapter 1 introduces the research background, highlighting the emergence of AI and ML in the construction industry and the need for digital transformation. It outlines the problem statement, research aim, objectives, research questions, scope of the study, and significance of the research.

Chapter 2 presents a review of relevant literature on AI and ML applications within the construction project lifecycle. It discusses the concept of Construction 4.0, current practices in the Malaysian construction industry, and challenges related to technology adoption. This chapter also examines existing theoretical frameworks, particularly the Technology–Organisation–Environment (TOE) framework, which forms the basis for identifying factors influencing AI and ML adoption.

Chapter 3 describes the research methodology adopted in this study. It explains the research design, data collection methods, and sampling approach, focusing on questionnaire surveys distributed to Malaysian construction practitioners registered with the Construction Industry Development Board Malaysia (CIDB). The chapter also outlines the data analysis techniques used to evaluate the identified factors.

Chapter 4 presents and analyses the findings obtained from the data collection process. The results are interpreted using appropriate statistical methods to identify key factors influencing AI and ML adoption. Discussions are provided to relate the findings to the research objectives and existing literature.

Chapter 5 concludes the study by summarising the key findings and highlighting their implications for the construction industry. It also provides recommendations for improving AI and ML adoption among construction practitioners in Klang Valley and suggests areas for future research.

CHAPTER 2

LITERATURE REVIEW

2.1 Construction 4.0

The evolution of technologies is on the fast pace over the past few decades, and it alters our daily lifestyle and working techniques. The term fourth industrial revolution (4IR) was introduced by Klaus Schwab, the World Economic Forum founder (Park, 2016). This 4IR emphasises on utilisation of computer and cyber-physical systems, involving the transition process from physical to digital, and subsequently from digital to physical. A lot of people thought this 4IR will only apply to manufacturing industry, but it actually applies to all kind of industries including construction industry. This is due to the fact that construction industry is traditionally characterised by fragmentation, low productivity growth, high uncertainty, and heavy reliance on manual decision-making. These structural inefficiencies make the sector slower in adopting digital innovations compared to manufacturing.

Therefore, Construction 4.0 is introduced in construction industry to integrate with the advanced technologies. The main goal of construction 4.0 is to transform the industry from labour-intensive, experience-based practices towards data-driven, interconnected and automated processes, emphasising real-time data exchange, cyber-physical systems, and intelligent decision-making. Augmented virtual reality (AR/VR), blockchain, and laser scanning, etc are part of construction 4.0 technologies and it significantly contribute to efficiency and innovation in construction industry (Jaafar et al., 2024). Among construction 4.0 technologies, AI and ML play a pivotal role as they enable predictive analytics, optimisation, and automated decision-making, transforming raw construction data into actionable insights.

This technological development aims to help construction industry to work in more efficient and productive ways. It will not just revolutionise the construction process, but also the organizational and project structure by helping the industry to make a strategic decision and planning (Dallasega et al., 2018). It will help to enhance the quality of works, timely completion of projects and better safety. This technological advancement had been applied for several years, and it is proven that they can help the construction industry to achieve the objective of stainable built environment and sustainable decision-making in building technology (Zavadskas et al., 2017).

Despite construction industry is one of main contributors in Malaysia economy, there are very little research and development efforts to adopt advanced technologies to incorporate with Construction 4.0 and Malaysian construction practitioners rather rely on the cheap manual labour (Jaafar et al., 2024). In order to accelerate the adoption of Construction 4.0 in Malaysia construction industry, Malaysia government's Ministry of Works through, CIDB implemented Construction 4.0 Strategic Plan (2021 – 2025) to serve as a blueprint for Malaysian construction practitioners to maintain its competitiveness in the market. However, the adoption remains uneven in Malaysian construction industry (CIDB, 2024). A lot of Malaysian construction practitioners are also still preferring traditional method of construction despite facing existing challenges (Jaafar et al., 2024). The implementation is more challenging in construction than in manufacturing due to project-based operations, temporary organisations and inconsistent data environments.

Therefore, understanding the factors influencing AI and ML application becomes critical, as these technologies form the intelligence layer of Construction 4.0 and determine whether digital transformation can be effectively realised across the project lifecycle.

2.2 Overview of Artificial Intelligence (AI) and Machine Learning (ML)

AI refers to advanced computational systems designed to have features of human cognition, including learning, reasoning, and decision-making. (Shibu, 2023). ML is a subfield of AI that helps in forming a set of algorithms and data to acquire knowledge over the time or experience, thereby facilitating AI to enhance decision-making and performance (Mohaghegh, 2020). Alan Turing who is father of modern computer science, did an intelligence test with his modern computer in 1950 and marked a significant breakthrough in the history of AI as it exceeds the conventional technological expectations and mathematical possibilities about feasibility of intelligent machines (Chu, 2010). However, the term itself was introduced by John McCarthy in 1956 (John, 1956). After sixty years, intelligence machines have evolved and proven outperforming human in multiple domains by taking advantages from big data and computer process power (Brynjolfsson et al, 2019). The concept of AI is to perform tasks like human but at better efficiency and proficiency (Rich et al., 2010). AI is possible to achieve it with ability to process vast amount of data non-stop with speed that we cannot comprehend because it would not be affected by emotion and mentality issue like human. This ability of AI and ML is suited to data-intensive and uncertain environments such as construction projects where prediction, optimisation and pattern recognition are essential for decision making. Having said that, AI and ML system could not replace human and perform tasks in fully automated manner as every construction project is unique but rather provide managerial and operational decisions.

AI and ML system are data-driven based and depends on system capability and integration for accurate analysis and prediction. However, construction projects often suffer from fragmented data, inconsistent documentation, low digital maturity and lack of standardisation, making AI and ML application ineffective and unreliable (Adebayo et al., 2025). This results in hindering AI and ML adoption in construction industry. Such issues are not relying on technical capabilities only, but organisational readiness and environmental support is playing a crucial role in enabling AI and ML adoption in construction industry (Übellacker, 2025).

2.2.1 Artificial Intelligence (AI)

AI systems are commonly classified into three levels based on capability: narrow intelligence (ANI), general intelligence (AGI), and superintelligence (ASI). The lowest level of AI is ANI which is also known as weak AI where the machine could only perform cognitive within particular domains (Baum et al., 2017). ANI could normally perform tasks in its own area of expertise such as playing chess, making sales predictions, providing movie suggestions, language translation, and weather forecasting (Franklin, 2007).

AGI is called as strong AI as it can perform tasks similar to human level. It has board range of analytic abilities and can excel jobs across various domains at human proficiency levels (Franklin, 2007). The examples of AGI are advanced customer service chatbots (such as Apple Siri, Amazon Alexa, etc) and autonomous self-driving cars. The highest level of AI, ASI is still a hypothetical software with intellectual scope beyond human intelligence, it has cutting-edge cognitive functions and highly developed thinking skills more sophisticated than any human exists (Mucci & Stryker, 2023). ASI can improve itself and continuous learning through experience to achieve beyond human-like intelligence without explicit programming (Mucci & Stryker, 2023). The example of ASI could be humanoid robot where they can perform tasks like human and could be able to perform complex technical operations at the same beyond human capability.

The main parts of the artificial intelligence are perception, knowledge presentation, learning, planning, action, and communication (Russell & Norvig, 2016). AI has advanced over the decades in the industry and identified various sub-fields of AI which are automated planning and scheduling, knowledge-based system, machine learning, computer vision, natural language processing, optimisation and optimisation (Abioye et al., 2021). Figure 2.1 illustrates the overview of levels/ types, components and subfield of AI.

AI systems used in construction today fall under Artificial Narrow Intelligence (ANI), which is designed to perform specific tasks such as prediction, classification, and optimisation. Higher-level concepts such as AGI and ASI remain theoretical and are not relevant to current construction applications. In construction, these subfields especially machine learning which will learn over the time for more accurate predictions and translate it into practical uses such as computer vision for safety monitoring, optimisation algorithms for scheduling, and machine learning for cost and risk prediction.

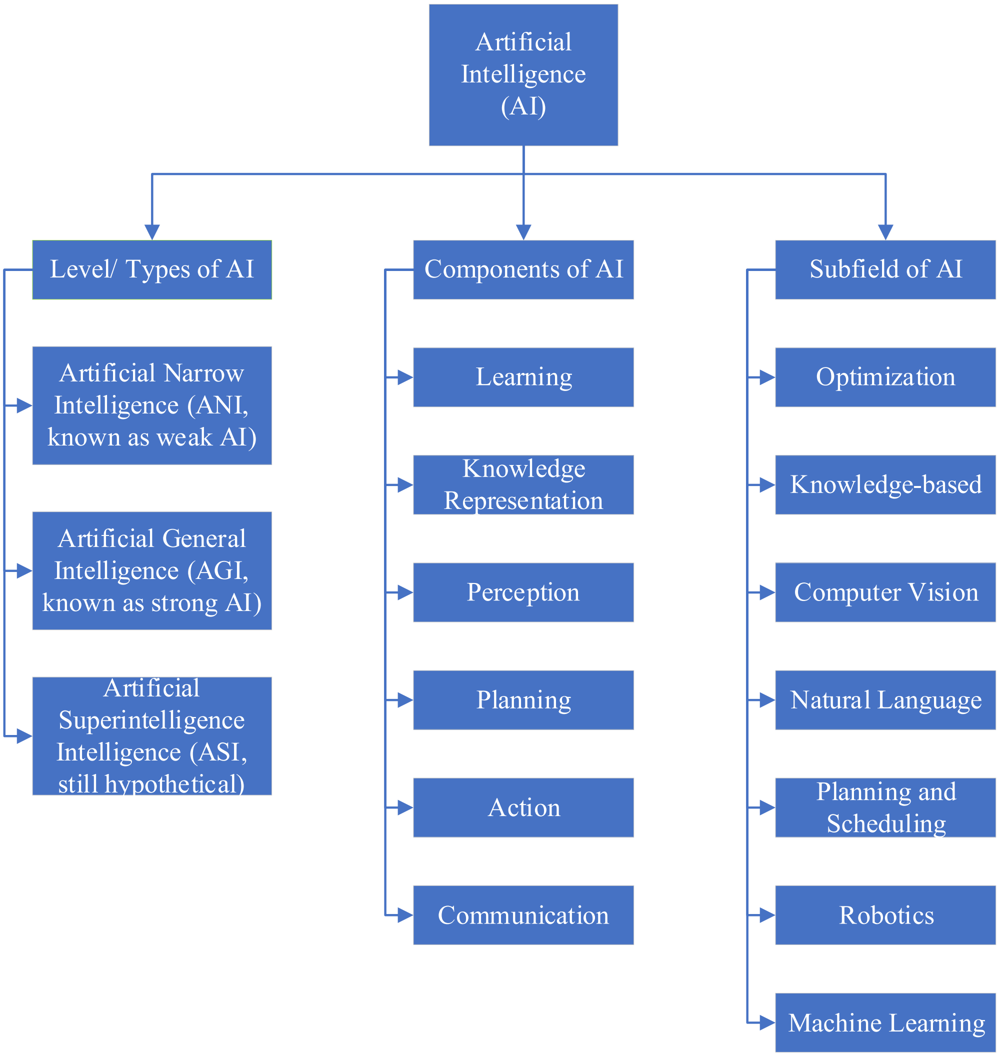

Figure 2.1: Level/types, components and subfield of AI.

2.2.2 Machine Learning (ML)

ML is a sub-field of AI that utilises computational algorithms to acquire knowledge from the past data or experiences. It will help to make decisions or predictions by using statistical techniques to perform tasks without explicit programming. Machine learning approaches are typically grouped into three categories: supervised learning, unsupervised learning, and reinforcement learning, each differing in how models are trained and optimised.

Supervised Machine Learning is the field of study where the models are trained using datasets with predefined outputs, whereas unsupervised learning focuses on identifying hidden patterns within unlabelled data. This field of study can be divided into two categories which are classification and regression techniques. Classification is a technique categorise data into predefined classes and data, while regression technique uses statistical method to predict the numerical values (Kotsaintis, 2007).

Unsupervised Machine Learning is the field of study where the machine learns the essential data structures in unlabelled datasets. The difference between Unsupervised Machine Learning and Supervised Machine Learning are there is no training set for the data and no cross-role validation, hence no guarantee that optimal solution can be obtained (Gentleman & Carey, 2008). This field of study can be divided into two categories which are clustering and dimension reduction techniques. Clustering is a technique classify the similar data for comparison of choice of use and algorithm to use, while dimension reduction diminishes the challenges of the complex data before going for comparison of algorithm to use (Gentleman & Carey, 2008).

Reinforcement Learning is a field of study where the machine learns from outcome of interaction and environmental to get the maximum reward or reinforced signal. It requires a computational framework that obtain knowledge through interaction and in its environment (Sutton, 1992). The more interaction the better the result will be obtained.

Deep Learning is the most advanced machine learning which has proven to give most accurate results compared to with other traditional machine learning techniques. It acquires knowledge through numerous layers of deep neural networks and finds the intricate pattern from data (LeCun, 2015). Deep neural network is an advanced form of artificial neural networks. It uses back propagation algorithms to change its internal parameters that used to compute each layer from previous layer (LeCun, 2015).

