ADOPTION OF INDUSTRY 5.0 TECHNOLOGICAL INNOVATIONS: A PERSPECTIVE FROM MINING INDUSTRY IN INDONESIA ON TECHNOLOGY ACCEPTANCE AMONG EMPLOYEES

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ABSTRACT

The advent of the industry 5.0 (i5.0) paradigm, marked by the convergence of human-centric processes and advanced technological innovations such as Mixed Reality (MR) and Generative Artificial Intelligence (GenAI), presents significant opportunities to enhance and optimize industrial operations, particularly in the mining industry, which operates in challenging environments that demand stringent safety measures and operational efficiency. Despite its potential, guidance and research on the application of i5.0 technologies remain limited, especially within the mining sector and particularly in developing countries. To address these gaps and to support the successful adoption and integration of these innovations, this research aims to investigate the factors influencing the acceptance of i5.0 technological advancements among employees in Indonesia's mining industry.

Drawing from the theory of Technology Acceptance Model (TAM), this research explores how perceived usefulness, perceived ease of use, perceived compatibility, perceived novelty, shape mining employee’s attitudes towards the adoption of MR and GenAI technologies. Survey data from Indonesia’s mining employee (n = 258 for MR and n = 254 for GenAI), collected via judgmental sampling and in-office survey, provides the basis for Partial Least Square-Structural Equation Modelling (PLS-SEM) to test hypothesized relationships. The findings underscore distinct considerations for each i5.0 innovative technology. For the MR model, perceived usefulness and compatibility emerge as critical factors significantly influencing both user attitudes and intentions, whereas perceived ease of use is not a significant determinant. Notably, while perceived novelty contributes significantly to shaping attitudes, it does not directly affect intention in the MR model. Conversely, the GenAI model reveals a different set of dynamics. Although perceived ease of use does not significantly influence intention, it does play a crucial role in shaping user attitudes. Moreover, perceived novelty emerges as a key factor, significantly affecting both attitudes and intentions. This research offers valuable theoretical contributions and practical recommendations for all related stakeholders aiming to facilitate the adoption of advanced technologies in the mining industry.

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Wecka Imam Yudhistyra

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CHAPTER 1

INTRODUCTION

1.1 Background

The mining industry has long been a cornerstone of global economic development, providing essential raw materials for various sectors. However, reliance on outdated portfolios and practices is no longer viable in today's dynamic and highly competitive landscape (Winzenried et al., 2023). The growing demand for efficiency, sustainability, and safety in mining operations necessitates the adoption of advanced technological solutions (Sánchez & Hartlieb, 2020). Simultaneously, the advent of industry 5.0 (*forth* i5.0) marks a transformative shift in industrial paradigms, offering the potential to revolutionize traditional mining practices. Advanced technologies, including Mixed Reality (MR), Generative Artificial Intelligence (GenAI) and automation (Maddikunta et al., 2022; Raja Santhi & Muthuswamy, 2023), are poised to foster more integrated and synergistic relationships between human operators and technological systems (Adel, 2022; Maddikunta et al., 2022), thereby enhancing efficiency and innovation across the mining sector. The convergence of human-centric innovation with intelligent technologies aims to achieve significant advancements in productivity, safety, and sustainability (L. Chen et al., 2022; Sánchez & Hartlieb, 2020; Wang et al., 2023). Notably, even incremental improvements in productivity and resource utilization within the mining industry can yield substantial benefits. Innovators leveraging intelligent digital mining operations can achieve cost savings and increase profit margins by as much as 20%, underscoring the transformative potential of these advancements (Lath & Peacocke, 2020).

While i5.0 technologies hold immense potential to revolutionize the mining sector, their implementation, particularly in developing countries, is fraught with significant challenges (Arbulu, Lath, Mancini, Patel, & Tonby, 2018; Lath & Peacocke, 2020; Loh, Mohammad, Tripathi, van Nieker, & Yanto, 2023). Developing countries often grapple with the paradox of being rich in mineral and material resources yet lacking the capacity to transform these resources and advanced technologies into sustainable economic wealth (Drucker, 2007). Meanwhile, the mining industry itself presents additional hurdles, including harsh working conditions, a limited emphasis on innovation, and a traditionally conservative outlook that resists change (Sánchez & Hartlieb, 2020). These factors often manifest as substantial employee resistance to adopting new technologies (Lath & Peacocke, 2020; Sánchez & Hartlieb, 2020). Further complicating these challenges is the absence of comprehensive guidance in the academic literature on effectively facilitating such technological transitions, leaving stakeholders with limited frameworks to navigate this complex landscape (Gruenhagen & Parker, 2020).

That is why understanding how individuals adopt or reject technology continues to be the most challenging issue in business information technology ranging from the past (Davis, Bagozzi, & Warshaw, 1989; Swanson, 1974) to more recent studies (Hőgye-Nagy, Kovács, & Kurucz, 2023; Jayawardena, Ahmad, Valeri, & Jaharadak, 2023; Kelly, Kaye, & Oviedo-Trespalacios, 2023; Lun et al., 2024; Rodríguez-López, Higueras-Castillo, Rojas-Lamorena, & Alcántara-Pilar, 2024). The successful adoption of technological innovation in industry depends not only on the technological capabilities but also on the willingness and ability of employees to embrace these technologies (Ali, Murray, Muhammed, Dwivedi, & Rashiti, 2022; Ren, 2019). According to model of innovation adoption proposed by (Rogers, 2003), the process of adopting technological innovation involves a series of stages that individuals go through prior their adoption. Hence, it is essential to carefully examine the acceptance of i5.0 technologies like MR and GenAI by employees in mining industries. This is crucial in the transition period towards i5.0 era, as inadequate level of employee acceptance may impede the realization of desired benefit (Talukder, 2019), potentially leading mining industries to abandon the benefits offered by these technologies.

Given the range of prior research findings and uncertainty related to technologies innovation adoption success (Arbulu et al., 2018; Laumer & Eckhardt, 2010; Ren, 2019; Schein & Rauschnabel, 2023; Skiti, 2020), the acceptance at an individual level of i5.0 technologies for driving digital transformation and boosting productivity in a mining industry is investigated in this research. Understanding the factors that influence this acceptance is essential for facilitating the adoption process and ensuring that the transition to i5.0 is both efficient and effective.

1.2 Research Gap

The present research addresses a multidimensional gap encompassing industry, technology, geography, and theoretical perspectives. Although an extensive body of literature on technological innovation has explored the adoption of advanced technologies across various industries, significant deficiencies persist regarding the adoption of i5.0 innovations in the mining sector, particularly within the context of developing countries (Gruenhagen & Parker, 2020).

Existing research on technology adoption predominantly focus on industries characterized by more predictable and controlled operational environments, such as architecture (C.-Y. Lin & Xu, 2022; Stals & Caldas, 2022), manufacturing (I. J. Lee, 2020), education (Luo, Li, Feng, Yang,

& Zuo, 2021), healthcare (García-Batista et al., 2020), or tourism and hospitality (M. J. Kim, Lee, & Jung, 2020). These industries differ significantly from the mining sector, which is characterized by high-risk operations, reliance on traditional practices, and resistance to disruptive change. Consequently, the unique challenges of the mining industry, such as its harsh working conditions and cultural hesitancy towards innovation, have been largely overlooked in existing research.

Furthermore, despite the rapid advancement of technology, research on the adoption of the latest i5.0 innovations, specifically MR and GenAI, remains notably limited. Existing research predominantly focus on technologies such as autonomous vehicles and driving systems (L. Chen et al., 2022; Ribeiro, Gursoy, & Chi, 2022), or advanced robotics (H. Lin, Chi, & Gursoy, 2020) which often emphasize the replacement of human labour through automation. In stark contrast, MR and GenAI prioritize human-machine collaboration, a fundamental shift that warrants deeper exploration. Moreover, existing literature tends to adopt a technical perspective, focusing primarily on technological specifications, functional capabilities, and potential benefits while often neglecting critical human factors such as user perceptions, attitudes, and behavioural intentions, elements that are pivotal to the successful implementation and acceptance of emerging technologies (Davis et al., 1989; Ursavaş, 2022). This limitation is particularly pronounced in the mining sector, where research addressing human-centric factors in the context of i5.0 technologies is exceptionally scarce (Gruenhagen & Parker, 2020). Note that, understanding the factors that influence technology acceptance or rejection has long been regarded as a critical area of research. First, technology adoption is a complex and socially driven developmental process rather than a straightforward technical implementation. Second, individuals form unique yet adaptable perceptions of technology, which significantly shape their willingness to adopt and utilize it. Finally, cognitive, emotional, and contextual concerns must be carefully addressed to facilitate the successful and sustainable integration of i5.0 innovations into industrial environments.

From a geographical perspective, most studies on technology acceptance have been conducted in developed countries (Davis, 1989; Davis et al., 1989; Mohr & Kühl, 2021), where robust infrastructure and institutional frameworks support the seamless adoption of advanced technologies. In contrast, there is a marked paucity of research investigating the adoption of i5.0 technologies in developing countries. This gap is especially evident in the mining sector, which often exhibits a slower rate of technological adoption due to structural, cultural, and resource-related constraints (Arbulu et al., 2018; Gruenhagen & Parker, 2020; Lath & Peacocke, 2020). For instance, while mining companies in Indonesia acknowledge the potential of advanced technologies, their adoption has been slow and cautious. This sluggish progress can be attributed to several challenges, including a shortage of digital skills, limited awareness of digital ecosystems, and a scarcity of local reference cases that demonstrate successful implementation. These factors collectively hinder the effective adoption of advanced technologies within Indonesia's mining sector.

Furthermore, the absence of empirical research exploring technology adoption in this context presents a significant opportunity to investigate how socio-economic, infrastructural, and cultural divergences influence the uptake of such innovations. These factors may create distinct barriers and drivers, which have yet to be comprehensively examined (Chatterjee, Rana, Khorana, Mikalef, & Sharma, 2023; Tarhini, Hone, Liu, & Tarhini, 2017). Notably, the underrepresentation of mining industry employees from Indonesia in the broader discourse on technology adoption underscores a critical gap in the scientific literature, emphasizing the need for context-specific research. By addressing these gaps, this research seeks to provide detailed and actionable insights into the factors shaping the acceptance and integration of i5.0 technological innovations, particularly Mixed Reality (MR) and Generative Artificial Intelligence (GenAI), within the Indonesian mining industry.

1.3 Research Aims, Objectives, and Questions

Aiming to facilitate the seamless adoption and integration of i5.0 advanced technological innovations, this research systematically investigates the key determinants influencing the acceptance of MR and GenAI technologies within the Indonesian mining industry. By addressing these critical factors, the study not only enhances the understanding of technology adoption in this specialized sector but also bridges the existing multidimensional research gaps, thereby contributing to both theoretical advancements and practical implementations in mining operations.