The machine learning commonly used in construction industry is supervised learning where the historical project data are referred to as input and make forecasting in cost overruns, schedule delay and risk level (Atkare et al., 2024). Deep learning is also exploit in construction industry, particularly tasks involve unstructured visual data (Pal and Hsieh, 2021). In short, deep learning can facilitate in real-time monitoring and detecting any abnormalities in construction sites based on the images or video captured through technique like convolution neural networks and artificial neural network.

2.3 Application of AI and ML in Construction Lifecycle

AI and ML can be applied in every stage of construction throughout the project life cycle, not only on the planning and construction stage only, AL and ML can also be applied after construction stage such as operation, maintenance, demolition and recovery. These applications vary in function across the construction lifecycle stage, reflecting the distinct information requirements and decision context of each phase.

2.3.1 AI and ML Application in Planning Stage

Planning is a fundamental task in construction, and it is one of the most crucial stages in the project lifecycle. It determines the overall project schedule, cost, quality and quantity. The planning and prediction require extensive input from experienced persons. The tasks involved in planning stage are cost analysis, scheduling and risk assessment for every works to be carried out during construction. This process usually takes extensive time and will create a lot of conflicts during discussion.

Fortunately, the innovation of AI and ML have proven to optimise the planning and scheduling of construction processes over the years. For example, Akinboboye et al. (2022) had applied AI and ML application for project schedule and budget forecasting and found out AI and ML outperformed the traditional forecasting methos which are earned value management and earned schedule. It was found that the error in budget forecasting is reduced by 46.2% and reduced by 52.3% in schedule forecasting. In addition, AI model can also help to determine the most suitable arrangement for the cranes to operate effectively within construction site by implementing genetic algorithms (Albahbah et al., 2021).

This innovation will further help in project arrangements and scheduling more predictable. However, based on reviewed case studies, it is reported that 41% of contractors in construction industry often has incomplete and fragmented datasets which will lead to inaccurate prediction and decision making (Adebayo et al., 2025). This issue causes the AI and ML application unreliable as the effectiveness of this prediction depends heavily on the quality and availability of structured historical datasets (Tian et al., 2025).

2.3.2 AI and ML Application in Design Stage

With current technology, 3D AutoCAD interface is often employed during design phase to give a better presentation of the design and better understanding of the design. In current era, there are various visual techniques and devices such as unmanned aerial vehicles (UAV), camera and laser scanner that can generate valuable data repository which are 3D point clouds to construct model in drawing or design software such as Building Modelling Information (BIM). BIM is a digital representation of the physical and functional building in computer. These models and drawings can only show the plan layout, but it doesn't reflect the constructability or feasibility of the material to be used.

With the integration of AI and ML framework, it can further optimise the design in terms of layout, material selection, and energy performance while also automating resolve repetitive tasks such as clash detection between architectural, structural, mechanical services and electrical services (Bagasi, Nawari and Alsaffar, 2025). This feature will assist the engineer in early design stage by reducing the period to study the constructability and avoid error before proceeding to next stage of construction especially in mega project. For example, A research carried out by Vahdatikhaki et al. (2022) had successfully applied AI BIM-based generative design model to improve the photovoltaic (PV) modules layout on a façade of high-rise buildings by increasing the energy yield and energy efficiency.

BIM is widely applied in construction industry especially major construction contractors involve in mega projects. However, full integration of AI and ML with BIM still remains the hindrance in practice. This is mainly caused by the interoperability and data exchange issue. There is various BIM software offered in the market, and they may have different data scheme and format which lead to difficulty in interoperate between contractors. To make best use of AI and ML in BIM during design stage, it requires consistent access to semantic and model design. BIM replies on custom scripts, third party plug-ins or manual data transfer rather than seamless end-to-end integration which limit the scalability and repeatability across projects (Semjén and János Szép, 2025).

Although there is a standard file format which allows model exchange, known as Industry Foundation Class (IFC), but it does not fully address the needs of complex design automation and analytic (Giovanni, 2025). This fragmentation and data format hinders the adoption of AI and ML applications workflows in the construction industry and often blame on the trading partner readiness and software compatibility.

2.3.3 AI and ML Application in Construction Stage

Construction stage is where the extensive physical work executed at site, and it is also the stage where project lifecycle undergoes most significant change. Looking at the current trend, Malaysia construction industry is using many kinds of machineries to get the job done during construction stage. However, those machineries still require human intervention and monitoring, rather than self-driven and some tasks are still relying on the labour manual.

The introduction of AI and ML technology have marked a significant milestone in construction industry, representing cutting-edge technologies. The innovations comprise robotic bricklaying, autonomous installation, printing technology tailored for foam concrete, automated spraying, structural analysis, etc. There are study shows that automation and robotic with AI and ML technologies could help to reduce construction cost by minimising labour involvement hour as the robot can work for nonstop without rest (Son et al., 2010).

The traditional methods are prone to human error, and it becomes a challenge when it requires interpreting design data. Sacks et al. (2020) had employed total station survey layout system driven by AI-programmed robot during construction set up and found out that it can help in minimizing the error in interpreting design data amidst empty land and help in marking on the site accurately. Besides, Aung et al. (2025) had deep learning based computer vision applied to monitor the structural damage and it is proven more accurate and after than manual inspection as the inspection heavily replies on knowledge and experience. This innovation can help to identify types of issues in a glimpse of second and might be able to identify defects that could not be easily seen by human eyes. It could also be providing suggestions to rectify the issues based on the site condition in the future.

Construction site safety can also be monitored by using deep learning and computer vision technologies. For example, safety monitoring systems have been designed to automatically recognise worker presence, unsafe postures (e.g., falls from height), and compliance with personal protective equipment protocols such as helmet and vest usage (Lee and Lee, 2023). These object recognition models help supervisors identify hazards as they arise, enabling real-time alerts and response actions that improve worker safety outcomes.

Despite there are many benefits of AI and ML application in construction stage, it requires purchase of various equipment and software to realise the benefits and fully deploy at site. These equipment and software often require huge investment and technical operate to achieve, which has always been a challenge to construction practitioners (Abioye et al., 2021).

2.3.4 AI and ML Application in Operation and Maintenance Stage

Collecting and manging the data from the equipment especially mechanical and electrical equipment is crucial in operation and maintenance stage. By collecting these data, AI and ML will analyse the real-time and provide signal of maintenance or error to maintain the best efficiency of the project. This also directly enables predictive maintenance, making sure the equipment is running in tip top condition as intended. Besides, AI and ML play a significant role in improving operational efficiency by supporting facilities management, supply chain coordination, real-time monitoring, energy simulation, and predictive maintenance management.

For example, Bouabdallaoui et al. (2021) had applied machine learning based predictive maintenance frameworks for heating, ventilation and air conditioning (HVAC) in a sport facility building, where internet of Things (IoT) sensors and building management interface collect data on temperatures, humidity, equipment cycles and performance metrics. The AI and ML model will be trained on the data collected to identify the patterns associated with equipment faults, assisting the facility managers to take proactive maintenance action rather relying on manual inspection on fixed schedule.

Some researchers have found that the AI and ML could help in improving resource allocation and reduce unnecessary maintenance task by focusing on actual system conditions rather than time-based maintenance (Adhikari, Karunaratne and Sumanarathna, 2025). This feature will help in saving manpower and time in maintenance, leading to lower operation cost as well. However, to achieve such robust predictive maintenance in real practice, it requires large and high-quality datasets for AI and ML model training which most of the organisation could not achieve (Adhikari, Karunaratne and Sumanarathna, 2025).

This is mainly due to the capability and lack of standardised data structure from the Building Management System (BMS) and Computerised Maintenance Management System (CMMS). In addition, low digital maturity of facilities management is also factor, where organisations do not have sufficient sensors to record the reading for accurate AI training (Adhikari, Karunaratne and Sumanarathna, 2025). Therefore, it has contextualised that organisation and technological factors are crucial determinants of successful adoption in the construction industry’s operation and maintenance stage, not just relying on the AI and ML capability only.

2.3.5 AI and ML Application in Demolition and Recovery Stage

Demolition and recovery are the stage where the structure or system will be demolished and rebuilding the item in order to meet the desired result or specification. This stage often associated with the most construction waste. Huang et al. (2011) highlighted that construction industry contributed total generated construction waste of approximately 35% among all the industries. The construction waste has associated with carbon emission and waste of cost as well.

There some studies had proven that AI and ML applications could facilitate in construction waste management while optimising the cost. Akanbi et al. (2020) had applied AI to estimate the waste to be produced during demolition based on BIM models. No doubts there are a lot of waste such as nail and screws will be left all over the site. This kind of waste can actually be recycled for other works instead of disposing. There is a study where AI is applied to facilitate the robot round in work in an unfamiliar place and to utilise the quicker R-CNN technique to detect leftover pins and screw in real time, enabling the robot to retrieve the leftover pins, nail or screws (Borja et al., 2012).

Besides, by integrating with AL and ML, the robot can efficiently sort out the construction debris which can be recycled for other purposes (Wang et al., 2020).

Unlike the construction phase, the demolition and recovery phase involves distinct processes and operational priorities within the building lifecycle. The application of AI and ML in this phase remains relatively underdeveloped compared to other stages, indicating a gap in both research and industry implementation. Therefore, there is significant potential to expand the use of AI and ML technologies in demolition and recovery activities.

2.4 Status of AI and ML Application in Malaysian Construction Industry

Construction industry is impactful to the global economy (Hashim, Shen and Barati, 2021). In Malaysia, the construction industry is rather significant contributor in terms of the Goods Domestic Products (GDP) growth and its ability to boost the production of other industries by fabricating various structures and equipment. Malaysian construction industry has grown 6% in 2025, worth RM58.8 billion and it is expected to have average growth rate of 4.4% between 2026 and 2029 (Research and Markets, 2025). Malaysia has the fastest pace in development in the world as the industry demand grows quickly (Ibrahim, Esa and A. Rahman, 2021).

To further accelerate Malaysia's journey towards becoming high-income nation or fit into first-world country, Malaysia government's Ministry of Works through CIDB introduced Construction 4.0 Strategic Plan (2021 – 2025) in 2016 as a blueprint for Malaysian construction practitioners to adopt 4IR in construction industry including AI and ML application. In Malaysia Budget 2020, total amount of 105 million USD was allocated by Malaysian government to aid small and medium enterprises (SMEs) in adopting the advanced technologies especially AI and ML application to improve project performance, reducing costs and delay (Tham and Atan, 2021). This initiative is meaningful as the SMEs often have financial difficulties as the advanced technologies and upgrade works needed are considered burden. To implement the AI and ML application effectively, technological proficiency and skilled labour in understanding AI and ML application in construction industry are relatively important. Malaysia government through Ministry of Human Resources and Human Resource Development Corporation (HRD Corp) are providing, training particularly in AI and ML application for all Malaysian (The Edge Malaysia, 2025). These trainings and education initiatives are crucial to foster a future-ready workforce to leverage AI and ML application in construction industry to further improve the project performance.

Although there are many initiatives taken by the government, only approximately 25% to 35% of Malaysian construction companies are using construction 4.0 technologies including AI and ML application in the operation and construction activities (Jaafar et al., 2024). Majority of the Malaysian construction companies are still construction 2.0 technologies (Jaafar et al., 2024). This data is indicating that Malaysian construction companies are resistant and hesitant to realign their goals towards advanced technologies adoption including AI and ML application. Mainly adopt manual labour or traditional methos in construction practices. This slow rate of adoption may result in lower productivity, constant material waste and safety risks which will significantly impact on the society and Malaysia economy (Kasim, Razali and Kasim, 2021).

2.5 Technological-Organisational-Environmental (TOE) Framework

Tornatzky and Fleischer (1990) developed TOE framework to explicit behavioural intentions and implementation of innovation at a firm level, not individual user acceptance. It focuses on three aspects of an organisation’s interconnected contexts which are technology context, organisational context and environmental context that will influence the process of technology adoption (Tornatzky & Fleischer, 1990).

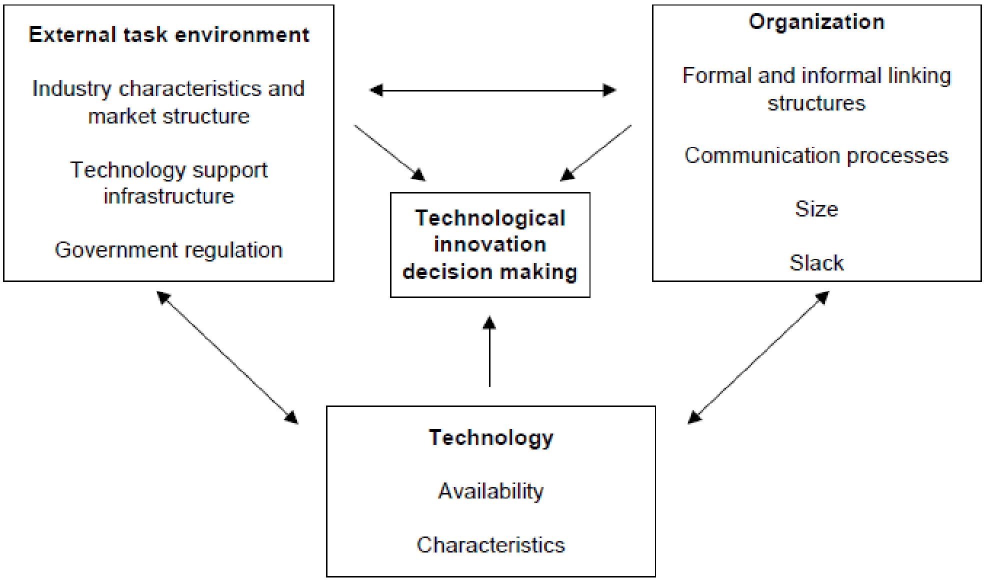

Figure 2.2: TOE framework (Tornatzky & Fleischer, 1990)

The technological context represents how an organisation evaluates and integrates new technologies based on its existing systems, capabilities, and perceived benefits. It can be understood by comparing the organisation existing Information Technology (IT) infrastructure with the characteristics of potential innovations. These characteristics include the relative advantages over existing solutions, compatibility with current system s, complexity and perceived benefits (Awa, Ojiabo and Orokor, 2017). The potential innovation, whether it will enhance or disrupt existing operations, and whether it will enhance the work efficiency or radical changes fall under this dimension. Ultimately, technological context reflects to the organisation's capability and needs in in assessing the potential benefits new technologies in the market may bring.