In addition, to provide a structured approach to achieving the research aim, the specific research objectives are articulated as follows:

1) To investigate the fundamental determinants influencing employee acceptance of i5.0 technologies, specifically MR and GenAI, within the Indonesian mining industry.
2) To evaluate the interaction among the fundamental determinants influencing employee acceptance of i5.0 technologies, specifically MR and GenAI, within the Indonesian mining industry.
3) To provide insights and guidance on technology acceptance in the mining industry, particularly in Indonesia, while contributing to academic and practical advancements.

Following the delineation of the research objectives, it is imperative to formulate precise research questions that align with these objectives. These questions provide a structured framework to systematically guide the investigation, facilitating a comprehensive analysis of the factors influencing the acceptance of i5.0 advanced technological innovations. Accordingly, the research questions are articulated as follows:

1) What are the fundamental determinants influencing employee acceptance of i5.0 technologies, specifically MR and GenAI, within the Indonesian mining industry?
2) To what extend do those fundamental determinants influencing employee acceptance of i5.0 technologies, specifically MR and GenAI, within the Indonesian mining industry?
3) How can the findings be applied in real-world settings, particularly in terms of practical implications and theoretical contributions?

1.4 Scope of the Research

1.4.1 Industrial and geographical scope

This research focuses on the mining industry, addressing a significant gap in the adoption of technological innovations within this sector (Gruenhagen & Parker, 2020). Despite its vital role in global economic development, the mining industry has received limited empirical attention regarding the contextual and systemic factors that influence the adoption of innovation (Ediriweera & Wiewiora, 2021). This research seeks to bridge this gap by exploring these dynamics, with a particular emphasis on Indonesia. As shown in **Figure 1.1**, Indonesia, the largest country in Southeast Asia, is a major global producer of coal and mineral resources (Loh et al., 2023). The mining sector contributes 9.3% to Indonesia's GDP and accounts for 22% of its export value (Winzenried et al., 2023).

However, the mining industry in Indonesia faces persistent challenges in adopting technological innovations and undergoing digital transformation. These challenges are compounded by a limited digital capability among individuals and a cultural resistance to change (Lath & Peacocke, 2020; Laumer & Eckhardt, 2010), making Indonesia a particularly suitable focus for this research. A McKinsey survey of Southeast Asian companies highlights these obstacles (Arbulu et al., 2018). While over 80% of Indonesian companies reported awareness of cutting-edge technologies, nearly 85% have not moved beyond the pilot stage of implementation. This lack of progress underscores a critical issue: without adoption, even the most advanced technologies cannot enhance industrial performance.

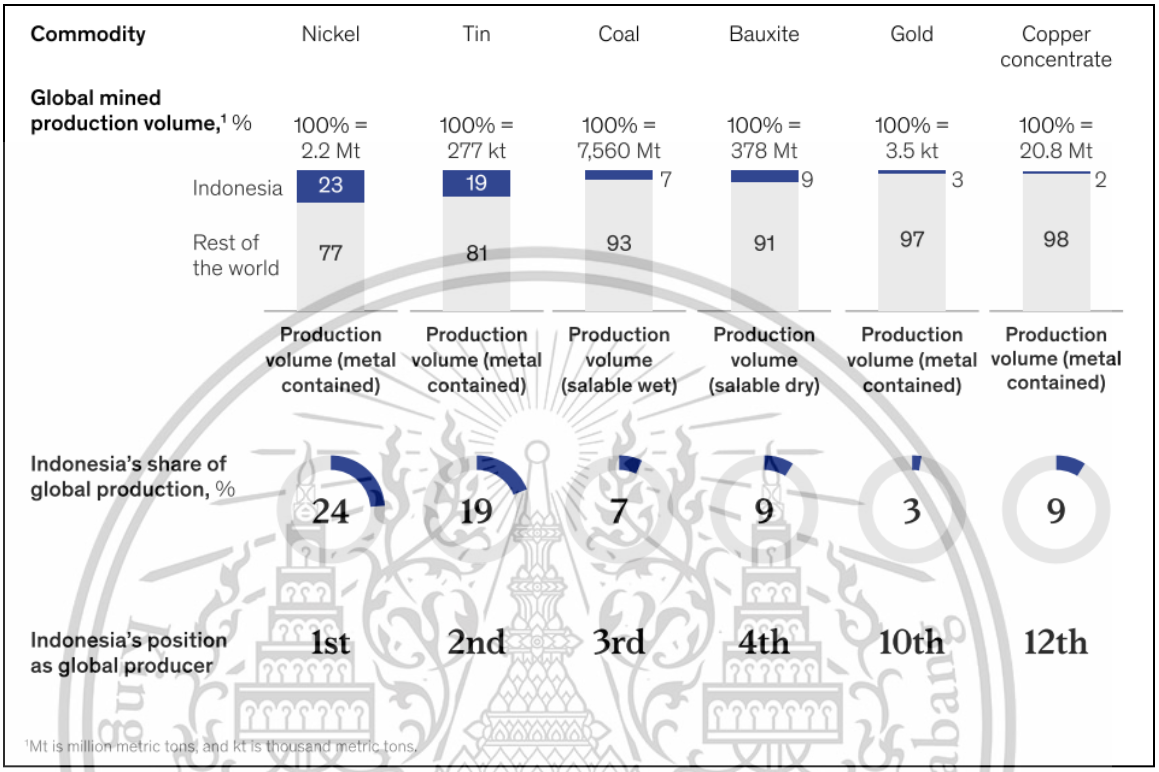

Figure 1.1 Indonesia is one of the world's largest producers of mineral resources

Sources: Loh et al. (2023)

1.4.2 Technological and theoretical scope

Meanwhile, the selection of i5.0 technologies focuses on MR and GenAI technologies for research in the mining industry is driven by several compelling reason. Compared to other advanced technologies, (i.e., AI robot, autonomous vehicles, or unmanned aerial vehicle), these technologies do not eliminate the role of humans but integrate them with human capabilities and then redefine work dynamics in company business operation (Leng et al., 2022). In the context of the mining industry, MR technology can improve safety and training experience, allowing employees to train in a safe and controlled environment (Gürer, Surer, & Erkayaoğlu, 2023). This is especially important in the mining industry, where safety is paramount. The technology can simulate hazardous scenarios in the mining industry, helping workers prepare without real-world risks. In addition, MR technology also facilitates data visualization, allowing workers to see critical information overlaid on their physical environment that can enhance their decision-making and operation awareness, especially in complex mining environments. With MR, experts can provide remote assistance to on-site workers, reducing the need for travel and enabling immediate support in challenging conditions. This is particularly valuable in remote mining locations (Davidson & Narendran, 2017).

In another side, GenAI can analyse vast amounts of data to optimize mining operations. It helps in predictive maintenance, resource allocation, and process optimization, leading to increased productivity and reduced costs. For instance, AI can streamline logistics and enhance mineral processing, making operations more efficient. Both MR and GenAI contribute to more sustainable practices. GenAI can minimize environmental impact through precision drilling and efficient resource management, while MR can help visualize and manage environmental data effectively. Embracing these technologies positions mining companies at the forefront of innovation, allowing them to adapt to industry changes and improve their competitive edge.

The Technology Acceptance Model (TAM) serves as the theoretical foundation for the development of the conceptual model in this research. TAM's simplicity, flexibility, and adaptability make it an ideal framework for application across diverse contexts and research scenarios (Kelly et al., 2023), avoiding the complexity associated with alternative frameworks such as the Theory of Planned Behaviour (TPB) or Unified Theory of Acceptance and Use of Technology (UTAUT), which incorporates additional social variables or constructs (Rejali, Aghabayk, Esmaeli, & Shiwakoti, 2023; Shachak, Kuziemsky, & Petersen, 2019; Venkatesh, Thong, & Xu, 2016). In this case, TAM offers a more streamlined and pragmatic approach (Granić & Marangunić, 2019). This is particularly relevant in the mining industry, where the harsh and high-risk operational environment renders such social constructs less significant in influencing technology acceptance. Moreover, TAM's user-centric focus aligns well with the objectives of this research, enabling an effective exploration of technology acceptance within the mining industry, a field with limited prior investigation (Gruenhagen & Parker, 2020). Furthermore, the adaptability of the TAM facilitates future modifications by incorporating additional variables tailored to the specific context of the mining sector (Rosli, Saleh, Md. Ali, Abu Bakar, & Mohd Tahir, 2022). Specifically, perceived compatibility, perceived ease of use, perceived usefulness, and perceived novelty are hypothesized to influence attitude, which, in turn, directly affects the intention to adopt both MR and GenAI technologies. This tailored approach ensures the model's relevance and applicability in understanding the factors influencing technology adoption within the mining industry.

1.5 Research Significance

The significance of this research lies in its capacity to resolve a number of challenges and provide potential positive effects in various aspects, particularly in advancing the understanding of technology adoption. Specifically, it provides valuable insights into user acceptance and behaviour, which can be leveraged by various stakeholders to facilitate the effective integration of i5.0 technologies. More precisely, the significance of this research is demonstrated by the following key points:

First, fill a critical research gap and impact to the body of scientific literature with mining industry-specific insights. This research aims to contribute fresh insights to the scientific literature regarding the acceptance of i5.0 advanced technological innovation, specifically MR and GenAI, within the Indonesian mining industry. While substantial research has been conducted on the adoption of technological innovations in other industries that have specific requirements and characteristics (Stergiou, Kavakli, & Kotis, 2023), limited empirical research explore how mining employees perceive and accept i5.0 technologies, particularly in regions where the adoption of such technologies has been slower (Gruenhagen & Parker, 2020; Lath & Peacocke, 2020). By providing new insights into the factors that influence employee acceptance, this research contributes valuable empirical data to the relatively underexplored intersection of technological innovation and mining. Simultaneously, it extends existing theoretical frameworks, particularly the Technology Acceptance Model (TAM), by contextualizing them within an industry and technological domain that has yet to receive significant scholarly attention.

Second, advance the understanding of human-centric technology adoption. i5.0 emphasizes the integration of advanced technologies with human capabilities, making employee perceptions and attitudes crucial in determining successful adoption within the context of Indonesian mining industry. This research explores how key factors, such as perceived usefulness, ease of use, compatibility, and novelty shape mining employees' attitudes toward MR and GenAI technologies.

Third, guidance for policymakers and related stakeholders within the Indonesian mining industry. This research places the employee at the centre of the analysis by focusing on their perceptions, attitude, and intention to adopt i5.0 technological innovation. This employee-centred approach facilitates the design and refinement of technologies that meet the requirements, preferences, and expectations of employees. Thus, the research offers guidance on creating policies and initiatives that support the adoption of advanced technologies in the mining sector. By recognizing the barriers to acceptance and the factors that encourage employee buy-in, policymakers and related stakeholders can develop programs that foster innovation adoption and dismiss resistance to change, particularly in developing countries where infrastructure and technological readiness may be limited.