Organisational context is referring to the characteristics and arrangement of the firm. This includes the internal factory such as the communication process, linking structures between employee (eg: centralised vs. decentralised), firm size, resources and so on. The resources are the financial, competent persons, technological asset and so on. Besides, support from top management, organisation's commitment in innovation, organisation's overall innovation are also the key aspects of this dimension (Aboelmaged, 2014). Essentially, organisational context studies the organisation internal characteristic and capability in adopting potential technological innovations.

Environmental context encompasses the external factors that would affect the organisation decision in adopting new technologies (Lin and Chen, 2023). The external factors are skilled labour available, intensity of market competition, industry lifecycle, availability of service providers, government support and so on. The influence of market leader and government are playing significant role in influencing the adoption of new technologies in the industry. This dimension covers the how the external force and market condition drive both opportunities and constraints in innovation adoption by organisation.

TOE framework is often applied for IT adoption studies and assimilation of different types of IT innovation due to its solid theoretical basis, consistent empirical support and the potential of applications to IS innovation domains, though specific factors identified within the three contexts may be vary across different studies (Oliveria & Martins, 2011).

This framework is widely used in studies on adopting various technologies innovations until today. For instance, Khan et al. (2021) exploited TOE framework to study the organisation's behaviours in adoption and usage towards mobile payments and identify the importance of relative advantages, compatibility, top management support and competitive pressure on actual use across firms in China and Pakistan. However, the framework has lack of specific variables within each context and its focus on the adoption decision rather than the implementation process (Oliveira & Martins, 2011).

TOE framework rather can enable organisation to understand the factors that lead the organisation technology adoption decision through the technological, organisational and environmental contexts. Therefore, TOE framework is adopted in this research to posits an organisation's decision to adopt AI and ML applications in project lifecycle of construction industry in Klang Valley Malaysia to aid in escalating implementation process.

2.6 TOE Dimension in Malaysian Construction Industry

2.6.1 Technological Context

Despite Malaysia government's Ministry of Works through, CIDB implemented Construction 4.0 Strategic Plan (2021 – 2025) in 2016 as a blueprint for

Malaysian construction practitioners to respond to rapid changes of 4IR in construction industry which includes the AI and ML adoption acceleration, there is only around 30-40 percent of large and medium scale Malaysian construction firms have integrated AI technology into their workflow in 2025 (Erda, 2025). The adoption of advanced technologies is a complex process and requires a lot of efforts. This includes technical compatibility, limited attention, technical malfunctions and even misalignment with organisation processes which can affect the adoption timeline and results in inefficiencies (Demirkesen and Tezel, 2021).

AI and ML reliability in construction industry adds another layer of complexity to successful integration with the existing operation system. Malaysian construction industry may have different practices from other countries construction practices and there are not a lot of successful examples can be found in Malaysia. Construction practitioners often turn down advanced technologies due to high uncertainty of outcomes, and these technologies are relatively new in market with low testing and experimenting time (Smith, 2014). Within Klang Valley, major construction firms such as Gamuda Berhad and Sunway Construction Group has demonstrated in AI and ML application in their projects (Erda, 2025). However, 80-90% of the registered Malaysian construction practitioners are fall under small and medium category (DOSM, 2024). These organisations often have limited digital infrastructure and cost constraints. Therefore, many Malaysian construction practitioners especially small and medium scale organisation face hesitation to adopt AI and ML technologies and fear of changing to new method.

These factors of infrastructure compatibility, system readiness and the system reliability are considered in this research.

2.6.2 Organisational Context

Malaysia construction practitioners often operate in a centralised, hierarchical structure where the organisation innovation depends on the top management decision. Such structure may suppress the advanced technologies adoption if top management unwilling to explore latest innovation. (Siddiquee, 2005). Where frontline innovation implementation is driven by professional advocacy rather than mandate, bottom-up organisation structure can foster stronger commitment to AI and ML adoption in their operation.

Workforce readiness is also a challenge to AI and ML adoption in Malaysia construction industry. AI and ML implementation requires knowledgeable and competent persons to develop and manage AI and ML system in daily operation. Limited skilled labour to operate the system and retention issues are often the impedance to adopt AI and ML technology effectively (Tyagi, Aswathy and Abraham, 2020). Furthermore, every organisation has different risk appetite. This is due to the fact of light that adoption of new technologies like AI and ML may require huge investment, and the return may not happen in short period. Acquire and maintain such technology incurs significant cost and not every organisation could afford (Smith, 2014). The organisation scale also could be another factor that foster AI and ML adoption as the larger organisation are generally more likely to adopt innovation as technical personnel are important in AI and ML application.

These elements of leadership support, organisation readiness, absorptive capacity, workforce capacity and organisation scale are operationalised in this study for AI and ML adoption in Malaysia construction industry.

2.6.3 Environmental Context

While not mandated, AI and ML adoption in Malaysian construction industry is relatively slow. Only the major companies such as Gamuda Berhad and Sunway Construction Group are actively exploiting the benefits of these technologies (Erda, 2025). The benefits include improve efficiency in monitoring workers' compliance with safety, project management and cost optimisation. Leading countries in Asia such as Singapore is rapidly adopting AI and ML technology to improve the project performance. Singapore, through its Building and Construction Authority uses AI-powered drones for a building façade inspection, results in reducing inspection time from weeks to days and improving safety (Erda, 2025). To keep pace with the market competitiveness, Malaysian construction industry should be proactive in exploring the AI and ML application which can further the project performance in term of safety, schedule and planning.

Skilled labour in AI and ML application shortage is also a barrier to AI and ML adoption in Malaysian construction industry. 49% of Malaysian construction companies pointed out that digital expertise is needed to fully adopt the advanced technologies (Ismail, 2024). Therefore, upskilling and training initiative for the private sector and public sector are much needed to equip the worker with necessary skills in AI and ML application. Additionally, advanced technologies often require huge upfront investment and the senior management often see them as a burden and low return in investment. Advanced technologies such as AI and ML application often pose great threat when there is low knowledge of advanced technologies, low research investment and high cost of technologies implementation especially in small and medium enterprise (SME) (Costin and Teizer, 2015). To bridge the gaps to full potential of AI and ML application in Malaysia construction industry, government support is playing vital role in providing grants, incentives, subsidies and training to empower all construction practitioners to integrate AI and ML in their operation. These market demand, competitiveness pressure, government support and trade partner readiness are captured and measured in this study.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Design

This study adopts quantitative research design grounded in positivist paradigm to examine the factors for AI and ML application in construction industry in Klang Valley Malaysia as well as the perceived performance effects by the AI and ML application. A quantitative approach is considered appropriate as it enables the collection of measurable data and supports statistical analysis for identifying relationships among variables.

Descriptive analysis or mean ranking analysis is applied to evaluate the relative importance of the factor by examine the mean value and standard deviation of the factor and perceived performance effects of AI and ML application in construction industry in Klang Valley Malaysia. Besides, Principal Component Analysis (PCA) or factory is applied to test the hypothesised relationship among the technological, organisational and environmental constructs and their perceived performance effects. Factor analysis will help to investigate the underlying relationship between the factors identified. Based on the empirical findings, a conceptual framework for achieving improve construction industry project lifecycle success through AI and ML applications in the project lifecycle of the construction industry as influenced by technological, organisational and environmental dimensions.

3.2 Data Collection Method

Data collection used is done by random sampling across the Malaysian construction contractors, developers and consultants by utilising questionnaire survey created in Google Forms. Quantitative research technique is applied because it allows quantification and generalisation of the result.

The tool for data collection used in this research is closed-ended questions. Zohrabi (2013) stated that closed-ended questions help to get responses from large numbers of people and could reduce work in analysing and statistical data. Five-point Likert scale was used to measure the factor for AI and ML application in construction industry from respondents ranging from 1 to 5; 1 = strongly disagree, 2 = disagree, 3 = neither agree or disagree, 4 = agree and 5 = strongly agree.

The respondents are selected from CIDB professional construction directory 2023 and personal contact list. There are a lot of developers, contractors and consultants in Malaysia Klang Valley, ranging from Grade 1 to Garde 7 and only a portion of developers, contractors and consultants are recorded in the CIDB directory. Assuming the developers, contractors and consultants in Malaysia Klang Valley proportion is 0.5 and unlimited population size, minimum sample size required for this study can be calculated using Cochran's formula as indicated in with Equation (3.1 with 90% confident level and 5% margin of error.

$$n = \frac{z^2 X\, p(1-p)}{e^2} \tag{3.1}$$

Where:
n = Minimum sample size required
z = Z-score from confident level
e = Margin of error
p = population proportion

Thus, for this case, the sample size of at least 270.61 is necessary. To make it as whole number, minimum sample size of 271 is needed. It is important to note that Cochran's formula provided a useful estimation of minimum sample size required for this study, several other factors may influence the accuracy and representativeness of the resulting sample. These include the sampling method employed, the overall survey design, potential response bias. Therefore, these considerations should be taken into account when interpreting the findings.

It may be tough to obtain 271 respondents less than 2 months for this study. However, a total 480 electronic questionnaire survey were formally distributed to the Malaysian construction practitioners. Ultimately, 65 responses were collected, recording response rate at 13.54%. The low response rate is expected as there are some studies by Yap et al. (2021) and Yong and Mustaffa (2013) had response rate lower than 10% among Malaysian construction practitioners. This trend mainly attributes to heavy work commitment and general reluctance to participate in research activities (Yap et al. (2021). Therefore, the response rate over 10% captured in this research is deemed good. According to de Winter, Dodou and Wieringa (2009), minimum 50 sample size of 50 is acceptable for a large sample size in exploratory factor analysis. Besides, Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy shows the sampling size is sufficient for the factor analysis.

3.3 Measurement of Variables

The selection of constructs for the TOE frameworks was guided by three key considerations: theoretical relevance, empirical validation needs and contextual appropriateness for AI and ML application in Malaysian construction industry. Based on the extensive literature review, several constructs were identified and evaluated according to the dimensions of Technological-Organizational-Environmental (TOE) framework. These well-defined constructs (including internal and external) portray perspectives to clarify how to formulate AI and ML application in project lifecycle of the construction industry in Klang Vally Malaysia. Each construct was chosen based on its theoretical significance in AI and ML adoption theory, empirical support in related studies and specific relevance to the Malaysian construction context.

Before questionnaire survey is formally distributed, pilot survey was carried out with total 9 experienced professional (3 developers, 3 contractors and 3 consultants) to evaluate the variables, considering any factors could be added or deleted based on Malaysia construction industry trends. They also evaluate the questionnaire design flow to ensure the questionnaires are understandable and effective.

Following careful examination and discussion, final set of eighteen (18) proposed factors for AI and MI application in project lifecycle of construction industry in Klang Valley Malaysia were incorporated into the questionnaire design. Furthermore, the survey also evaluates construction industry project lifecycle success in term of time, cost, quality, safety and environmental performance through AI and ML application. The Questionnaire survey is presented in APPENDIX.

The overall research process for examining the factor for AI and ML applications in the project lifecycle of the construction industry in Klang Valley Malaysia is illustrated in Figure 3.1.

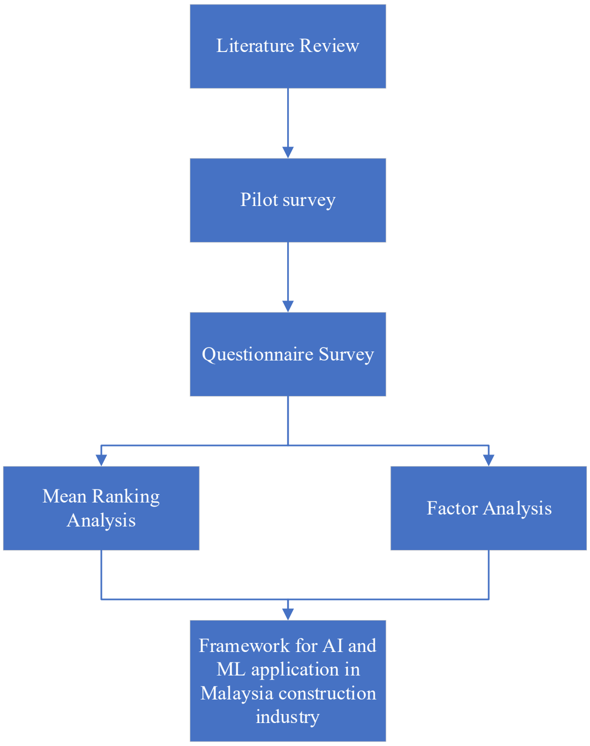

Figure 3.1: Research Framework

3.3.1 Technological Dimension

Technology dimension refers to the innovation of AI and ML application in Malaysian construction activities including the usefulness of the technologies to current operation or practices, compatibility with existing system, risk and its complexity. In the technology dimension of the questionnaire survey encompasses eight (8) variables as follow.