Fourth, contribute to future research and theory development. By investigating the acceptance of i5.0 technologies in the mining industry, this research sets the groundwork for future research into the technological transformation of similar high-risk, traditional sectors. The empirical findings from this research can be used to refine existing models of technology acceptance, such as the TAM, and inspire further studies on the adoption of innovative technologies in industries where change has been historically slow.

1.6 Definition of Terms

Table 1.1 provides the operational definitions of key terminology utilized throughout this dissertation, ensuring clarity and consistency in the discussion of core concepts. By systematically defining these terms, the table facilitates a comprehensive understanding of the subject matter, enabling readers to engage more effectively with the research findings and theoretical framework presented herein.

Table 1.1 Terminology and the definition

TERMINOLOGY		DEFINITIONS
Intention **(I)**	⇒	While intention itself is not a behaviour, it strongly predicts whether the behaviour will occur. In this sense, intention is closely linked to the behavioural component but is not the behaviour itself. In this research, intention is aiming at something and wanting to do it, in other words, it refers to the extent to which an employee has formulated conscious plan to adopt i5.0 technologies (MR/GenAI).
Attitude **(A)**	⇒	The employees' favourable or unfavourable evaluation of the idea to adopt i5.0 technologies (MR/GenAI).
Perceived Usefulness **(PU)**	⇒	The extent to which an employee perceives that the adoption of i5.0 (MR/GenAI) would be useful and could enhance their work performance.
Perceived Compatibility **(PC)**	⇒	The extent to which an employee perceives that the adoption of i5.0 (MR/GenAI) is consistent with the existing values and need of the potential adopters in the company.
Perceived Ease of Use **(PEOU)**	⇒	The extent to which an employee perceives that that the adoption of i5.0 technologies (MR/GenAI) in the company could be easily understood and operated.
Perceived Novelty **(PN)**	⇒	The extent to which an employee perceives i5.0 technologies (MR/GenAI) to be new to an existing technology.

Table 1.1 Terminology and the definition (Continue)

TERMINOLOGY		**DEFINITIONS**
Industry 5.0 **(i5.0)**	⇒	Industry 5.0 (i5.0) is termed as the revolution in which humans and machines are finding ways to improve the efficiency, adding human-centric, sustainable, dan resilient concepts to the industrial revolution (Maddikunta et al., 2022).
i5.0 Key Innovative Technologies	⇒	Within the context of this research refers to Mixed Reality (MR) technology and Generative Artificial Intelligence (GenAI) technology (Raja Santhi & Muthuswamy, 2023).
Mixed Reality **(MR)**	⇒	Mixed Reality (MR) refers to technologies that has capability to combine digital and real-world objects that can interact with each other in real-time (Kent, Snider, Gopsill, & Hicks, 2021).
Artificial Intelligence **(AI)**	⇒	Technology or machine that could imitate various complex human intellectual ability, including visual and speech recognition, decision making and language translation (Chui et al., 2023).
Generative AI **(GenAI)**	⇒	AI that is typically built using foundation models and has capabilities that earlier AI did not have, such as the ability to generate content (i.e., text or image) (Chui et al., 2023).
Technology Acceptance Model **(TAM)**	⇒	TAM is a well-established theoretical framework widely recognized for its simplicity, adaptability, and effectiveness in explaining technology adoption across various industries. In this research, TAM serves as the foundational framework for developing the conceptual model aimed at investigating the acceptance of i5.0 innovative technologies within the largely unexplored context of Indonesia's mining industry, a sector characterized by unique operational and cultural challenges.
Cognitive Response	⇒	It involved the employee's beliefs, perception, and evaluations about a technology (Davis, 1993). The concept of perceived compatibility, perceived ease of use, perceived usefulness, and perceived novelty are primarily considered as cognitive responses.
Affective Response	⇒	Emotional responses or feelings towards an object (Davis, 1993).

CHAPTER 2

LITERATURE REVIEW

2.1 Etymology and Philosophical Foundation of Industrial Revolution

The industrial revolution is a sequence of transformative epochs in human history (**Figure 2.1**), marked by technological advancements and their profound societal and economic impacts. The first industrial revolution (i1.0) began in the late 18th century (Stearns, 2018), characterized by the widespread adoption of steam engines as a core technology in manufacturing. This pivotal innovation replaced reliance on human and animal labour, leading to significant changes in agriculture, mining, and urbanization. It also spurred mass migrations to urban centres, where individuals sought employment in newly emerging industrial environments.

The second industrial revolution (i2.0), occurring in the 19th century, represented a leap forward in transportation, electrical, and communication technologies (Leng et al., 2022; Stearns, 2018). Key developments included the steam locomotive and steamboat, which revolutionized the transportation of goods, and the telegraph, which significantly accelerated long-distance communication. The rise of large-scale factories and assembly line production techniques further epitomized this era (Raja Santhi & Muthuswamy, 2023).

The third industrial revolution (i3.0), emerging in the mid-20th century, introduced groundbreaking technological advancements and the advent of automation (Maddikunta et al., 2022). The integration of computers and electronics transformed manufacturing, administration, and communication sectors. The increasing adoption of robotics and automation enhanced efficiency across industries, while information technology, particularly the advent of computerization and the internet, facilitated unprecedented levels of global connectivity (Leng et al., 2022; Maddikunta et al., 2022).

The fourth industrial revolution (i4.0), which emerged in the early 21st century (S. Huang et al., 2022), encompasses the integration of digital technology, the internet, and artificial intelligence. The Internet of Things (IoT) facilitates the collection of substantial volumes of data, which is subsequently subjected to analysis by artificial intelligence algorithms to enable more intelligent and informed decision-making processes. This revolution has led to the emergence of smart manufacturing facilities and highly automated production processes, advancing efficiency and innovation in industrial practices (Grabowska, Saniuk, & Gajdzik, 2022; S. Huang et al., 2022; Maddikunta et al., 2022).

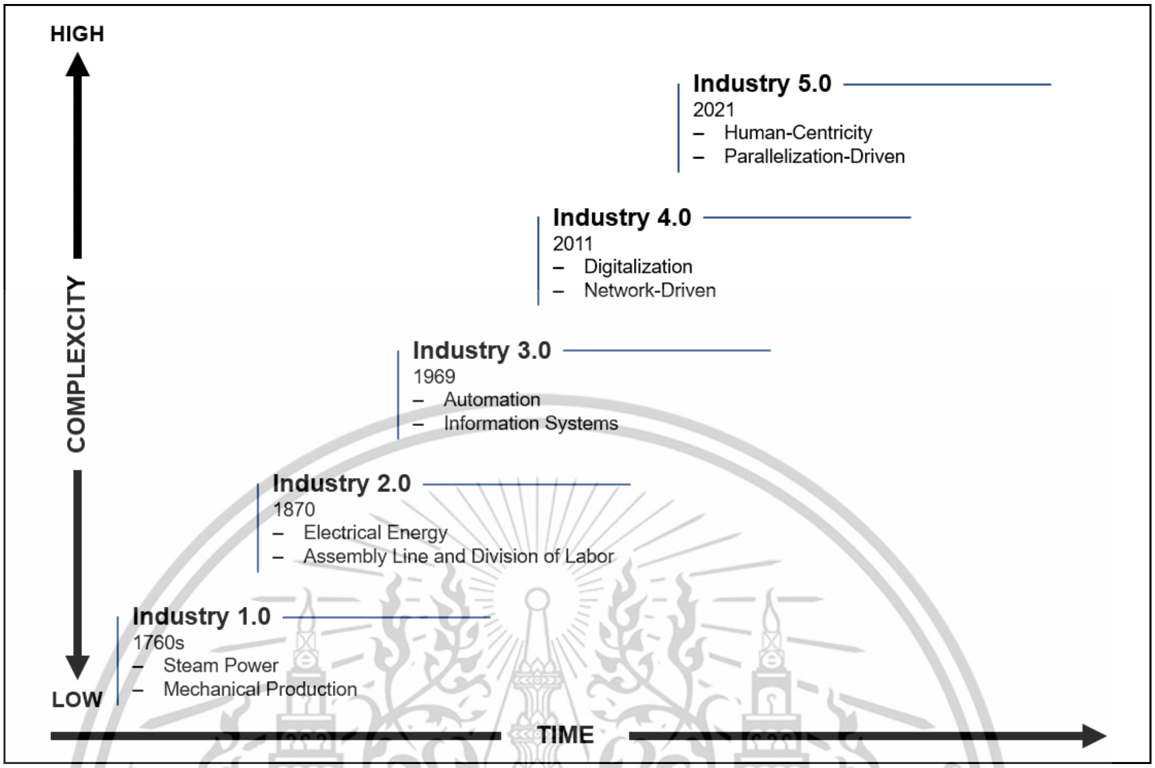

Figure 2.1 Industrial revolution

Source: Maddikunta et al. (2022); Wang et al. (2023)

Now, The Fifth Industrial Revolution (Industry 5.0) is an emerging paradigm of industrialization that emphasises the harmonious integration of human workers with robotic systems and intelligent technologies (Adel, 2022). The philosophical foundations of i5.0 are rooted in three core principles: sustainability, human-centricity, and resilience (Adel, 2022; Grabowska et al., 2022). The goal of i5.0 is to improve the standard of living and creativity with high-quality custom-made products to lead to sustainable production (Grabowska et al., 2022). It is about robots helping humans work better and faster by leveraging advanced technologies like the Internet of Things (IoT), big data, Mixed Reality (MR), and Artificial Intelligence (AI). i5.0 adds a personal human touch to the industry 4.0 (i4.0) pillars of automation and emphasizes the significance of the human factor in industrial systems (Adel, 2022; Ghobakhloo et al., 2023; Ordieres-Meré, Gutierrez, & Villalba-Díez, 2023; Rajesh, 2023; Xu, Lu, Vogel-Heuser, & Wang, 2021). It is a collection of guidelines, concepts, and instructions for the future development of industrial automation and digital transformation (Adel, 2022; Y. Lu et al., 2022; Xu et al., 2021). i5.0 acknowledges industry's capacity to fulfil social objectives beyond employment and development, in order to become a sustainable source (Akundi et al., 2022).

2.2 Mining 5.0

The Industrial Revolution has evolved into a series of five distinct stages, each characterized by specific features including the utilization of machinery, the advent of electricity, the development of information systems, the establishment of interconnected networks, and the implementation of parallelization techniques (L. Chen, Xie, et al., 2023; S. Huang et al., 2022; Maddikunta et al., 2022). These stages are commonly referred to as Industry 1.0 through 5.0. In accordance with this, the mining sector has similarly performed a comparable metamorphosis (L. Chen, Xie, et al., 2023; Maddikunta et al., 2022; Wang et al., 2023), as depicted in **Figure 2.2**.