1) Perceived usefulness (F01)
2) Perceived ease of use (F02)
3) Technology optimism (F03)
4) Technological capability (F04)
5) Compatibility (F05)

6) Relative advantage (F06)
7) Trialability (F07)
8) Observability (F08)

These eight (8) variables reflect the multifaceted and complex of the AI and ML applications in Malaysian construction Industry in Klang Valley. This assessment is essential for the understanding the benefits perceived by Malaysian construction industry in Klang Valley and its adoption readiness. This extended approach which not only covers the innovative of the technologies and also ensures coverage of technological factors while maintaining theoretical coherence and consistence with the TOE framework on the technological evaluation in complex organisational contexts (Rakibul, 2024).

3.3.2 Organisational Dimension

Organisational dimension refers to the internal characteristics of the organisation which reflets the internal capability to adopt and implement AI and ML applications in construction operations including organisation size, resources availability and management supportiveness. In the organisational dimension of the questionnaire survey encompasses six (6) variables as follow.

1) Organisational Scale (F09)
2) Organisational readiness (F10)
3) Absorptive Capacity (F11)
4) Top management support (F12)
5) Human Resources (F13)
6) Managerial support (F14)

These six (6) variables enable the comprehensive assessment of organisational readiness while maintaining theoretical parsimony and statistical manageability emphasised in TOE framework on the organisational construct measurement.

3.3.3 Environmental Dimension

Environmental dimension refers to the external pressure to push AI and ML adoption in Malaysian construction industry in Klang Valley including market pressure, support from government and partners readiness. In environmental dimension of the questionnaire survey encompasses four (4) variables as follow.

1) Market demand (F15)
2) Competitive pressure (F16)
3) Government support (F17)
4) Trading partner readiness (F18)

These four (4) variables reflect on multiple environmental pressure while maintaining focus on the environmental factors that will directly influence on AI and ML adoption in Malaysian construction industry in Klang Valley. This measurement enables comprehensive environmental assessment emphasised in the TOE framework.

3.3.4 Perceived Performance Effects

Perceived performance effects refer to expected improvements in Malaysian construction industry in Klang Valley through the AI and ML adoption. The performance effects evaluated based on the key project management dimensions, namely time, cost and quality performance which are the fundamental definition to the successful project management. In addition, environmental performance as well as health and safety performance are also considered as they are critical indicators of sustainable and effective construction project management. In perceived performance effects of the questionnaire survey encompasses five (5) variables as follow.

1) Improved Time Performance
2) Improved Cost Performance
3) Improved Quality Performance
4) Improved Health and Safety Performance
5) Improved Environmental Performance

These five (5) variables enable the comprehensive assessment of perceived performance effects of the AI and ML adoption in Malaysian construction industry in Klang Valley.

3.4 Data Analysis Techniques

Statistical tests ought to be carried out for further analysis by treating the survey data as a whole (Wang and Yuan, 2010). In this research, reliability test will be carried out prior any further analysis. Mean ranking method and factor analysis are used to analyse the factor for AI and ML application in project lifecycle of construction industry in Klang Valley Malaysia. For ease of analysis, IBM Statistical Package for Social Package (SPSS) 27 is utilised for the analysis.

3.4.1 Reliability Test

To ensure all the data collected are trustable for further analysis, reliability test shall be done prior. Reliability refers to consistency or precision of measurement that will improve as the obtained value increases which is known as internal consistency coefficient (Rosaroso, 2015). In statistic study, this internal consistence coefficient that shows how close the sets of items are related as a group is also known as Cronbach's Alpha. It is often used to assess validity and reliability of psychrometric tests for a group of respondents and provide an estimate of their reliability for the subject (Rosaroso, 2015). According to the criteria proposed by George and Mallery (2024), the Gronbach Alpha formula values are categorised as shown in Table 3.1. Therefore, the reliability coefficient shall be 0.7 or higher to be acceptable. Cronbach's alpha is determined the number of questions and the average inter-correlation among the questions as indicated in Equation (3.2.

$$\alpha = \frac{N\,c}{v + (N-1)c} \tag{3.2}$$

Where:

α = Cronbach's Alpha

N = Number of questions

c = average inter-item covariance among the questions

v = average variance

Table 3.1: Gronbach's Alpha's Value Category

Gronbach’s Alpha Value, α	Category
α≥0.9	Excellent
0.8≤α<0.9	Good
0.7≤α<0.8	Acceptable
0.6≤α<0.7	Questionable
0.5≤α<0.6	Poor
A<0.5	Unacceptable

3.4.2 Mean Ranking Analysis

Statistical tests ought to be carried out for further analysis by treating the survey data as a whole (Wang and Yuan, 2010). In this research, mean ranking method and factor analysis were used to analyse the factor for AI and ML application in project lifecycle of construction industry in Klang Valley Malaysia. For ease of analysis, IBM Statistical Package for Social Package (SPSS) 27 is utilised for the analysis.

Mean ranking method is a simple and effective method to identify the relative importance of the factor by calculating the mean value and standard deviation of the factor. Any mean score value that is more than three (3) deemed to be insignificant for the study as it falls below the neutral rating, while the mean score is above 3 are worth highlighted as critical factor for AI and ML applications in project lifecycle of construction industry in Klang Valley Malaysia. As for standard deviation value, the value less than 1.0 indicates the consistency in agreement among respondents on the factor (Field, 2005). If two factors have the same mean value, the lower standard deviation should be treated as more important than the other as standard deviation is a measure of variation of the value of the factor about the mean value.

3.4.3 Factor Analysis

Factor analysis is used to investigate the underlying relationship between the factors identified. It is almost similar to principal component analysis, but it uses correlations matrix that produce eigenvalues and eigenvectors (Robert and Gillen, 2020). Owusu and Badu (2009) highlighted that factor analysis is best the method to reduce the large number of variable and group related variables into one component. It applies statistical procedures to identify the underlying dimensions that explain relationships between multiple variables to provide evidence for the construct validity of the measure (Tavakol and Wetzel, 2020).

There are two types of factor analysis which are exploratory factory analysis and confirmatory factor analysis. They serve different purpose in statistical studies. Exploratory factor analysis is specifically used to study the correlation between the item and latent variables that cannot be assessed directly which are known unmeasurable data (Tavakol and Wetzel, 2020). It often provides two constructs which are factors related to professionalism and factor related to leadership (Tavakol and Wetzel, 2020). This analysis is often used to study the relationship of behaviour, attitude and depositions of the interest construct. On the other hand, confirmatory factor analysis is a model-driven approach that tests how well the observed variable "fit" to proposed model or theory. It applies the statistical procedures to evaluate the internal structure of instruments. Maximum likelihood estimation is usually applied in the analysis and follow a distinct set of criteria to determine whether the construct measured is appropriate (Tabachnick and Fidell, 2013). Maximum likelihood estimation is a statistical method used to identify the best-fit parameters (such as mean or variance in normal distribution) by selecting the values that make the observed data most probable (Tabachnick and Fidell, 2013).

In this research, exploratory factor analysis is applied as the research aims to identify the theoretical constructs connections between underlying TOE frameworks dimensions of the factors of AI and ML applications in project lifecycle of construction industry in Klang Valley Malaysia. The factors provided in the survey questionnaire are latent as the factors of AI and ML application in Malaysia construction industry in Klang Valley cannot be measured. The factor loadings will be computed for every factor to define how good the correlation between the item and the factors. Factor loading of more than 0.30 is showing a moderate correlation between the item and the factors (Tavakol and Wetzel, 2020). The related factors will be grouped into several components. These components are identified as a critical variable to drive the AI and ML applications in project lifecycle of construction industry in Klang Valley as shown in Figure 3.2.

Figure 3.2: Factor Analysis Flows

Before to proceed factor analysis, the data obtained should be assessed to determine how well the data can be fit for exploratory factor analysis. The assessment will be done by Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity. KMO value indicates the sampling adequacy for each variable in the model. The higher the KMO values, the more suitable the data for factor analysis. Field (2000) pointed out that the data is sufficient for factor analysis if the value of KMO is higher than 0.50 and for KMO $\leq$0.50, the data cannot be accepted for factor analysis as the correlation matrix becomes too dispersed. The KMO can be calculated through the Equation (3.3.

$$KMO = \frac{\sum r^2}{\sum r^2 + \sum q^2} \tag{3.3}$$

Where:
r = correlation matrix
q = Partial correlation matrix

On the other hand, Bartlett's test of sphericity is also used to test appropriateness of exploratory factor analysis by examining whether the correlation matrix is significantly different from an identity matrix (Tobias and Carlson, 1969). An identity matrix is a matrix in which all of the values along the diagonal are 1 and all of the other values are 0. Significant level is used to indicate whether the corelation matrix is an identity matrix or the variables are significant correlated to each other. The significant level is assumed at 0.05. If the significant level is lower than 0.05, the variables are assumed not orthogonal in the correlation matrix (Tobias and Carlson, 1969). Therefore, the test is said to be significant and suitable for exploratory factor analysis. This significant level can be computed by the Equation (3.4.

$$T = -\left(N - 1 - \frac{2p + 5}{6}\right) \log_e |R| \tag{3.4}$$

Where:
n = sample size
p = number of variables
$|R|$ = determinant of the sample correlation matrix

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Respondents' Profile

Among the respondents, 49.2% are contractors, 30.8% are consultants and 20.0% are developer. From this data, it is noted that the survey has received responses from different types of organisations.

Table 4.1: Type of Organisation Response Percentage

Type of Organisation	Frequency	Percent	Valid Percent	Cumulative Percent
Developer	13	20.0	20.0	20.0
Consultant	20	30.8	30.8	50.8
Contractor	32	49.2	49.2	100.0
Total	65	100.0	100.0	

As for the category of work as shown in Table 4.2, 76.9% of the respondents are under building work category and only 23.1% of respondents are under non-building work category. This data is showing that most of them are from buildings works, not just supplier or vendor. While for the position in firm as shown in Table 4.3, 24.6% of respondents are under lower management which could be engineers, supervisors, coordinator, etc. 50.8% of respondents are under middle management which represents the project manager, construction manager, manger, etc. The last 24.6% of respondents are under higher management which represents the general manager, project director, head of department, etc. Besides, referring to Table 4.4, 76.9% of respondents have 5 years and above in working experience in the construction industry, and only 23.1% of respondents have less than 5 years of experience. Hence, the data reliability and quality are proved as the respondents are from all levels of management and mostly are in building works and have 5 years and above working experience in construction industry.

Table 4.2: Category of Work Response Percentage

Category of Work	Frequency	Percent	Valid Percent	Cumulative Percent
Building	50	76.9	76.9	76.9
Non-building	15	23.1	23.1	100.0
Total	65	100.0	100.0	

Table 4.3: Position in the Firm Response Percentage

Position in the Firm	Frequency	Percent	Valid Percent	Cumulative Percent
Lower Management	16	24.6	24.6	24.6
Middle Management	33	50.8	50.8	75.4
Upper Management	16	24.6	24.6	100.0
Total	65	100.0	100.0	

Table 4.4: Year of Working Experience Response Percentage

Year of Working Experience	Frequency	Percent	Valid Percent	Cumulative Percent
Less than 5 years	15	23.1	23.1	23.1
5 years and above	50	76.9	76.9	100.0
Total	65	100.0	100.0	

4.2 Reliability Test

IBM Statistical Package for Social Package (SPSS) 27 is used to calculate the Cronbach's Alpha value. The sample of sixty-five (65) respondents are 100% valid, resulting in no responses are excluded. The obtained Cronbach's Alpha value is 0.957 which indicates the data obtained is highly reliable for further analysis. The overall reliability test can be referred to the Table 4.5 and Table 4.6.

Table 4.5: Case Process Summary for Reliability Test

Case Process Summary

		N	%
Cases	Valid	65	100.0
	Excluded	0	0.0
	Total	65	100.0

Table 4.6: Reliability Statistics

Reliability Statistics

N of items	Cronbach's Alpha
23	0.957

4.3 Factors for AI and ML Application in the Project Lifecycle of Construction Industry in Klang Valley Malaysia

A Google Form survey was formally distributed to the professionals involved in construction industry in Klang Valley Malaysia. They survey adopted Five-point Likert scale to measure the TOE- based factors of AI and ML application in project lifecycle of construction industry in Klang Valley Malaysia. They survey comprises few sections which are:

1) Technological factors of AI and ML applications in project lifecycle of construction industry in Klang Valley Malaysia.
2) Organisational factors of AI and ML applications in project lifecycle of construction industry in Klang Valley Malaysia.
3) Environmental factors of AI and ML applications in project lifecycle of construction industry in Klang Valley Malaysia.