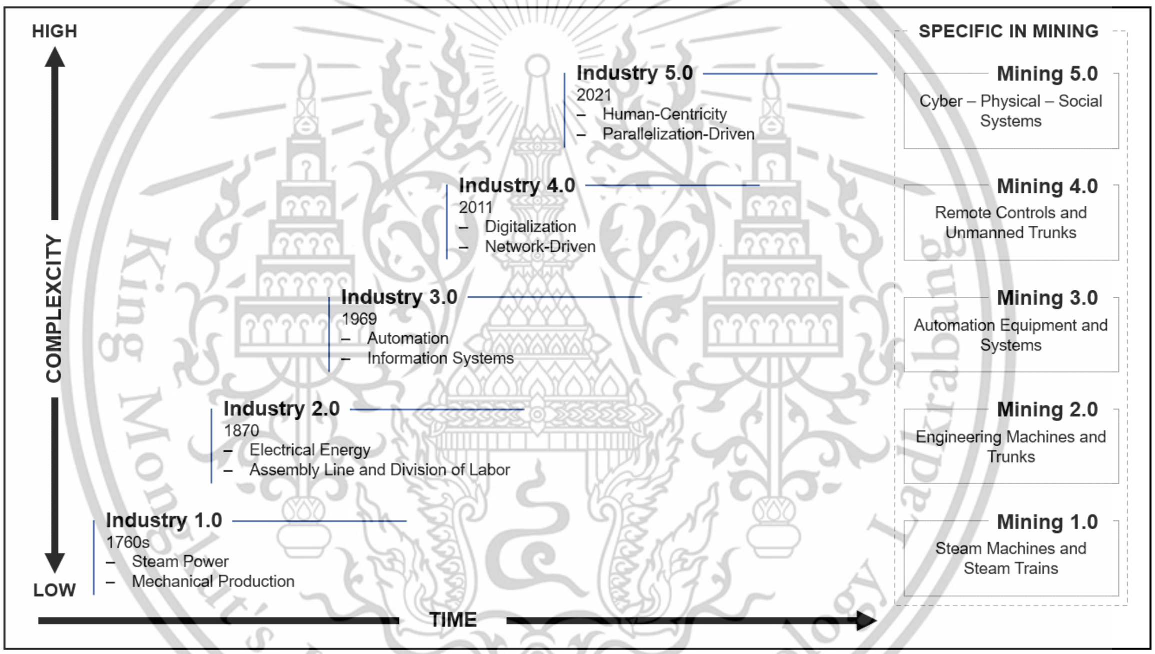

Figure 2.2 Industrial revolution in Mining

Sources: Maddikunta et al. (2022); Wang et al. (2023); L. Chen, Xie, et al. (2023)

The period known as Industry 1.0 and Mining 1.0 was characterized by the advent of mechanization, wherein steam engines gradually supplanted the reliance on manual labour. The transition from steam to oil, gas, and electricity in Industry 2.0 and Mining 2.0 marked a significant energy change, marking the advent of the electrification period. This technological advancement facilitated the integration of machinery into the forefront of mining operations, hence enhancing the ability of trucks to navigate challenging terrains. During the advent of Industry 3.0 and Mining 3.0, the introduction of computers and automation equipment became prominent, signifying the onset of the era of informatization. The advent of Industry 4.0 has brought about the emergence of interconnected systems, which may be attributed to the increasing prevalence of the internet and the proliferation of digital information. This innovation made remote monitoring possible, allowing unmanned mining vehicles and freeing up personnel (L. Chen, Li, et al., 2023; L. Chen et al., 2022; Ge et al., 2022; Teng et al., 2023; Tian et al., 2021).

The advent of Industry 5.0 will entail the further consolidation of information and physical systems, resulting in the emergence of intricate Cyber-Physical-Social Systems (CPSS). This integration will be characterized by the complete assimilation of the industry into society. The primary components of CPSS will consist of virtual artificial systems, thereby propelling the sector into the era of parallelization (L. Chen et al., 2022; Wang et al., 2023). The implementation and utilization of Mining 5.0 have the potential to improve mining safety, economic viability, and environmental sustainability. It serves as a crucial element in achieving the "6S" objectives, namely Safety, Security, Sustainability, Sensitivity, Service, and Smartness, within the mining sector (L. Chen, Xie, et al., 2023; Wang et al., 2023).

2.3 Industry 5.0 Technological Innovation for Mining Industry Transformation

This research centres on MR and GenAI as transformative i5.0 technological innovations, with substantial potential to revolutionize the mining industry. Unlike contemporary advanced technologies such as autonomous vehicles, electric vehicles, advanced robotics, and blockchain, many of which aim to minimize human involvement, MR and GenAI emphasize the integration of human intelligence with technological systems. This collaborative approach aligns seamlessly with the core principles of i5.0, emphasizing human-centricity and fostering a synergistic relationship between human operators and intelligent technologies.

The scholarly contribution of Adel (2022), Raja Santhi and Muthuswamy (2023), and Maddikunta et al. (2023) identify MR and GenAI as pioneering technologies of significant relevance to i5.0. Their work underscores the transformative potential of these innovations in reshaping industrial practices and advancing operational excellence. Similarly, research conducted by Sánchez and Hartlieb (2020), Zhironkin and Ezdina (2023), and Wang et al. (2023) align with the finding of Adel (2022), Raja Santhi and Muthuswamy (2023), and Maddikunta et al. (2023) corroborates these findings, positioning MR and GenAI as vital components of the Mining 5.0 framework. These technologies are recognized as not only innovative but also instrumental in addressing the unique challenges of the mining industry, including operational efficiency, worker safety, and sustainability.

By focusing on human-machine integration, MR and GenAI transcend the limitations of traditional automation technologies. They enable the mining industry to harness the power of intelligent systems while maintaining the critical involvement of human expertise. This dual emphasis on technological innovation and human-centricity situates MR and GenAI as pivotal enablers of sustainable, adaptive, and intelligent mining operations, marking a paradigm shift in the evolution of the industry. Their exploration in this research is thus timely and vital, offering significant contributions to the discourse on i5.0 and its application in the mining sector.

2.3.1. Mixed Reality (MR)

Mixed Reality (MR) is a subcategory of Extended Reality (XR) technologies, alongside Virtual Reality (VR) and Augmented Reality (AR). These technologies occupy different positions along the continuum of real and virtual environments, with MR uniquely blending physical and digital worlds, enabling seamless interactions between the two (Kent et al., 2021). Unlike VR, which fully immerses users in a completely virtual environment, MR shares more functional similarities with AR (**Figure 2.3**). However, MR distinguishes itself through advanced capabilities such as precise head tracking, gesture sensing, and depth mapping, allowing for accurate 3D spatial anchoring. These features provide MR systems with significantly enhanced visual and interactive experiences compared to traditional AR technologies, solidifying its status as a distinct and more immersive innovation (Bressan, Scarpa, & Peron, 2024). To be more specific MR in this research refers to technologies that has capability to combine digital and real-world objects that can interact with each other in real-time. In the context of the mining industry, MR technology holds immense potential to transform operations by addressing critical challenges and enhancing efficiency, safety, and collaboration. Specifically, MR enables the following advancements (Davidson & Narendran, 2017; Gürer et al., 2023; Yudhistyra & Srinuan, 2024):

- Seamless communication among team members across geographically dispersed locations.
- Rapid remote expert support for diagnostics and real-time guidance, including immediate access to instructions for repairing malfunctioning or faulty equipment.
- Execution of ‘follow-complete-document’ workflows directly on-site, streamlining procedural compliance and documentation processes.
- Enhanced occupational health and safety training, offering immersive simulations of hazardous mining environments to improve worker preparedness and reduce risks.

These applications demonstrate MR's potential as a transformative tool for the mining industry, driving operational excellence while fostering safer and more efficient practices in complex and challenging environments.

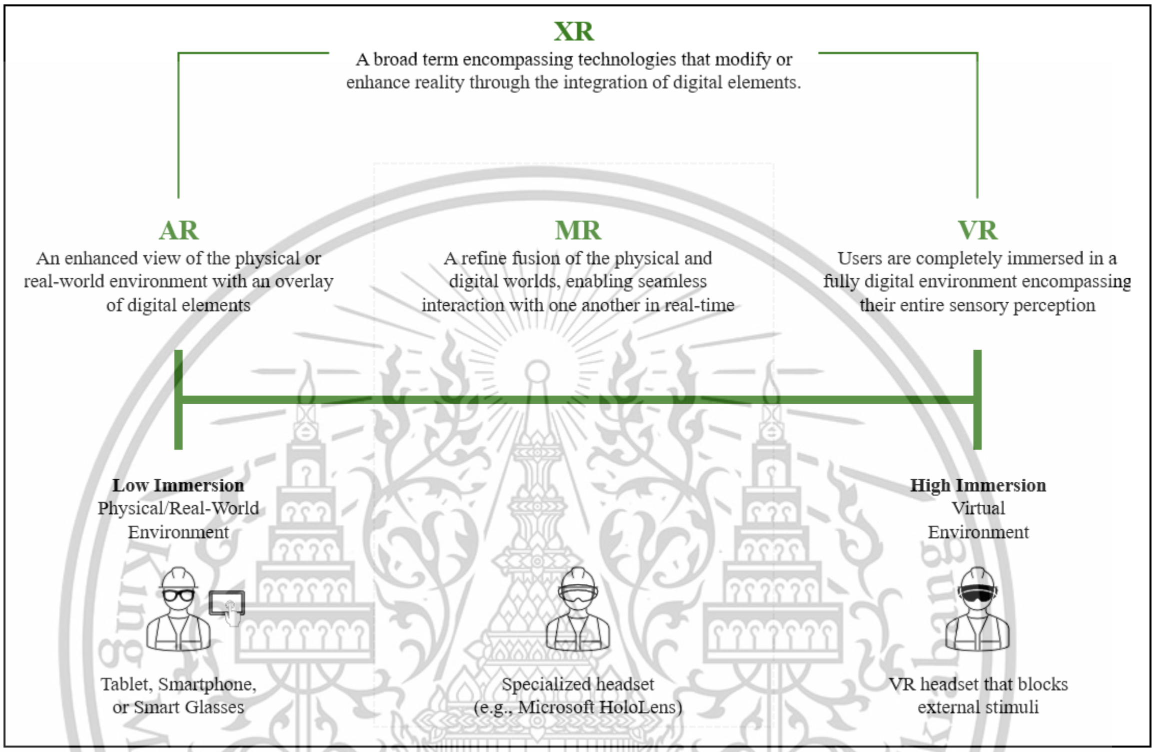

Figure 2.3 Mixed Reality (MR) Technology

Sources: Bressan et al., 2024; Gürer et al. (2023); Yudhistyra and Srinuan (2024)

2.3.2. Generative Artificial Intelligence (GenAI)

In addition to MR technology, Artificial Intelligence (AI) is increasingly recognized as a prospective and innovative technology of substantial relevance within the framework of i5.0 (Adel, 2022; Maddikunta et al., 2022; Raja Santhi & Muthuswamy, 2023), including its specific application in the mining sector under the Mining 5.0 (Sánchez & Hartlieb, 2020; Wang et al., 2023; Zhironkin & Ezdina, 2023). While AI encompasses diverse definitions, it is generally described as computer systems capable of performing tasks typically requiring human intelligence, such as visual and speech recognition, decision-making, and language translation (Davidson & Narendran, 2017). In its strictest sense, AI is defined as the simulation of human intelligence by computers (Sheikh, Prins, & Schrijvers, 2023).