The findings provide insight into the respondents' demographics factor of AI and ML adoption in project lifecycle of construction industry in Klang Valley Malaysia.

4.3.1 Mean Ranking Analysis

Mean ranking analysis is adopted to identify the critical factors for AI and ML application in the project lifecycle of the construction industry in Malaysia, Klang Valley. The mean ranking analysis was done with IBM SSPS 27 and the result of the mean ranking is shown in Table 4.7.

The result shows that all the factors mean value has a range from 3.4615 to 4.0769 which is implying all the factors in the survey is critical for AI and ML application in the project lifecycle of the construction industry in Klang Valley Malaysia. It is worth highlighting that 4 out of 18 factors have mean value of higher than 4.0000 which are relative advantage, trialability, observability and perceived usefulness. These factors are related to technological innovation instead of purely organisational or external pressure. This is clearly shown that the adoption of AI and ML application in Klang Valley construction industry is driven by perceived technological value, which aligns closely with the Construction 4.0 Strategic Plan under CIDB to modernise the construction sector through digitalisation, automation and integration of advanced technologies.

The highest-ranked factor, relative advantage, indicates that Malaysia construction industry is more inclined to adopt AI and ML when clear benefits are perceived in their daily operation such as improved efficiency, cost reduction, manpower reduction and enhanced decision making. This result aligns with Diffusion of Innovation theory, which posits the perceived benefits are the most significant determinant of innovation adoption (Rogers, 2003).

Closely following, the high ranking of trialability and observability supports the importance of experimental learning and visible outcomes in influencing adoption decisions. The ability to carry out experiment with AI and ML application in real practice is very important as any project failure will results in significant financial implications. Construction industry is governed by limited time to complete the project, and the construction practitioners need to compensate liquidated damage to the client if the project is delivered later than stipulated date. Therefore, the uncertainty and perceived risk should be identified before application. In fact, the technology can be applied in a variety of ways by testing the relative importance of each characteristic on nonsignificant task to stimulate the technology (Outcault et al., 2022). Similarly, observability allows organisations to witness successful implementations, thereby boosting confidence in the AI and ML application. These findings highlight the importance of demonstrable results and pilot testing in accelerating advanced technologies acceleration (Venkatesh et al., 2003).

The 4th ranked factor, perceived usefulness, further supports the relevance of Technology Acceptance Model, which suggests that users' belief in the performance-enhancing capabilities of a technology significantly influences their intention to adopt it (Davis, 1989). Interestingly, perceived ease of use, ranks considerably lower (rank 14), implying that construction practitioners in Klang Valley are willing to tolerate complexity as long as the technology delivers substantial benefits. This finding contrasts with traditional IT adoption studies but is increasingly observed in advanced technology contexts where functionality outweighs usability concerns.

Technological capability (rank 5) is relatively important but not the dominant factor to AI and ML adoption in Malaysia construction industry. This shows that organisations recognise the importance of having adequate technical resources, they may not view it as a main trigger in AI and ML adoption. Instead, organisations value the perceived benefits of AI and ML application more as reflected by the highest ranking of relative advantages.

Organisational-related factors such as organisational scale (rank 7), managerial support (rank 8), and top management support (rank 9) demonstrate moderate importance. There are some studies suggested that larger organisational scale tend to have greater differentiation, greater formalisation, more decentralization managerial decision-making authority, greater task specialisation and more complex form of communication which will influence the organisation innovation adoption (Lee & Xia, 2006). However, this study found that these elements are necessary to facilitate implementation, but they are not the primary drivers of adoption. This suggests that even if organisations possess the required infrastructure and leadership support, adoption may not occur unless the perceived value of AI and ML technologies is clearly established. Additionally, human resources (rank 11) indicates that skill availability remains a concern, reflecting the industry's ongoing struggle with digital competencies.

External environment factors, including government support (rank 6) and market demand (rank 13), also show moderate influence. The relatively high ranking of government support reflects the impact of national initiatives such as Malaysia’s Construction 4.0 agenda, which aims to promote digital transformation within the sector. However, the lower ranking of competitive pressure (rank 15) suggests that AI and ML adoption is not yet driven by industry rivalry but rather by internal strategic considerations and the value of the AI and ML application could bring to the project. This indicates that the construction industry in Klang Valley is still in the early to intermediate stage of digital transformation, where adoption is voluntary rather than mandatory.

The lowest-ranked factors, organisational readiness (rank 17) and absorptive capacity (rank 18), reveal potential structural and capability-related limitations. Absorptive capacity, which refers to an organisation’s ability to recognise, assimilate, and apply new knowledge, is critical for the successful implementation of advanced technologies. Its low ranking suggests that many firms may lack the necessary learning mechanisms and knowledge integration processes to fully leverage AI/ML. This could hinder long-term adoption and reduce the overall effectiveness of digital transformation efforts.

In terms of variability, the standard deviation values (ranging from 0.8655 to 1.0858) indicate a moderate level of agreement among respondents. Factors such as trialability show relatively low variation, suggesting consensus on their importance, whereas factors like top management support and government support exhibit higher variability, reflecting differing organisational contexts and experiences across respondents.

Overall, the findings suggest that AI and ML adoption in the Klang Valley construction industry is predominantly driven by perceived technological benefits and the ability to experiment and observe outcomes, rather than by external pressures or internal readiness alone. This highlights the need for stakeholders to prioritise demonstration projects, pilot implementations, and clear value propositions to accelerate adoption. Furthermore, efforts should be made to enhance organisational learning capabilities and workforce skills to ensure sustainable integration of AI and ML technologies.

Table 4.7: Mean ranking of factor for AI and ML application in the project lifecycle of the construction industry in Klang Valley Malaysia.

	Factors	Mean	Standard Deviation	Mean Rank
F06:	Relative Advantage	4.0769	0.9067	1
F07:	Trialability	4.0308	0.8655	2
F08:	Observability	4.0154	0.8925	3
F01:	Perceived Usefulness	4.0154	0.9436	4
F04:	Technological Capability	3.9231	0.9067	5
F17:	Government Support	3.9231	1.0798	6
F09:	Organisational Scale	3.9077	0.9308	7
F14:	Managerial Support	3.9077	1.0713	8
F12:	Top Management Support	3.9077	1.0858	9
F03:	Technology Optimism	3.8615	0.8817	10
F13:	Human Resources	3.8462	1.0343	11
F05:	Compatibility	3.8154	0.9167	12
F15:	Market Demand	3.8154	1.0737	13
F02:	Perceived Ease of Use	3.7538	1.0005	14
F16:	Competitive Pressure	3.6923	1.0447	15
F18:	Trading Partner Readiness	3.6615	0.9400	16
F10:	Organisational Readiness	3.5846	0.9825	17
F11:	Absorptive Capacity	3.4615	0.9532	18

4.3.2 Factor Analysis

The data collected for 18 factors for AI and ML application in project lifecycle of construction industry in Klang Valley Malaysia were transfer to IBM SPSS 27 for factor analysis. As discussed earlier, the data were validated through two statistical tests namely Kaiser-Meyer-Olkin Measure and Bartlett's test of sphericity to ensure they are appropriate for factor analysis. In this research, the KMO obtained is 0.876 which indicates the data is sufficient for study. While for the Bartlett's test of sphericity, the chi-square ($\chi2$) obtained 928.135, with significant value of <0.001, indicating that null hypothesis of the corelation matrix is being identical is rejected. Therefore, the data obtained is suitable for factor analysis.

Table 4.8: Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity Result for the factors of AI and ML application in project lifecycle of construction industry in Klang Valley Malaysia.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.876
Bartlett's Test of Sphericity	Approx. Chi-Square ($\chi2$)	928.135
	Degree of Freedom (df)	153
	Significant level (Sig.)	0.000

Next, referring to the Table 4.9 which is generated by IBM SPSS 27, three (3) components were extracted with eigenvalue greater than 1.0 through varimax rotation of principal component analysis. Each factor belongs to only to one component with loading value on each factor more than 0.30. The total cumulative variance explained by the five components is at 71.483%.

Table 4.9: Total variance explained for factors of AI and ML application in project lifecycle of construction industry in Klang Valley Malaysia.

Factors	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	9.825	54.581	54.581
2	2.035	11.313	65.894
3	1.006	5.589	71.483
4	0.714	3.967	75.450
5	0.662	3.679	79.129
6	0.579	3.214	82.343
7	0.527	2.930	85.274
8	0.473	2.630	87.903
9	0.383	2.128	90.032
10	0.366	2.035	92.066

Factors	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
11	0.315	1.748	93.814
12	0.249	1.381	95.195
13	0.218	1.210	96.405
14	0.182	1.009	97.414
15	0.170	0.945	98.360
16	0.122	0.677	99.037
17	0.105	0.583	99.620
18	0.068	0.380	100.00

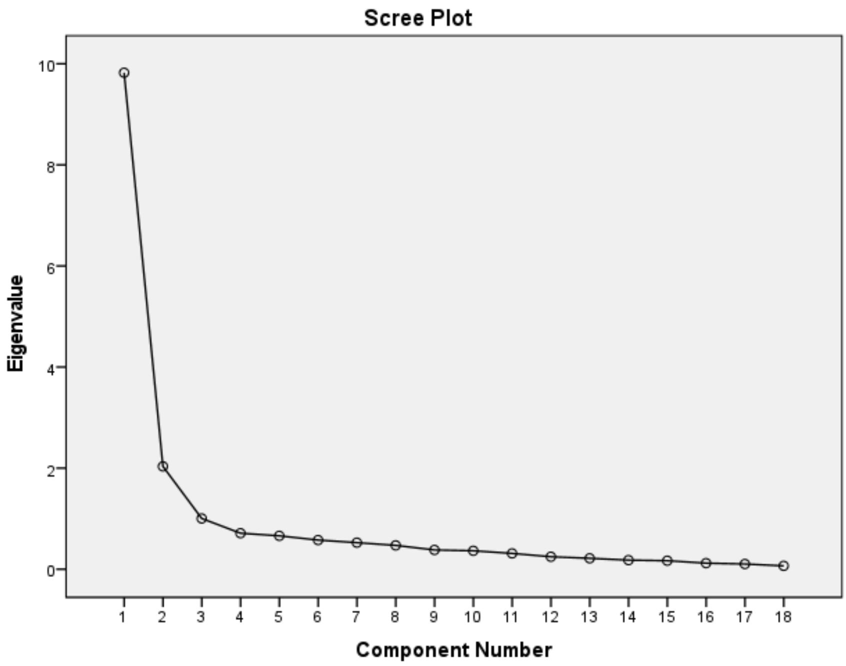

Figure 4.1: Eigenvalue Scree Plot for factors of AI and ML application in project lifecycle of construction industry in Klang Valley Malaysia.

Furthermore, varimax method which is part of orthogonal rotation in exploratory factor analysis is adopted for factors that correlated among each other and to provide a realistic structure where there underlying dimensions are related (Brown, 2009). Each of the eighteen (18) critical factors belong to only one of the three (3) factors with factor loading value exceeding 0.5. The factors rotation among the three (3) factors that were selected from Table 4.9 is shown in Table 4.10.

Table 4.10: Rotated component matrix of factors for AI and ML application in project lifecycle of the construction industry in Klang Valley Malaysia.

Factors		Component		
		1	2	3
F03:	Technology Optimism	0.785		
F06:	Relative Advantage	0.777		
F05:	Compatibility	0.757		
F04:	Technological Capability	0.752		
F08:	Observability	0.749		
F07:	Trialability	0.745		
F02:	Perceived Ease of Use	0.693		
F01:	Perceived Usefulness	0.675		
F12:	Top Management Support		0.882	
F14:	Managerial Support		0.849	
F13:	Human Resources		0.820	
F10:	Organisational Readiness		0.781	
F18:	Trading Partner Readiness		0.706	
F17:	Government Support		0.703	
F11:	Absorptive Capacity		0.624	
F09:	Organisational Scale		0.494	
F16:	Competitive Pressure			0.837
F15:	Market Demand			0.719

The factors categorised in a component serves as a foundation for naming the components with consideration of the item dimensions (Abdi and Williams, 2010). The first component has factors such as technology optimism, relative advantages, compatibility, technological capabilities, observability, trialability, perceived ease of use and perceived usefulness which are related to technological dimension. Therefore, the first component is be named as "Technological factors".

The second component comprises factors such as top management support, managerial support, human resources, organisational readiness, trading partner readiness, government support, absorptive capacity and organisational readiness. These factors are related to organisational dimensions and external forces. Therefore, the second component is named as “Organisational and Ecosystem Supports”.

As for the third component, it has only two factors which are competitive pressure and market demand. These factors are related to environmental dimension. Thus, the third component is named as “Market Requirements”. The summary of the components name is shown in the table

Table 4.11: Naming for each component for factors of AI and ML application in project lifecycle of construction industry in Klang Valley Malaysia

Component	Component’s Name
1	Technological Factors
2	Organisational and Ecosystem Supports
3	Market Requirements

4.3.2.1 Component 1: Technological Factors

The dominance of component 1, technological factors include technology optimism, relative advantages, compatibility, technological capabilities, observability, trialability, perceived ease of use and perceived usefulness which are technology-related perceptions and characteristics.

This component reflects how organisations evaluate the benefits of AI and ML adoption based on expected performance outcomes, ease of integration, and experiential interaction with the technology. Among these variables, relative advantage and technology optimism demonstrate particularly strong influence, suggesting that firms are not only motivated by tangible benefits but also by a broader positive attitude towards technological innovation. This implies that adoption decisions are shaped by both rational evaluation such as efficiency to be improved and cognitive perception such as belief in technological progress.

The strong presence of compatibility further indicates that organisations prioritise technologies that can be integrated with existing workflows, systems, and industry practices, such as Building Information Modelling (BIM) and other digital platforms. This is especially critical in construction, where fragmented processes and legacy systems often pose barriers to digital transformation. Hence, even if AI and ML technologies offer substantial benefits, adoption may be constrained if they are not aligned with current operational structures.

Additionally, trialability and observability highlight the importance of learning-by-doing and evidence-based validation in reducing uncertainty. The ability to test AI and ML applications on pilot projects allows organisations to evaluate risks and performance before committing to full-scale implementation. Similarly, observability enables firms to learn from successful case studies and industry best practices. This is particularly relevant in the construction sector, where risk aversion is high due to the financial and operational complexity of projects.

These findings strongly support the Diffusion of Innovation Theory, which emphasises that innovation adoption is significantly influenced by attributes such as relative advantage, compatibility, trialability, and observability (Rogers, 2003). At the same time, the inclusion of perceived usefulness and perceived ease of use aligns with the Technology Acceptance Model, which posits that user perceptions of performance enhancement and system usability determine adoption behaviour (Davis, 1989).

However, an important nuance emerges in this study: while perceived usefulness shows strong loading, perceived ease of use is comparatively less influential in the overall ranking. This suggests a shift from traditional IT adoption patterns towards a performance-oriented adoption logic, where organisations prioritise outcome-driven benefits over operational simplicity. Such a trend has been observed in recent studies on advanced digital technologies, where complexity is often accepted as a trade-off for higher capability and functionality (Oesterreich & Teuteberg, 2016).

From a critical perspective, the dominance of technological factors indicates that AI and ML adoption in the Klang Valley construction industry is still largely technology-value driven, rather than being fully integrated into organisational strategy or market competition. While this highlights strong awareness of technological benefits, it may also suggest an over-reliance on perceived value without sufficient consideration of implementation challenges, such as organisational readiness and skill availability.

Furthermore, the clustering of both cognitive and functional variables within the same component suggests that perception and capability are not entirely distinct in practice but rather interact dynamically in shaping adoption decisions. This reinforces the idea that successful AI and ML implementation in Klang Valley construction industry requires not only technical feasibility but also positive organisational mindset and cultural readiness towards innovation.

In the context of Malaysia's construction industry, this finding suggests that AI and ML adoption is currently in a transitional and exploratory phase, where interest and perceived value are high, but practical implementation maturity is still developing. While this aligns with national initiatives promoting digital transformation, it also highlights the need for stronger emphasis on capability development, system integration, and user training to ensure that technological adoption translates into actual performance improvements.

4.3.2.2 Component 2: Organisational and Ecosystem Supports

Component 2, Organisational and Ecosystem Supports, encompasses factors such as top management support, managerial support, human resources, organisational readiness, government support, trading partner readiness, organisational scale, and absorptive capacity. The strong factor loadings particularly for top management support at 0.882, managerial support at 0.849 and human resource at 0.820 instituting that these factors collectively represent an impactful motivation for the successful implementation of AI and ML technologies in Klang Valley construction industry.

At its core, this component reflects the structural, and relational capacity of organisations to translate technological intent into operational reality. Unlike Component 1 which captures the pushing forces for organisation to adopt AI and ML application in construction industry. Component 2 explains whether and how they are capable of doing so.

The prominence of leadership-related factors (top management support and managerial support) highlights the critical role of strategic direction and organisational commitment in digital transformation. Strong top management support is often associated with resource allocation, policy formulation, and the creation of innovation culture. This is consistent with prior research, which emphasises that leadership commitment is a key determinant of successful technology adoption, particularly in complex and high-risk environments such as construction (Rinchen, Banihashemi and Alkilani, 2024). However, the findings of this study suggest an important nuance, leadership is statistically significant, it does not rank among the top drivers in the descriptive analysis. This implies that leadership may be necessary but not sufficient, functioning more as an enabler than a trigger of adoption.

Human resources and organisational readiness further highlight the importance of internal capability development, particularly in terms of digital skills, technical expertise, and organisational processes. AI and ML adoption requires not only IT infrastructure but also personnel capable of interpreting data, managing algorithms, and integrating insights into decision-making processes. However, their moderate-to-low ranking suggests that many organisations may still be in the early stages of developing such competencies. This reflects a broader industry issue, where digital skill shortages and resistance to change hinder the adoption of advanced technologies.

A particular factor within this component, absorptive capacity, which refers to an organisation's ability to recognise, assimilate, and apply new knowledge. The concept, introduced by Wesley M. Cohen and Daniel A. Levinthal (1990), is widely regarded as essential for innovation success. In this study, although absorptive capacity loads significantly within the component, it ranks lowest in the descriptive analysis. This discrepancy reveals a critical structural weakness. Organisations may be aware of AI and ML technologies in construction industry but lack the learning mechanisms and knowledge integration processes required to effectively implement them.

This gap suggests that adoption is currently knowledge-constrained rather than technology-constrained. In other words, the limitation is not the availability of AI and ML application, but the organisation's ability to understand, adapt, and utilise them. Without sufficient absorptive capacity, the organisations could not exploit the AI and ML application effectively and would not fully leverage the perceived benefits. This will result in limited performance improvement and significant impact to the project success.

The presence of government support and trading partner readiness extend this component beyond internal factors to include the broader ecosystem context. Government initiatives, particularly led by Construction Industry Development Board (CIDB), is playing a crucial role in promoting digital transformation through policies, incentives, and infrastructure development. Government incentives and providing free workshop to training the staffs are the most strategies way to drive the digital transformation in construction industry (Hwang et al., 2021). Similarly, readiness among trading partners is essential in a highly interconnected industry like construction, where project success depends on multi-stakeholder collaboration. The AI and ML adoption would be accelerated when everyone in the construction industry is ready to implement and exploit it effectively.

However, the moderate influence of these ecosystem factors suggests that external support mechanisms are not yet fully effective in driving adoption. This may indicate a misalignment between policy initiatives and industry needs, where programmes exist but are either underutilised or insufficiently tailored to organisational realities, especially for small and medium-sized enterprises (SMEs).

Another important dimension within this component is organisational scale, which reflects the size and resource capacity of firms has the lowest loading factor at 0.494. There are some studies suggested that larger organisational scale tend to have greater differentiation, greater formalisation, more decentralization managerial decision-making authority, greater task specialisation and more complex form of communication which will influence the organization innovation adoption (Lee & Xia, 2006). However, its relatively lower loading compared to leadership and external factors suggests that scale alone does not guarantee readiness, reinforcing the idea that strategic intent and capability development are more critical than organisational size. This is due to the fact that some tasks could be simplified when the AI and ML applications are properly utilised.

The contrast between the strong statistical grouping of these variables and their lower mean rankings highlights a significant paradox. While these factors are structurally essential for adoption, they are not perceived as immediate priorities by respondents. This indicates a reactive rather than proactive approach to digital transformation, where organisations focus first on technological benefits and only later address organisational readiness.

From a broader perspective, this component reveals that AI and ML adoption in the Klang Valley construction industry is constrained by a capability maturity gap. While there is growing awareness and interest in digital technologies, the supporting organisational structures, skills, and ecosystems are not yet sufficiently developed to sustain widespread adoption.

4.3.2.3 Component 3: Market Requirements

Component 3, labelled as Market Requirement, comprises Competitive Pressure and Market Demand, representing the external forces that typically drive innovation adoption through industry dynamics and client expectations. Both variables exhibit strong factor loadings at 0.837 and 0.719 respectively, indicating that they form a statistically coherent construct. However, their relatively low mean rankings in the descriptive analysis reveal a critical insight, while market forces are conceptually important, they are not yet practically influential in driving AI and ML adoption within the Klang Valley construction industry.

This finding presents a notable divergence from established literature, particularly studies conducted in more technologically mature markets, where competitive pressure is often a primary catalyst for innovation. For instance, research on digital transformation highlights that organisations frequently adopt advanced technologies to maintain competitiveness, respond to industry disruption, and meet evolving customer expectations (Piepponen et al., 2022). In such contexts, innovation becomes a strategic necessity rather than a discretionary choice.

Current findings found that the Malaysian construction industry is still operating in a low competition digital environment, where the adoption of AI and ML application is not yet perceived as essential for survival or differentiation in the market. This implies that organisations are not experiencing any significant pressure from competitors or clients to digitalise their operations. Instead, adoption decisions appear to be driven more by internal motivations or perceived benefits and policy encouragement, rather than external compulsion.

The relatively low influence of market demand further reinforces this observation. In theory, increasing client expectations such as demands for faster project delivery, cost efficiency, and better quality should act as a strong catalyst for adopting AI and ML technologies. However, the findings indicate that such demand is either not sufficiently developed or not explicitly articulated within the market. This may be attributed to the traditional nature of the construction sector, where clients often prioritise cost and time over technological sophistication, thereby limiting the incentive for Malaysian construction practitioners to innovate. This is due to the fact that adopting such technologies may incur significant cost especially SMEs and the return may not happen in short period (Smith, 2014)

From a critical perspective, this situation suggests a demand and supply misalignment in digital transformation. While AI and ML applications are increasingly available and promoted at the policy level, the market itself has not yet fully internalised their value. As a result, there is limited pressure on organisations to adopt these technologies, leading to a slower and more uneven diffusion process in Malaysia Klang Valley construction industry.

Moreover, the strong factor loading of competitive pressure despite its low mean ranking indicates that respondents conceptually recognise its importance but do not yet experience it in practice. This reflects a latent influence, where competitive dynamics may become more significant in the future as digital adoption becomes more widespread. In other words, the industry may be approaching a tipping point, beyond which organisations that fail to adopt AI and ML could face competitive disadvantage.

Another important implication is that the current stage of adoption can be characterised as policy-driven rather than market-driven. Initiatives by bodies such as the Construction Industry Development Board under the Construction 4.0 Strategic Plan play a central role in promoting digital transformation. However, without corresponding market demand, such initiatives may struggle to achieve widespread and sustained impact. This highlights the need for stronger client-side awareness and demand creation, where organisations actively require or incentivise the use of digital technologies.

Additionally, the low influence of market forces may also reflect the fragmented structure of the construction industry, where numerous SMEs operate with limited resources and minimal exposure to global competition. In such environments, innovation is often incremental rather than disruptive, and organisations may prioritise short-term project delivery over long-term technological investment.

Critically, the weak role of market requirements raises concerns about the sustainability of AI and ML adoption. Without external pressure or demand, adoption may remain sporadic and driven by early adopters rather than becoming an industry norm. This could result in a two “era” industry, where a small number of technologically advanced firms coexist with a majority of traditional players, potentially widening the digital divide.

4.4 Perceived Performance Effects of AI and ML Applications in Project Lifecycle of Construction Industry

The Google Form survey was formally distributed to the professionals involved in construction industry in Klang Valley Malaysia also has a section to measure the perceived performance effects of AI and ML applications in the project lifecycle of construction industry.

The findings provide insight into the respondents perceived performance effects of AI and ML adoption in project lifecycle of construction industry in Klang Valley Malaysia.

4.4.1 Mean Ranking Analysis

Mean ranking analysis is also adopted to identify the perceived performance effects of AI and ML application in the project lifecycle of the construction industry in Klang Valley Malaysia. The mean ranking analysis was done with IBM SSPS 27 and the result of the mean ranking is shown in Table 4.12.

The prominence of improved time performance aligns strongly with recent studies, which identify scheduling optimisation and delay reduction as key applications of AI and ML. This shows the importance of time management in construction projects, where delays often lead to cost overruns and contractual disputes. Contemporary research highlights that AI and ML technologies, such as predictive analytics and automated planning tools, significantly enhance project timelines and workflow efficiency (Gao et al., 2026). A study found that AI and ML application can demonstrate superior accuracy in predicting construction delays compared to traditional methods, enabling proactive decision-making and mitigating schedule risk. This supports the Diffusion of Innovation Theory, which suggests that innovations are more readily adopted when their benefits are observable and measurable.

The second ranked benefit, improved cost performance is consistent with recent findings that AI and ML improve financial outcomes through more accurate cost estimation, resource optimisation, and real-time budget monitoring. Shamim et al. (2025) had done systematic review and found that AI and ML applications can achieve 85-95% accuracy in cost estimation, results in improved financial planning and control. Therefore, cost prediction accuracy can be significantly improved and reduce project overruns. This finding also aligns with the Technology Acceptance Model, where perceived usefulness often reflected in cost savings and performance improvement and plays a central role in influencing adoption decisions.

The third rank benefit, improved quality performance is also widely supported in recent literature. AI applications such as automated inspection, computer vision, and data-driven quality control systems have been shown to enhance construction accuracy and reduce human error. Datta et al. (2024) had done comprehensive review on the AI and ML application in project lifecycle of construction industry and shows that AI and ML application enhance overall project performance and productivity, including quality outcomes by enabling smarter and more accurate construction processes. However, consistent with the findings of this study, quality is seen as important but an indirect benefit, typically arising from improvements in time and cost efficiency rather than acting as a primary driver in Malaysia Klang Valley construction industry.