However, given the current state of AI, which primarily consists of advanced yet narrow applications, this traditional definition is insufficient for contemporary research contexts. Within this research, Generative Artificial Intelligence (GenAI) is emphasized, defined as an advanced form of AI that leverages deep learning models to produce human-like content, such as text, images, and other media, in response to complex and varied prompts, including languages, instructions, or questions (Marc et al., 2023). This capability enables GenAI to replicate nuanced human communication and creative processes, making it an integral tool for addressing complex challenges and enhancing productivity in diverse contexts. Some examples of GenAI technologies are ChatGPT, Copilot, or Gemini. These tools demonstrate the potential of AI to transform individual tasks through automation, creativity, and decision-making support.

While the exact trajectory of AI's influence on mining and metals industries remains uncertain, its transformative potential is widely acknowledged. AI technologies, including GenAI, are projected to significantly enhance productivity in these sectors by automating complex tasks and optimizing resource management (Dwivedi et al., 2023). Beyond mining, GenAI is expected to contribute to global productivity growth (**Figure 2.4**), with potential annual increases of 0.2% to 3.3% from 2023 to 2040, contingent on effective redeployment of labour hours (Chui et al., 2023). the integration of AI, particularly GenAI, represents a pivotal advancement for the mining sector within the i5.0 framework, promising enhanced efficiency, sustainability, and human-technology collaboration.

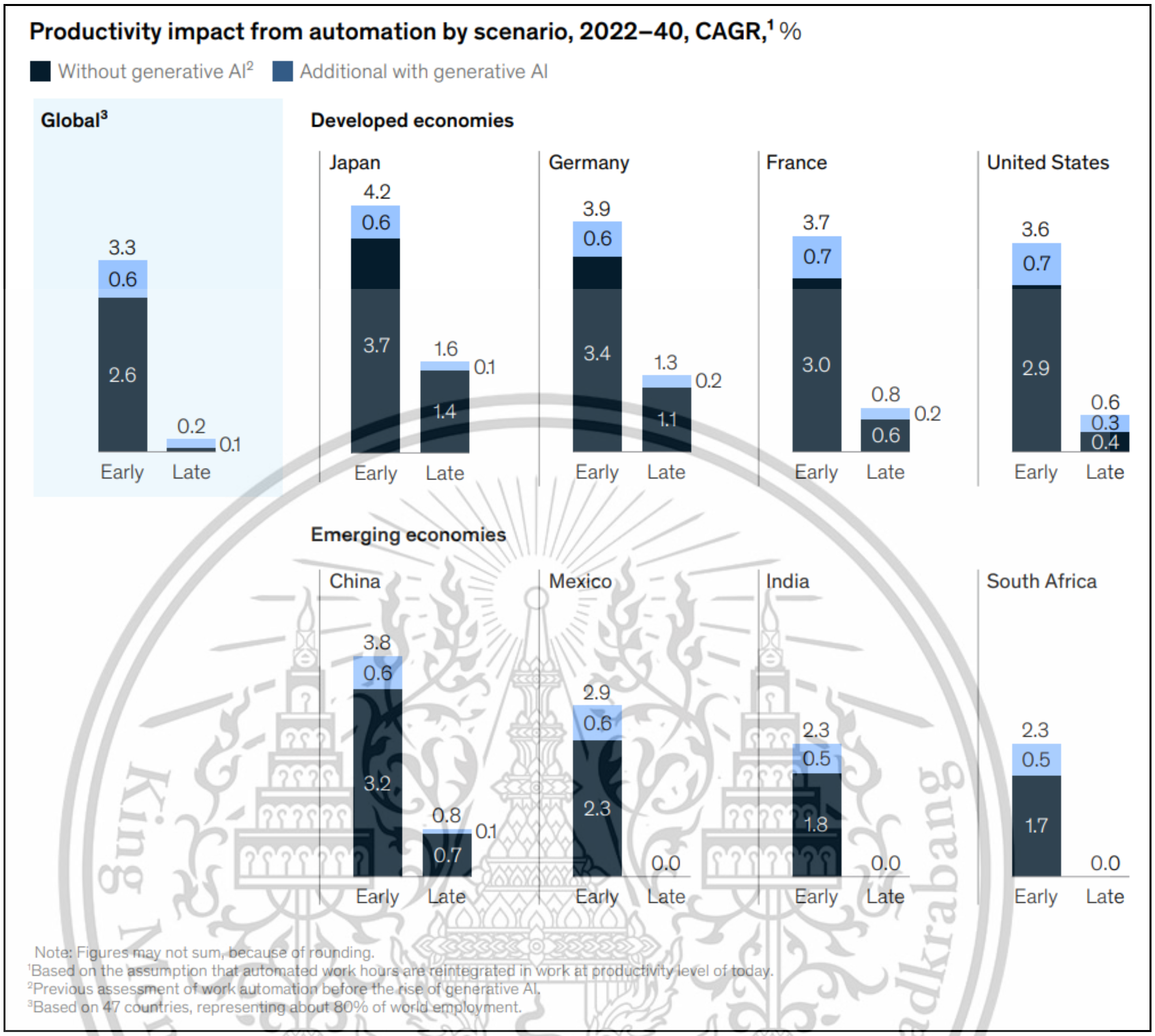

Figure 2.4 Impact of Generative Artificial Intelligence (GenAI) on productivity

Source: Chui et al. (2023)

2.4 Technology Acceptance Theories

Since the initial stages of technology integration into human society, a prevailing perspective emerged, leading the need for understanding the underlying factors influencing individuals' adoption or acceptance of technological advancements. The initial theoretical framework that emerged in the discourse surrounding this issue was the Theory of Reasoned Action (TRA) by Fishbein and Ajzen (1975, 2010). The primary objective of TRA (**Figure 2.5**) is to explain the relationship between attitudes and behaviour where behavioural intention serves as the primary driver of behaviour, while the influential factors that shape behavioural intention are individuals' attitudes and subjective norms (Fishbein & Ajzen, 2010).

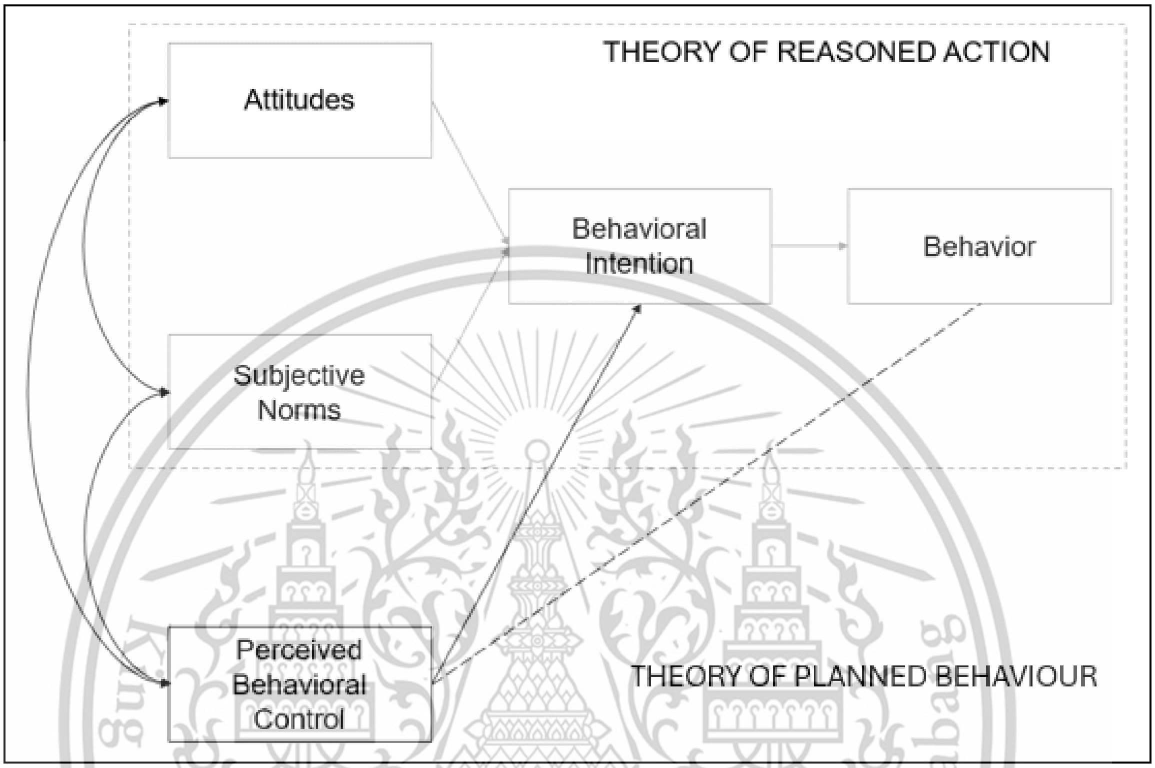

Figure 2.5 Theory of Reasoned Action (TRA) and Theory of Planned Behaviour (TPB)

Sources: Fishbein and Ajzen (1975); Ajzen (1985)

Fishbein and Ajzen (1975) originally established the Theory of Reasoned Action (TRA) within the realm of health in order to gain insights into health-related behaviours. However, the scholars posited that the TRA had the potential to be employed in other contexts to comprehend and perhaps forecast a wide range of human behaviours. In this context, TRA represent the origin of the Technology Acceptance Model (TAM) developed by Davis (1986) – TAM (**Figure 2.6**) emerged almost simultaneously with the Theory of Planned Behaviour (TPB), a revision of the TRA by including the construct of Perceived Behavioural Control (PBC, an extension of the theory of Self-Efficacy) into the TPB (Ajzen, 1985, 1991).