A notable divergence emerges in the case of improved safety and health performance. Gao et al. (2026) highlights that AI and ML applications such as Personal Protective Equipment (PPE) detection, fall risk monitoring and safety predictions as a major advancement in construction industry. However, in this study, safety is ranked lower, suggesting that it is perceived as a secondary benefits or compliance-related outcome, rather than a strategic driver. This indicates a gap between theoretical importance and industry perception, where safety improvements may not be fully leveraged as a motivation for adopting AI and ML technologies.

The most significant discrepancy is observed in improved environmental performance, which is ranked lowest despite increasing global emphasis on sustainable construction. Recent research highlights the role of AI in supporting sustainability through energy optimisation, waste reduction, and lifecycle analysis (Ehtsham et al., 2025). However, the findings of this study suggest that such benefits are not yet prioritised within the Malaysia Klang Valley construction industry. This divergence may be attributed to several factors. Environmental benefits are often long-term and less directly measurable, making them less attractive compared to immediate gains in time and cost performance. Additionally, the relatively lower market and regulatory pressure for sustainability may reduce the incentive for firms to adopt environmentally driven innovations.

Table 4.12: Mean Ranking Analysis for perceived performance effects of AI and ML application in project lifecycle of construction industry.

	Perceived Performance Effects	**Mean**	**Standard Deviation**	**Mean Rank**
CIPLS01:	Improve Time Performance	4.1846	0.93361	1
CIPLS02:	Improve Cost Performance	3.9231	1.00480	2

	Perceived Performance Effects	Mean	Standard Deviation	Mean Rank
CIPLS03:	Improve Quality Performance	3.8923	0.86824	3
CIPLS04:	Improve Safety and Health Performance	3.8000	0.90485	4
CIPLS05:	Improve Environmental Performance	3.6759	0.98596	5

4.4.2 Factor Analysis

The data collected for four (4) perceived performance effects of AI and ML application in project lifecycle of construction industry in Klang Valley Malaysia were transfer to IBM SPSS 27 for factor analysis. As discussed earlier, the data were validated through two statistical test which are KMO and Bartlett's test of sphericity to ensure they are appreciate for factor analysis. In this research, the KMO obtained is 0.714 which indicates the data is sufficient for study. While for the Bartlett's test of sphericity, the chi-square ($\chi 2$) obtained 138.829, with significant value of <0.001, indicating that null hypothesis of the corelation matrix is being identical is rejected. Therefore, the data obtained is suitable for factor analysis.

Table 4.13: Kaiser-Meyer-Olkin (KMO) and Bartlett's Test of Sphericity Result for the perceived performance effects of AI and ML application in project lifecycle of construction industry in Klang Valley Malaysia.

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.714
Bartlett's Test of Sphericity	Approx. Chi-Square ($\chi 2$)	138.829
	Degree of Freedom (df)	10
	Significant level (Sig.)	0.000

Next, referring to the Table 4.9 which is generated by IBM SPSS 27, only one (1) component was extracted with eigenvalue greater than 1.0 through varimax rotation of principal component analysis. Each factor belongs to only to one component with loading value on each factor more than 0.30. The total cumulative variance explained by the one component is at 59.526%. This finding indicates that all perceived performance effects are highly related to each other. By adopting AI and ML applications in project lifecycle of construction industry in Klang Valley Malaysia will directly improve cost, safety, environmental, time and quality performance.

Table 4.14: Total variance explained for perceived performance effects of AI and ML application in project lifecycle of construction industry in Klang Valley Malaysia.

Factors	Initial Eigenvalues		
	Total	% of Variance	Cumulative %
1	2.976	59.526	59.526
2	0.968	19.361	78.887
3	0.506	10.129	89.015
4	0.336	6.711	95.726
5	0.214	4.274	100.000

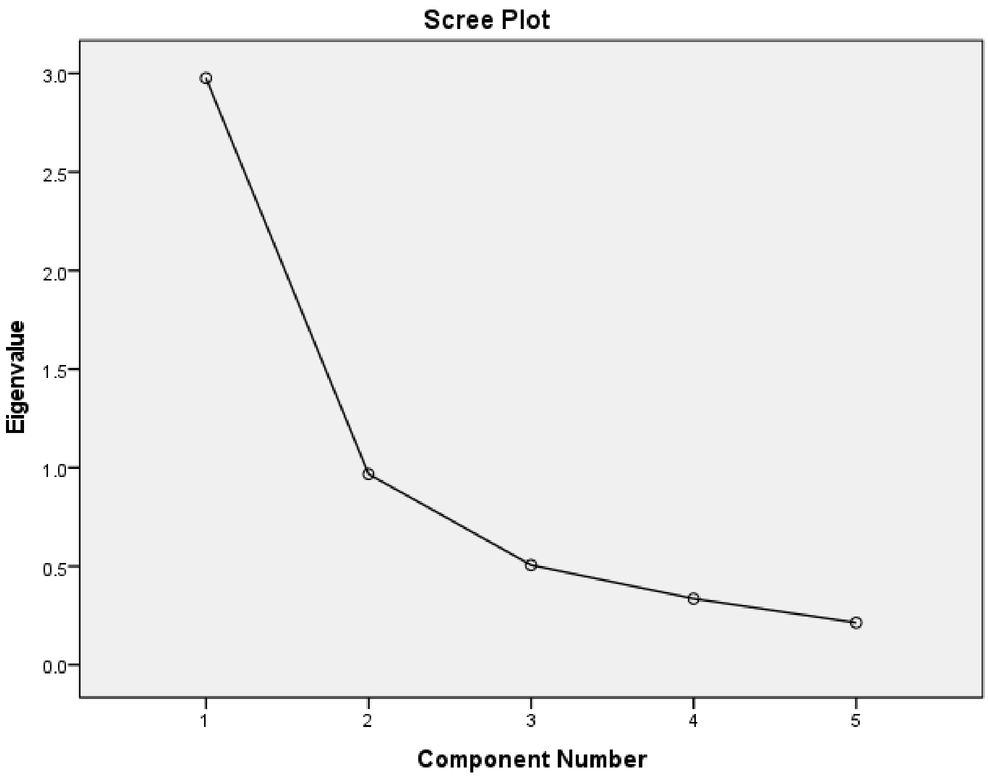

Figure 4.2: Eigenvalue Scree Plot for perceived performance effects of AI and ML application in project lifecycle of construction industry in Klang Valley Malaysia.

Each of the five (5) perceived performance effects belong to only one component with factor loading value exceeding 0.5. The factors rotation among the three (3) factors that were selected from Table 4.14 is shown in Table 4.15.

Table 4.15: Component matrix for perceived performance effects of AI and ML application in project lifecycle of construction industry for achieving construction industry project lifecycle success.

	Perceived Performance Effects	**Component 1**
ICIPLS03:	Improved Quality Performance	0.757
ICIPLS05:	Improved Environmental Performance	0.757
ICIPLS01:	Improved Time Performance	0.711
ICIPLS02:	Improved Cost Performance	0.682
ICIPLS04:	Improved Safety and Health Performance	0.515

Extraction Method: Principal Component Analysis.

a. 1 component extracted.

The only one component has all the perceived performance effects such as improved time performance, improved cost performance, improved safety performance, improved quality performance and improved environmental performance which are related to construction industry project lifecycle success. Therefore, the component is labelled as “Improved Construction Industry Project Lifecycle Success”.

Table 4.16: Naming for component for perceived performance effects of AI and ML application in project lifecycle of construction industry in Klang Valley Malaysia.

Component	**Component’s Name**
1	Improved Construction Industry Project Lifecycle Success

4.4.2.1 Component 1: Improved Construction Industry Project Lifecycle Success

A more comprehensive understanding emerges from the factor analysis, where all five benefit variables load onto a single component labelled "Improved Construction Industry Project Lifecycle Success". This indicates that despite differences in perceived importance, these perceived performance effects are structurally integrated and collectively contribute to overall project performance. Notably, quality and environmental performance exhibit the highest factor loadings, suggesting that they play a central role in defining lifecycle success, even though they are not the primary considerations in decision-making.

This divergence between perceived priority from mean ranking and structural importance from factor analysis reveals a critical insight. While organisations tend to prioritise efficiency-related benefits such as time and cost during the adoption phase, long-term project success is more strongly associated with holistic outcomes, particularly quality and sustainability. This reflects a decision–value gap, where short-term operational considerations dominate initial adoption decisions, but long-term value creation depends on broader performance dimensions.

From a critical perspective, these findings suggest that AI and ML adoption in the Malaysia Klang Valley construction industry is currently productivity-driven rather than sustainability-driven. While this is consistent with the industry's traditional focus on the "golden triangle" of time, cost, and quality, it may limit the full potential of digital transformation. The integration of environmental and safety considerations into project success frameworks remains underdeveloped, despite their increasing importance in global construction practices.

In the context of Malaysia, this pattern may be influenced by the current stage of digital maturity and the emphasis on efficiency improvements under national initiatives led by the CIDB. While such initiatives promote technological adoption, the findings suggest that greater emphasis is needed on aligning industry perceptions with the broader capabilities of AI and ML, particularly in supporting sustainable and safe construction practices.

The results demonstrate that AI and ML adoption has the potential to significantly enhance construction project lifecycle success through a combination of efficiency, quality, safety, and sustainability improvements. However, the current emphasis on short-term benefits highlights the need for a more balanced and strategic approach, where organisations recognise and leverage the full spectrum of benefits offered by these technologies.

4.5 Proposed Framework for AI and ML Applications in Project Lifecycle of Construction Industry in Klang Valley Malaysia

Based on the 18 factors identified in this research, several measures for accelerate the AI and ML adoption in project lifecycle of construction industry in Klang Valley Malaysia can be proposed. This section aims to develop a framework that integrate all factors identified and with the perceived performance effects of AI and ML applications in project lifecycle of construction industry in Klang Valley Malaysia. The framework integrates the key findings from both mean ranking analysis and factor analysis depicting how the three (3) critical factors (technological factors, market requirement, and organisational and ecosystem supports) collectively contribute to improved construction project lifecycle success as shown in the Figure 4.3.

The framework demonstrates that these three components are interconnected and collectively influence project lifecycle success. Technological factors initiate adoption by providing clear value propositions, organisational and ecosystem supports enable implementation, and market requirements shape the broader adoption environment.

Importantly, the framework reflects the earlier identified decision–value gap, where organisations prioritise short-term efficiency benefits or immediate result (time and cost improvement), while long-term success is structurally driven by broader factors such as quality and sustainability. This reinforces the need for a more holistic approach to technology adoption, where all performance dimensions are considered.

From a theoretical perspective, the framework integrates elements of both the Diffusion of Innovation Theory and the Technology Acceptance Model, providing a comprehensive explanation of AI and ML adoption in the construction context. It extends these models by incorporating organisational and ecosystem dimensions, which are particularly relevant in complex and fragmented industries such as construction.

From a practical perspective, the framework highlights that successful AI and ML adoption in Malaysia Klang Valley construction industry requires strong technological value propositions, adequate organisational readiness and capability, supportive policy and industry ecosystem and increase market demand and competitive pressure.

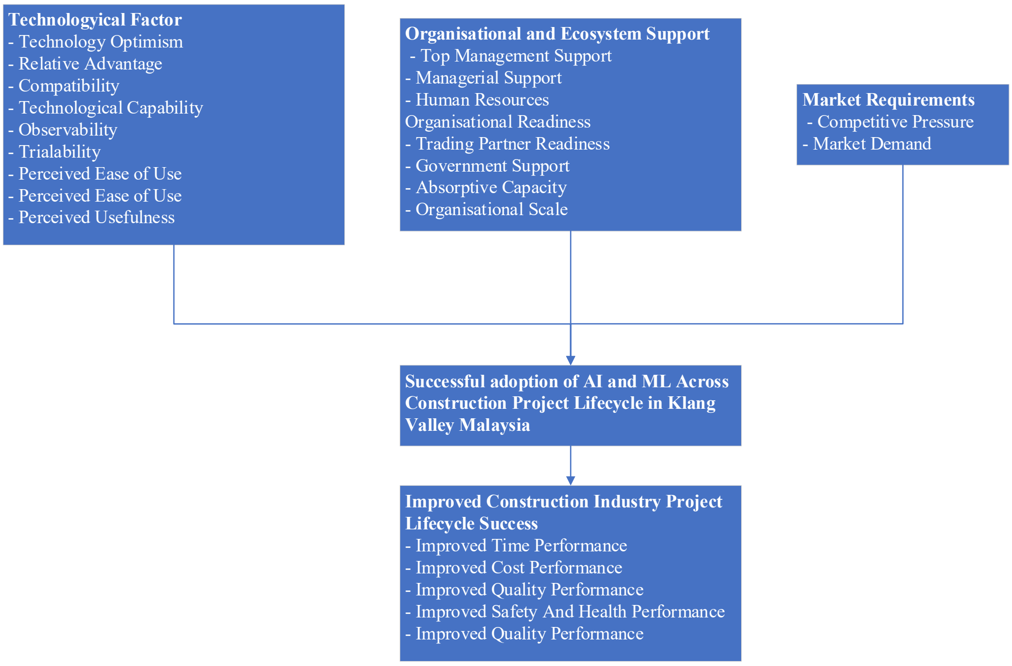

Figure 4.3: Framework for AI and ML applications in project lifecycle of construction industry in Klang Valley Malaysia.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This study aims to investigate the factors influencing the adoption of AI and ML applications in the construction project lifecycle in Klang Valley, Malaysia, as well as to evaluate their perceived performance effects in improving overall project lifecycle success. Through a combination of mean ranking analysis or descriptive analysis and factor analysis, the study provides a comprehensive understanding of how technological, organisational, and market-related factors shape adoption behaviour and project outcomes.