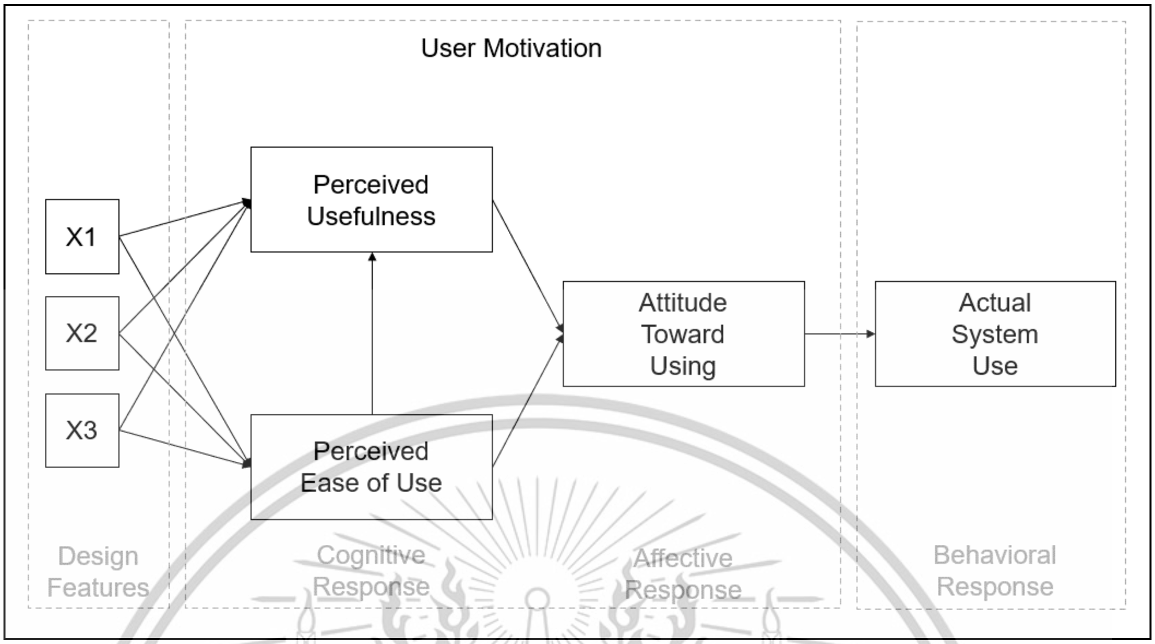

Figure 2.6 The proposed Technology Acceptance Model (TAM)

Source: F. D. Davis (1986)

Davis (1986) argued that the actual utilization of computer technology could be regarded as a manifestation of behaviour, therefore suggesting that the TRA could serve as an appropriate foundation for explaining and forecasting such behaviour. The proposed TAM concept suggested that the motivation of individuals or users could be explained by three key factors: perceived ease of use, perceived usefulness, and attitude toward using (Davis, 1986).

Davis (1986) hypothesized that the attitude of an individual or user towards computer technology played a significant role in determining an individual or user decision to either adopt or reject the technology (**Figure 2.7**). In this stage (Davis, 1986), perceived usefulness refers to the degree to which an individual believes that utilizing a specific system would improve their job performance, whereas the perceived ease of use is defined as the degree to which an individual believes that using the particular system would require minimal effort; both beliefs were hypothesized to be directly influenced by the system design characteristics (represented by X1, X2 and X3).

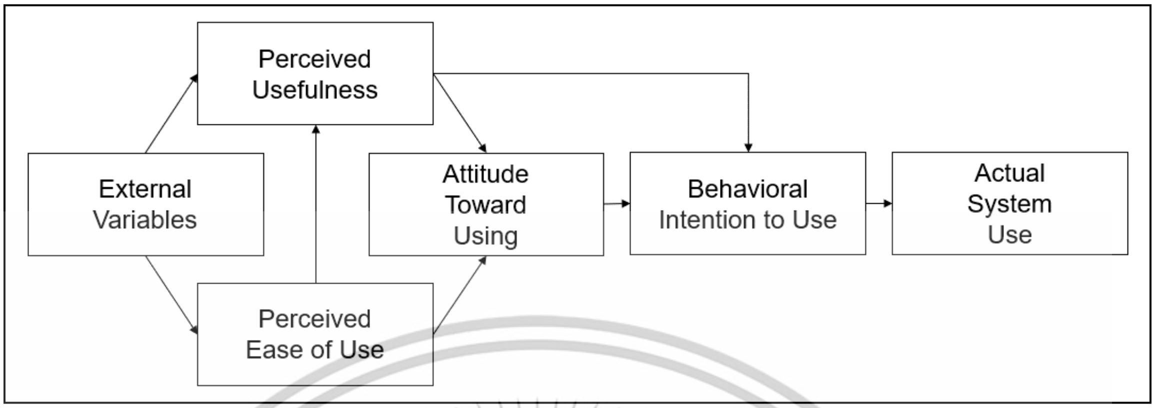

Figure 2.7 Later experimental stage of Technology Acceptance Model (TAM)

Source: F. D. Davies et al. (1989)

During later experimental stages, similar to TRA, the TAM argued that the utilization of computer technology was influenced by behavioural intention to use. However, TAM diverged from TRA by asserting that behavioural intention to use was influenced by both individual's attitude toward using the systems and perceived usefulness (Davis et al., 1989). The later attitude toward using – behavioural intention to use relationships were added based on the fundamental of TRA and other related models presented by Bagozzi (1981) and Triandis (1977).

Although TRA suggest that beliefs (i.e., in TAM case, the behaviour is actual system use) should be completely mediated by attitude toward using, the original conceptualization (the proposed TAM) and subsequent research have shown that attitude toward using only partially mediates the effect of perceived usefulness on behavioural intention to use. Davis et al. (1989) explained that in work context, individuals may employ a technology even if they do not have positive attitude toward using because it may provide productivity enhancement (i.e., be useful). Considering this, the original theoretical conceptualization of TAM incorporated attitude toward using. However, based on the empirical evidence, the final version of TAM framework (Davis, 1989; Davis & Venkatesh, 1996), exclude the attitude toward using construct because it did not fully mediate the effect of perceived usefulness on behavioural intention to use (**Figure 2.8**).

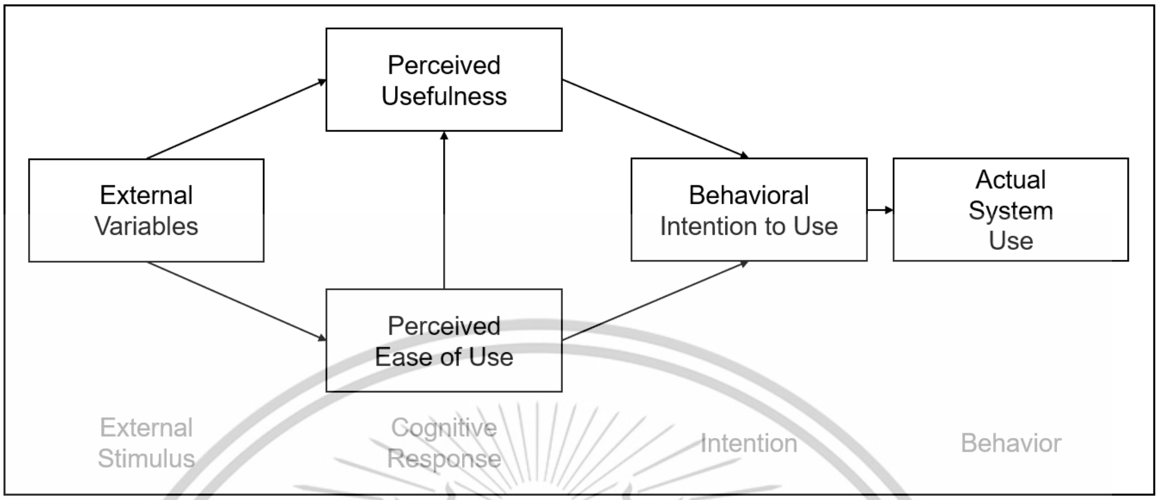

Figure 2.8 Final version of Technology Acceptance Model (TAM)

Sources: F. D. Davies et al. (1989), F. D. Davis and Venkatesh (1996)

In the same manner, other researchers have implemented and suggested various additions to TAM (Venkatesh & Bala, 2008). Continuous research constantly introduces new parameters that exert substantial influence on the key variables of the TAM framework (Venkatesh & Davis, 2000; Venkatesh, Morris, Davis, & Davis, 2003). Over the time of its development, the TAM has seen significant advancements, solidifying its position as a pivotal framework for comprehending the factors that influence human behaviour in relation to the possible acceptance or rejection of technology. The strength of the TAM model and the various variations of the model that have been confirmed by numerous researchers and their research emphasize the broad applicability of this TAM to a variety of technologies and contexts, including acceptance of information technology (Venkatesh & Davis, 2000; Venkatesh et al., 2003), e-commerce (Pavlou & Fygenson, 2006), hedonic information systems (van der Heijden, 2004), smartphones (Ooi & Tan, 2016), online learning (Liu, Chen, Sun, Wible, & Kuo, 2010) or mobile learning (Alasmari & Zhang, 2019) or simulation-based learning (Lemay, Morin, Bazelais, & Doleck, 2018), social media (Dumpit & Fernandez, 2017; Wirtz & Göttel, 2016), World-Wide-Web (Moon & Kim, 2001) or internet (J. Lu, Yu, Liu, & Yao, 2003), Virtual Reality (Jang, Ko, Shin, & Han, 2021) or augmented reality (Shen, Xu, Sotiriadis, & Wang, 2022), and Artificial Intelligence (Flavián, Pérez-Rueda, Belanche, & Casaló, 2022).

As time goes by, there is usually a lot of excitement or technology hype at the introduction of every technological advancement, but only after some time has passed will tell whether it be judged as mere hype or justified true acclaim. According to Beal and Bohlen (1957), the majority of emerging technologies adhere to a standardized technology maturity life cycle. This concept does not resemble a product life cycle but rather pertains to a complete technology or a certain generation of a technology. The adoption of technology is the predominant factor that propels the development of industries throughout their entire cycle. By exploring additional applications for resources, they eventually deplete the effectiveness of these processes, resulting in initial gains that are relatively effortless and substantial. However, as the technology advances, achieving further progress becomes increasingly challenging and demanding.

In addition, the process of adopting technology usually follows an S-shaped curve, as mentioned in the Diffusion of Innovations (DOI) theory (G. M. Beal, Rogers, & Bohlen, 1957). This is because people exhibiting varying responses to new products. As mentioned in DOI theory, individuals exhibit varying degree of readiness when it comes to embracing new technologies, and that the characteristics of a product have an impact on its overall adoption. Rogers (2003) categorized individuals into five distinct groups: innovators, early adopters, early majority, late majority, and laggards. The distribution of individuals related to the S-shaped curve is that innovators occupy 2.5%, early adopters 13.5%, early majority 34%, late majority 34% and laggards 16%, as depicted in **Figure 2.9**.

The remarkable advancement of new technology, the growing utilization of computers and Information Technology (IT) in organizations, and the significant increase in capital investment in IT — accounting for 50% of all new capital investment since the 1980s (Westland & Clark, 1994) — necessitate the improved acceptance, adoption, and utilization of technology by employees in order to enhance productivity. Implementing new technology necessitates significant investment, time, effort, and dedication from the entire organization. However, successful integration and achieving the desired Return on Investment (ROI) are demonstrated through the proper adoption, integration, commitment, and consistent utilization of the technology over an extended period of time (Bhattacherjee, 1998).