The findings reveal that technological factors are the primary drivers of AI and ML adoption in the construction industry. Factors such as relative advantage, trialability, observability, and perceived usefulness were ranked highest, indicating that organisations are more inclined to adopt AI and ML when the technologies demonstrate clear, observable, and measurable benefits. This reflects a performance-driven adoption behaviour, where decision-making is largely influenced by the perceived value and effectiveness of the technology.

In contrast, organisational and ecosystem supports, including top management support, human resources, organisational readiness, and government support were found to play a secondary but essential role. These factors act as enabling conditions, determining whether organisations possess the necessary capabilities to successfully implement AI and ML. However, the relatively lower ranking of these factors suggests the presence of a capability gap, where awareness of AI technologies exists but organisational readiness remains limited.

Similarly, market-related factors, such as competitive pressure and market demand, were identified as the least driving force. This indicates that the construction industry in Malaysia Klang Valley is still in a pre-competitive stage of digital transformation, where adoption is not yet driven by strong external pressures. Instead, adoption is largely influenced by internal motivations and policy initiatives, highlighting the need for stronger market demand and industry digital maturity.

In terms of perceived performance effects, the study finds that AI and ML adoption is primarily associated with improvements in time, cost, and quality performance ranked as the most significant benefit. These findings suggest that the industry is predominantly productivity-oriented, focusing on short-term operational efficiency. While safety and environmental performance are also recognised, they are comparatively less prioritised, indicating that sustainability and safety considerations are not yet central to adoption decisions.

However, the factor analysis of perceived performance effects presents a more holistic perspective. All benefit variables load onto a single component, labelled "Improved Construction Industry Project Lifecycle Success", demonstrating that these perceived performance effects are interconnected and collectively contribute to overall project performance. Notably, quality and environmental performance exhibit strong structural importance, despite being ranked lower in the mean ranking analysis. This highlights a critical decision-value gap, where organisations prioritise immediate efficiency gains while long-term success is driven by broader performance outcomes such as quality and sustainability.

The proposed framework developed in this study integrates these findings by illustrating how technological factors drive adoption, organisational and ecosystem supports enable implementation, and market requirements influence the external environment, ultimately leading to improved project lifecycle success. The framework also reflects the current imbalance in the industry, where technological awareness is relatively high, but organisational readiness and market demand remain underdeveloped.

Overall, this study concludes that while AI and ML have significant potential to transform the construction industry, their adoption in Klang Valley is still at an early and uneven stage. The current focus on short-term productivity benefits may limit the full realisation of AI and ML capabilities, particularly in areas related to sustainability and long-term value creation.

AI and ML adoption in the construction project lifecycle in Malaysia Klang Valley is primarily driven by technological benefits and short-term efficiency gains, while long-term success depends on the integration of organisational capabilities, ecosystem support, and broader performance dimensions such as quality and sustainability. Bridging this gap is essential for achieving meaningful and sustainable digital transformation in the construction industry

5.2 Achievement of Research Objectives

The research objective set in paper (refer to 1.6) are achieved and can be demonstrated through the explanation in the following subsections.

5.2.1 Research Objective 1: To Investigate the Factor for Artificial Intelligence and Machine Learning Applications in the Project Lifecycle of Construction Industry

Mean ranking analysis is adopted to identify the relative importance of the 18 factors identified and factor analysis is also applied to examine the underlying relationship among the factors. Through the mean ranking analysis, it is noted that relative advantage, trialability, observability and perceived usefulness are voted as the most critical factor for AI and ML applications in project lifecycle of construction industry in Klang Valley Malaysia, while organisational readiness and absorptive capacity are voted as the least important factor. Also, it is worth highlighted that all the factors have mean value higher than 3.000, implying all the factors are significant.

In factor analysis, three (3) components of grouped factors are extracted from the 18 factors with total variance explained at 71.483% through varimax rotation of principal component analysis. All loadings for all the factors are greater than 0.3 indicating a high absolute value. The three (3) components are labelled as “technological factors”, “organisational and ecosystem supports” and “market requirements”.

These findings reflect that Malaysia construction industry in Klang Valley has a performance-driven adoption behaviour, where decision-making is largely influenced by the perceived value and effectiveness of the technology. The adoption of AI and ML in project lifecycle of construction industry in Klang Valley is only happening when the technologies demonstrate clear, observable, and measurable benefits rather than internal motivation from the organisations or market driven.

5.2.2 Research Objective 2: To investigate the Perceived Performance Effects of Artificial Intelligence and Machine Learning in Project Lifecycle of the Construction Industry for Improved Construction Industry Project Lifecycle Success

Mean ranking analysis is adopted to identify the relative importance of the 5 potentials identified and factor analysis is also applied to examine the underlying relationship among the factors. Through the mean ranking analysis, it is noted that "time performance" was identified at the most potential benefit in project lifecycle success, while "improve environmental performance" is identified as the least potential benefit. Also, it is worth highlighted that all the factors have mean value higher than 3.000, implying all the factors are significant.

The factor analysis of perceived performance effects presents a more holistic perspective. All benefit variables load onto a single component, labelled "Improved Construction Industry Project Lifecycle Success", demonstrating that these perceived performance effects are interconnected and collectively contribute to overall project performance. Notably, quality and environmental performance exhibit strong structural importance, despite being ranked lower in the mean ranking analysis. This highlights a critical decision-value gap, where organisations prioritise immediate efficiency gains while long-term success is driven by broader performance outcomes such as quality and sustainability.

5.3 Research Contributions

The results revealed in this research are great benefits to both researchers or academic communities and industry practitioners. The researcher or academic communities can use the factors as a sound basis to develop strategies to adopt AI and ML applications that are tailored to construction industry in Klang Valley Malaysia. Besides, with these results, the industry practitioners' understanding about the major factors contributing to AI and ML applications in Construction Industry in Klang Valley Malaysia and they could develop strategies to accelerate the AI and ML applications in project lifecycle of construction industry in Klang Valley Malaysia.

5.4 Study Limitations

While this study provides valuable insights into the adoption of AI and ML application in the construction project lifecycle in Malaysa Klang Valley, several limitations should be acknowledged.

Firstly, the study is geographically limited to Klang Valley, Malaysia. Although this region represents one of the most developed and active construction hubs in the country, the findings may not be fully generalisable to other regions with different levels of economic development, infrastructure maturity, or digital readiness. Variations in regulatory environments and industry practices may influence adoption behaviour in other contexts.

Secondly, the study adopts a cross-sectional research design, where data were collected at a single point in time. As digital transformation is an evolving process, the findings may not capture changes in perceptions, technological maturity, or adoption trends over time. The construction industry is continuously adapting to emerging technologies, and longitudinal changes may significantly alter the observed patterns.

Thirdly, the analysis is based on perceptual data collected through questionnaires, which may be subject to respondent bias. Participants' responses reflect their personal experiences and understanding of AI and ML, which may vary depending on their level of exposure to digital technologies. This may result in potential overestimation or underestimation of certain factors and perceived performance effects.

Fourthly, the study focuses primarily on high-level organisational and technological factors, without examining detailed technical aspects of AI and ML implementation. Factors such as system integration challenges, data quality issues, cybersecurity concerns, and algorithm performance were not explored in depth, which may limit the comprehensiveness of the findings.

Finally, the use of factor analysis or Principal Component Analysis (PCA), while effective in identifying underlying factor structures, involves certain assumptions and limitations. The reduction of variables into components may oversimplify complex relationships, and the interpretation of components is subject to researcher judgement.

5.5 Recommendations for Future Research

In light of the above limitations, several avenues for future research are recommended.

Firstly, future studies could expand the scope beyond Klang Valley to include other regions in Malaysia or cross-country comparisons. This would provide a more comprehensive understanding of AI and ML adoption across different economic and regulatory environments, enhancing the generalisability of findings.

Secondly, there is a need for longitudinal studies to examine how AI and ML adoption evolves over time. Such studies would capture changes in industry readiness, technological maturity, and market dynamics, providing deeper insights into the progression of digital transformation in the construction sector.

Thirdly, future research could incorporate mixed-method approaches, combining quantitative analysis with qualitative methods such as interviews or case studies. This would allow for a more in-depth exploration of organisational challenges, implementation strategies, and real-world applications of AI and ML.

Fourthly, further investigation into technical and operational aspects of AI and ML implementation is recommended. This includes examining issues related to data management, system integration, interoperability, and cybersecurity, which are critical for successful adoption but were beyond the scope of this study.

Fifthly, future research could explore the impact of AI and ML adoption on specific project outcomes, such as productivity, risk management, sustainability performance, and lifecycle cost analysis. This would provide more concrete evidence of the value of AI and ML in construction.

Additionally, there is potential to extend the proposed framework by integrating other theoretical perspectives, such as organisational change theory or innovation ecosystem models, to provide a more comprehensive understanding of adoption behaviour beyond the Diffusion of Innovation Theory and the Technology Acceptance Model.

Finally, future studies could focus on emerging areas such as AI integration with BIM, Internet of Things (IoT), and smart construction systems, which are increasingly relevant under Malaysia's digital transformation initiatives led by the CIDB.

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APPENDIX

Appendix 1: Survey Questionnaire

Artificial Intelligence and Machine Learning Applications in the Project Lifecycle of the Construction Industry Questionnaire

Section A: Demographic Information
Please select only one answer for each item.

DI01) Organisation type:
1) Developer
2) Consultant
3) Contractor

DI02) Category of work:
1) Building
2) Non-building

DI03) Position in the organisation:
1) Upper management
2) Middle management
3) Lower management

DI04) Years of working experience:
1) Less than 5 years
2) 5 years and above

Section B: Technological Dimension
To what extent do you agree or disagree that the following technological dimension factors are important for artificial intelligence and machine learning applications in the project lifecycle of the construction industry?
1) Strongly disagree
2) Disagree
3) Neither agree nor disagree
4) Agree
5) Strongly agree

F01) Perceived usefulness	(1)	(2)	(3)	(4)	(5)
F02) Perceived ease of use	(1)	(2)	(3)	(4)	(5)
F03) Technology optimism	(1)	(2)	(3)	(4)	(5)
F04) Technological capability	(1)	(2)	(3)	(4)	(5)
F05) Compatibility	(1)	(2)	(3)	(4)	(5)
F06) Relative advantage	(1)	(2)	(3)	(4)	(5)
F07) Trialability	(1)	(2)	(3)	(4)	(5)
F08) Observability	(1)	(2)	(3)	(4)	(5)

Section C: Organisational Dimension
To what extent do you agree or disagree that the following organisational dimension factors are important for artificial intelligence and machine learning applications in the project lifecycle of the construction industry?
1) Strongly disagree
2) Disagree
3) Neither agree nor disagree
4) Agree
5) Strongly agree

F09) Organisational scale	(1)	(2)	(3)	(4)	(5)
F10) Organisational readiness	(1)	(2)	(3)	(4)	(5)
F11) Absorptive capacity	(1)	(2)	(3)	(4)	(5)
F12) Top management support	(1)	(2)	(3)	(4)	(5)
F13) Human resources	(1)	(2)	(3)	(4)	(5)
F14) Managerial support	(1)	(2)	(3)	(4)	(5)

Section D: Environmental Dimension
To what extent do you agree or disagree that the following environmental dimension factors are important for artificial intelligence and machine learning applications in the project lifecycle of the construction industry?
1) Strongly disagree
2) Disagree
3) Neither agree nor disagree
4) Agree
5) Strongly agree

F15) Market demand	(1)	(2)	(3)	(4)	(5)
F16) Competitive pressure	(1)	(2)	(3)	(4)	(5)
F17) Government support	(1)	(2)	(3)	(4)	(5)
F18) Trading partner readiness	(1)	(2)	(3)	(4)	(5)

Section E: Improved Construction Industry Project Lifecycle Success
To what extent do you agree or disagree with the following statements?
1) Strongly disagree
2) Disagree
3) Neither agree nor disagree
4) Agree
5) Strongly agree

ICIPLS01) Artificial intelligence and machine learning applications in the project lifecycle of the construction industry improve time performance.
(1) (2) (3) (4) (5)
ICIPLS02) Artificial intelligence and machine learning applications in the project lifecycle of the construction industry improve cost performance.
(1) (2) (3) (4) (5)
ICIPLS03) Artificial intelligence and machine learning applications in the project lifecycle of the construction industry improve quality performance.

(1) (2) (3) (4) (5)

ICIPLS04) Artificial intelligence and machine learning applications in the project lifecycle of the construction industry improve safety and health performance.

(1) (2) (3) (4) (5)

ICIPLS05) Artificial intelligence and machine learning applications in the project lifecycle of the construction industry improve environmental performance.

(1) (2) (3) (4) (5)