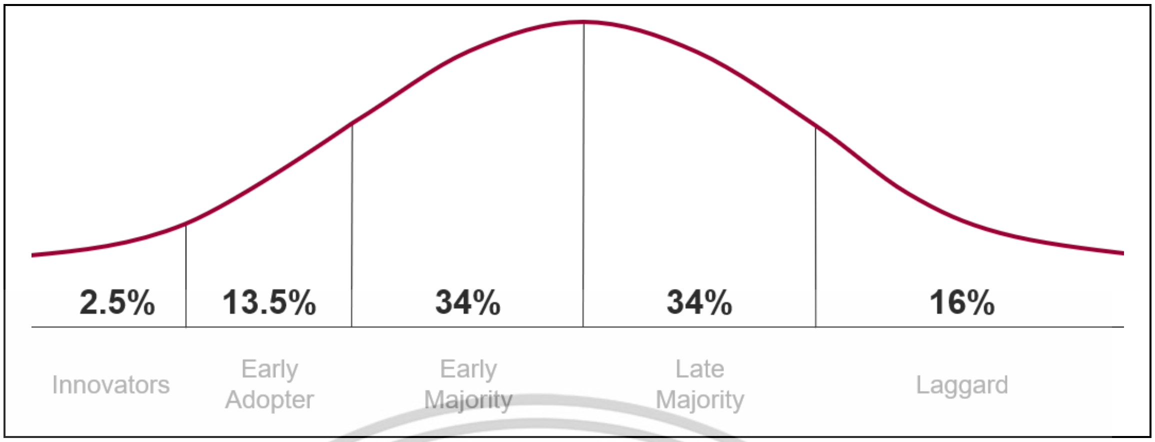

Figure 2.9 The categories of adopters

Source: Rogers (2003)

Furthermore, this dissertation adopts the TAM as the primary theoretical framework for investigating the adoption of MR and GenAI technologies within the mining industry. While the DOI theory (Rogers, 2003) emphasizes the characteristics of innovations and adopter categories, and the Unified Theory of Acceptance and Use of Technology (UTAUT) offers a comprehensive but complex approach (Venkatesh et al., 2003; Venkatesh, Thong, & Xu, 2012), TAM provides a more direct and predictive link between users' perceptions and their behavioural intentions (Davis, 1989). Its simplicity and effectiveness in predicting technology acceptance make it widely applicable across industries, including mining, where practical implementation is essential (Kelly et al., 2023).

TAM's emphasis on perceived usefulness and perceived ease of use makes it particularly advantageous for understanding how mining employees evaluate new technologies. Its flexibility enables integration with additional constructs such as perceived compatibility and perceived novelty, addressing industry-specific challenges (Rosli et al., 2022). Given the high-risk and operationally demanding nature of mining environments, user-centric models like TAM provide actionable insights into the psychological and behavioural drivers of technology adoption.

Moreover, the adaptability of TAM allows for future refinements by incorporating variables tailored to the mining sector. Specifically, this research hypothesizes that perceived compatibility, perceived ease of use, perceived usefulness, and perceived novelty influence employees' attitudes, which, in turn, shape their intention to adopt MR and GenAI technologies. This tailored approach ensures the model remains relevant and applicable in examining the determinants of technology adoption within the mining industry, a sector where research on human-centric adoption factors remains limited (Gruenhagen & Parker, 2020).

2.5 Concept of Innovation, Acceptance, and Adoption

Innovation refers to the use of novel methods in the areas of design, production, or marketing of goods or services, which result in the creation of value and provide the innovative organization with a competitive edge over rivals (Law, 2016). Innovation entails the implementation of a novel concept and is typically accomplished within the confines of an organization. Rogers (2003) defines innovation as an idea, practice, or object that is perceived as new by individual or other unit of adoption. The novelty or newness aspect of an innovation might be characterized by the acquisition of knowledge, persuasion, or a decision to adopt (Rogers, 2003). It incorporates a wide range of endeavours in the realms of science, technology, organization, finance, and business. Note that the context of this research specifically focuses on the technological innovation of i5.0 context.

In addition, acceptance is generally define as the opposite of rejection and refers to a positive decision to use an innovation (Ursavaş, 2022). In the context of technology acceptance, focused in this research, it can be defined as a user's willingness to employ technology for the tasks it is design to support (Teo, 2011). Nevertheless, it is important to note that acceptance does not automatically imply adoption, as adoption specifically refers to the acceptance and continued use of an innovation (Robertson, 1971). Rogers (2003) also perceives adoption as *a decision to continue use* of an innovation, hence it is crucial to establish a clear conceptualization and definition of the distinction between acceptance and adoption within the scope of this research. Bohlen (1964) specifically advocated for a distinct separation between acceptance and adoption, taking into account the time lag or delay between the mental acceptance and the actual act of adoption.

Furthermore, the concept of symbolic adoption of innovation emerged as an integral component of the adoption process, irrespective of whether the innovation being adopted is tangible or intangible (Klonglan & Coward, 1970). The fundamental assumption is that all innovation comprises a tangible component and that certain innovation also encompass an intangible component (Krampf, Burns, & Rayman, 1993). Therefore, adoption and rejection are associated with the behavioural stage in the adoption decision model, whereas acceptance and resistance are situated at the prior assessment and intention level (Frambach & Schillewaert, 2002; Ursavaş, 2022).

In alignment with the research conducted by Frambach and Schillewaert (2002) and Ursavaş (2022), the conceptual model proposed in this research focuses on the acceptance of individual in organization towards i5.0 technological innovation. However, the difference lies in the focus of innovation adoption which are at the intention stage and the mining industry context.

2.6 Conceptual Model and Research Hypotheses

A thorough review of the existing literature identified five core constructs (attitude, perceived compatibility, perceived ease of use, perceived usefulness, and perceived novelty) as the principal determinants influencing employees' intention to adopt MR and GenAI technologies within the mining industry. Intention, as conceptualized in this research, signifies an individual's explicit willingness and preparedness to engage in a specific behaviour. Grounded in seminal theories, intention is fundamentally predicated upon an individual's assessment of the likelihood or probability of engaging in a particular action, with higher subjective probabilities correlating with an increased likelihood of the behaviour's performance (Fishbein & Ajzen, 1975, 2010). This perspective underscores that intention is not merely a passive inclination but rather a conscious formulation of plans to undertake a specific behaviour.

Within the broader theoretical framework, intention has been defined as the extent to which an individual formulates deliberate plans to act (Islam, Low, & Hasan, 2013), the degree of conscious planning directed towards future behaviour (Warshaw & Davis, 1985), or the perceived relationship between oneself and a specific action (Jaccard & King, 1977). Intention is recognized as a critical construct for predicting complex human behaviours, which are inherently influenced by a multitude of interacting antecedents. While intention is the most immediate and essential antecedent of behaviour, its execution also depends on the extent of control an individual has over the behavioural context (Fishbein & Ajzen, 2010).

Despite its prominence across disciplines such as psychology, marketing, and behavioural sciences (Anderson, 1983; Fishbein & Ajzen, 1975, 2010; Islam et al., 2013; Jaccard & King, 1977; Raz, 2017; Warshaw & Davis, 1985), intention has often been underexplored or insufficiently defined in the domain of technology acceptance (Álvarez-Marín, Velázquez-Iturbide, & Castillo-Vergara, 2021; Ateş & Garzón, 2023; Barrett, Pack, Guo, & Wang, 2020; T. Chen, Chen, Or, & Lo, 2022). To address this gap, the current research adopts the definition of intention as the degree to which an employee consciously plans to adopt i5.0 technological innovations, specifically MR and GenAI technologies. This definition aligns with foundational theories in intention models (Fishbein & Ajzen, 1975, 2010; Islam et al., 2013; Jaccard & King, 1977; Kang & Shin, 2015). Intention is characterized by expressions of commitment, such as "I will engage in …," "I intend to engage in …," "I plan to engage in …," and similar declarative statements, which serve as reliable indicators of an individual's likelihood to perform a specified behaviour (Fishbein & Ajzen, 2010).

The measurement of intention in technology acceptance research has been validated through robust empirical studies. For instance,, Jang et al. (2021) and Kang and Shin (2015) adopted indicators consistent with the original Technology Acceptance Model (TAM) developed by Davis, (1989), and its extensions by Davis et al. (1989), and Venkatesh and Davis (2000). Similarly, Holdack et al. (2022) validated the construct within the domain of Extended Reality (XR) technologies. These methodological precedents provide a strong foundation for the operationalization of behavioural intention within this study. **Appendix C.1** presents an extensive collection of previous literature regarding the concept of intention.

To understand the acceptance of i5.0 innovations in the mining sector, it is crucial to examine the individual factors influencing behavioural intentions. The identified constructs (attitude, perceived compatibility, perceived usefulness, perceived ease of use, and perceived novelty) have been extensively validated in prior research as critical determinants of intention. These constructs offer a comprehensive framework for analysing employee responses to MR and GenAI technologies, which represent key innovations with transformative potential for the mining industry. By synthesizing insights from existing literature, this research seeks to elucidate the complex interplay between these factors and their collective impact on employees' acceptance of i5.0 technological innovations.

2.6.1 Attitude

The adoption of technological innovation is fundamentally viewed as a result of an accumulation of perceptions, collectively shaped as attitudes toward the technology. Attitude, as a cognitive precursor, reflects an individual's emotional capacity to define their evaluative stance and personality traits (Chatterjee et al., 2023; Wood, 2000). It is a predisposed mental state comprising a set of values, typically activated by reactive responses to stimuli such as a person, place, or object (Dixon, McKeever, Holton, Clarke, & Eosco, 2015). Within this research, attitude refers to the extent to which employees evaluate the adoption of i5.0 technological innovations, specifically MR and GenAI, as favourable or unfavourable within the mining industry context.

Attitude is often expressed through affective responses, which are inherently linked to emotions. Examples of such expressions include declarative statements such as, "I like the idea …," "Using … is interesting," "My general opinion regarding … is favourable," and similar declarative statements (Holdack et al., 2022; Shen et al., 2022). These affective indicators serve as reliable measures of an individual's evaluative response to a given technological innovation. As a construct, attitudes are intrinsically associated with behavioural intention, and the interaction between attitude and intention has been extensively observed in various domains, including consumer behaviour and technology adoption (Chatterjee et al., 2023; Kahle & Valette-Florence, 2015). **Appendix C.2** provides a comprehensive review of prior literature on the concept of attitude.

Theoretical and empirical research consistently highlights attitude as the primary determinant of technological innovation acceptance (Ajzen & Fishbein, 1980; Davis et al., 1989; Fishbein & Ajzen, 1975; Moore & Benbasat, 1991; Rogers, 2003; Tan & Teo, 2000). This construct also acts as a mediating factor between individual perceptions, such as perceived usefulness or ease of use, and an individual's intention to engage with a technology (Acikgoz, Elwalda, & De Oliveira, 2023). The evaluative function of attitudes, whereby individuals assign positive or negative values to an object or idea, serves as a pivotal element in predicting the likelihood of technology acceptance (Chanda, Vafaei-Zadeh, Hanifah, Ashrafi, & Ahmed, 2024; Holdack et al., 2022; Shen et al., 2022). Therefore, the first hypothesis is:

H1: Attitude positively influences employees' intention to adopt the i5.0 technological innovation (in this case are MR / GenAI technologies).

2.6.2 Perceived Compatibility

Compatibility is a key attribute of an innovation that influence its adoption (Hoffer & Alexander, 1992; Rogers, 2003). Its refers to the degree to which an innovation is perceived as consistent with the existing values, past experiences, and needs of potential adopters (Moore & Benbasat, 1991; Rogers, 2003). D. Kim and Ammeter (2014) describes perceived compatibility as the degree to which technologies (i.e., personal information system) are perceived as being consistent with the existing values, needs and pact experience of potential adopters. In the context of this research, perceived compatibility refers to the extent to which an employee perceives that the industry 5.0 technological innovation, specifically MR and GenAI, is consistent with the existing values and need of the potential adopters in the company. According to D. Kim and Ammeter (2014) perceived compatibility was significantly related to behaviour intention. To mitigate any resistance to the adoption of a new technology, a corporation is more inclined to embrace a technology that is more compatible with its existing operational capabilities (Tornatzky & Klein, 1982).

Perceived compatibility is commonly represented through cognitive expressions, which reflect deliberate thought processes and conscious evaluations. These are often conveyed through statements such as, "… aligns well with current needs …," "… seamlessly integrates with existing business operations …," or "… suits the company's infrastructure … (Ledesma-Chaves, Gil-Cordero, Navarro-García, & Maldonado-López, 2024; Oliveira, Thomas, & Espadanal, 2014)." Such expressions elaborated in **Appendix C.3** reliably indicate individuals' perceptions of technological innovation. As a conceptual construct, perceived compatibility is fundamentally intertwined with attitude, and their relationship has been extensively examined in diverse contexts, including recent investigations into consumer behaviour and the adoption of new technologies (Acikgoz et al., 2023; Gunnoo, Subadar, & Fauzel, 2023; Ledesma-Chaves et al., 2024). Therefore, the second hypothesis is:

H2: Perceived compatibility positively influences attitude toward adoption of the i5.0 technological innovation (MR / GenAI technologies).

2.6.3 Perceived Ease of Use

Perceived ease of use in the TAM model is defined as the degree to which a person believes that using a particular system would be free of effort (Davis, 1989). In the context of this research, perceived ease of use refers to the extent to which an employee perceives that the industry 5.0 technological innovation, specifically MR and GenAI, could be easily understood and operated. Perceived ease of use is similarly related to complexity, which refers to the perceived level of difficulty in using an innovation, according to the diffusion of innovation theory (Moore & Benbasat, 1991; Rogers, 2003). Prior research on the diffusion of innovation have also indicated a significant influence on perceived ease of use. According to Tornatzky and Klein (1982) in innovation adoption implementation research, finding that compatibility, relative advantage, and complexity as the key factors that strongly influence the adoption of various types of innovation.

Regarding the ease of use of technological innovation, various research has reproduced Davis's (1989) research to gather empirical evidence regarding the association between usefulness, ease of use, and systems use (Adams, Nelson, & Todd, 1992; Hendrickson, Massey, & Cronan, 1993; Segars & Grover, 1993; Subramanian, 1994; Szajna, 1994). Segars and Grover (1993) conducted a thorough analysis of Adams et al.'s (1992) attempt to replicate the Davis study. They put out an alternative model that revolves around three key concepts: usefulness, efficacy, and simplicity of use. The UTAUT model (Venkatesh et al., 2003) assessed the notions of effort expectancy, which is synonymous with the perceived ease of use.

Perceived ease of use is typically demonstrated through cognitive responses that reflect deliberate thought and evaluation. Such responses are often conveyed through statements like, "… is not complex or mentally demanding," "… is clear and easy to understand," or "… is flexible and facilitates smooth interaction (Holdack et al., 2022; Shen et al., 2022)." These cognitive indicators elaborated in **Appendix C.4** are reliable measures of an individual's evaluative perception of a technological innovation. As a theoretical construct, perceived ease of use is closely linked to attitude and the relationships between perceived ease of use and attitude have been widely documented across various disciplines, including recent research on consumer behaviour and technology adoption. Accordingly, the third and fourth hypotheses are:

H3: Perceived ease of use positively influences attitude toward adoption of the i5.0 technological innovation (MR / GenAI technologies).

2.6.4 Perceived Usefulness

Perceived usefulness in the TAM model is defined as the extent to which an individual believes that using a particular systems or technology would enhance his or her job performance (Davis, 1989). Perceived usefulness is a significant notion that offers valuable diagnostic insights into the influence of individual attitudes and intentions to use – perceived usefulness has a direct effect on intentions to use over and above its influence via attitude (Davis, 1989, 1993; Taylor & Todd, 1995). Prospective individuals' perception of the usefulness of a certain application or system is contingent upon their belief that said technology would enhance or accelerate their job performance within the setting of an organization (Yen, Wu, Cheng, & Huang, 2010). Consistent with prior studies, in the context of this research, perceived usefulness refers to the extent to which an employee perceives that the adoption of industry 5.0 technological innovation, specifically MR and GenAI, would improve their performance within the mining industry context. The UTAUT model (Venkatesh et al., 2003) investigated the concept of performance expectancy, which is equivalent to perceived usefulness.

Various literatures have replicated the original TAM model by Davis (1989) to provide empirical evidence on the relationship with the use of systems. Systems with higher perceived usefulness has a stronger and consistent relationship with system usage. Research has also demonstrated that perceived usefulness is a highly influential factor and maintains its significance throughout all stages of measurement (Agarwal & Prasad, 1998; Venkatesh & Davis, 2000; Venkatesh et al., 2003). If an individual believes that the new systems usage will improve efficiency, effectiveness, or provide better work control, they are more likely to adopt the innovation (Y. Lee, Kozar, & Larsen, 2003). The Perceived Usefulness (PU) of a systems has a robust and consistent correlation with systems usage (Davis, 1989; Igbaria, 1993).

Perceived usefulness is often expressed through cognitive responses that involve careful consideration and evaluation. These responses are commonly articulated through statements such as, "… is useful," "… could improve the quality of my work," or "… helps me complete tasks more efficiently." Such expressions detailed in **Appendix C.5** serve as dependable indicators of an individual's evaluative perception of a technological innovation. As a conceptual construct, perceived usefulness is strongly associated with attitude, a relationship that has been extensively validated across multiple disciplines, including recent studies on consumer behaviour and technology adoption (Chanda et al., 2024; Debasa, Gelashvili, Martínez-Navalón, & Saura, 2023; Holdack et al., 2022; Ngoc Su et al., 2023). Thus, the fourth hypothesis is proposed as follows:

H4: Perceived usefulness positively influences attitude toward adoption of the i5.0 technological innovation (MR / GenAI technologies).

2.6.5 Perceived Novelty

Perceived novelty in technological innovation is defined as the extent to which individuals perceive an innovation as distinctively new compared to existing technologies (Wells, Campbell, Valacich, & Featherman, 2010). Tokunaga (2013) characterizes perceived novelty as the recognition of a technology as novel, engaging, and clearly differentiated from other technologies known or used at the time of its introduction. Drawing on previous research, this research frames perceived novelty as the degree to which workers in the mining industry view MR technology as a new advancement over existing solutions. The significance of perceived novelty in driving technology adoption stems from its ability to evoke a sense of unfamiliarity and curiosity, thereby stimulating interest (Burke & James, 2008). This heightened sense of curiosity often leads to increased engagement, prompting individuals to seek deeper knowledge about the innovation (Magni, Susan Taylor, & Venkatesh, 2010).

Perceived novelty is frequently articulated through cognitive responses that capture thoughtful evaluation and deliberate assessment. These responses often manifest as statements such as, "… provides a novel experience," "… is new and revitalizing," or "… introduces a neat and novel way to work within the organization (Adapa, Fazal-e-Hasan, Makam, Azeem, & Mortimer, 2020; Dang, 2020; Hu, Liu, & Yan, 2023; Wells et al., 2010)." Such expressions detailed in

Appendix C.6 serve as robust indicators of an individual's evaluative perception of a technological innovation (Adapa et al., 2020). Conceptually, perceived novelty is deeply intertwined with attitude, and their relationship has been extensively validated across various disciplines, including contemporary research on consumer behaviour and the adoption of emerging technologies (Fazal-e-Hasan, Amrollahi, Mortimer, Adapa, & Balaji, 2021; Mani & Chouk, 2017; Sun et al., 2023).

In addition, perceived novelty has emerged as a crucial factor in influencing consumer attitudes and engagement with marketing communications. Novel experiences have been shown to cultivate favourable perceptions and stimulate heightened interest (Frasquet, Ieva, & Mollá-Descals, 2024). Adapa et al. (2020) have found that perceived novelty of a Smart Retail Technology (SRT) can increase the perceived shopping value, thus leading to higher retail store and loyalty and higher intention to use the SRT. Similarly, Pape and Toporowski (2023) identified perceived novelty as a key driver of positive word-of-mouth for experiential retail environments, further underscoring its influence on consumer behaviour. These findings collectively underscore the integral role of perceived novelty in driving consumer engagement and shaping behavioural intentions. Consequently, the fifth hypothesis is proposed as follows:

H5: Perceived novelty positively influences attitude toward adoption of the i5.0 technological innovation (MR / GenAI technologies).

Following a comprehensive examination of the literature, the researcher has identified the six fundamental hypotheses for the conceptual model mentioned above and **Table 2.1** summarizes the previous research supporting the five fundamental research hypotheses.

Table 2.1 Previous research supporting research hypotheses.

HYPOTHESIS				RESEARCH SUPPORTING THE HYPOTHESIS
H1	Attitude (ATT)	⇒	Intention (INT)	Ibili et al. (2019); Revythi and Tselios (2019); M. Lee et al. (2020); Zhong et al. (2021); Jiang et al. (2021); Chatterjee, Chaudhuri, et al. (2021); Alam et al. (2021); Shen et al. (2022); Gado et al. (2022); Holdack et al. (2022); Buranelli de Oliveira et al. (2022); Papakostas et al. (2022); T. Huang (2023); Debasa et al. (2023); Sun et al. (2023); Ngoc Su et al. (2023); Arli and Bakpayev (2023); Chatterjee et al. (2023); Acikgoz et al. (2023); Karkonasasi et al. (2023); Chanda et al. (2024); Saif et al. (2024).
H2	Perceived Compatibility (PC)	⇒	Attitude (ATT)	Jiang et al. (2021); Buranelli de Oliveira et al. (2022); Gunnoo et al. (2023); Arli and Bakpayev (2023); Karkonasasi et al. (2023); Acikgoz et al. (2023); Chatterjee et al. (2023).
H3	Perceived Ease of Use (PEOU)	⇒	Attitude (ATT)	Revythi and Tselios (2019); Chatterjee, Chaudhuri, et al. (2021); Zhong et al. (2021); Gado et al. (2022); Papakostas et al. (2022); T. Huang (2023); Ngoc Su et al. (2023); Karkonasasi et al. (2023); Saif et al. (2024).
H4	Perceived Usefulness (PU)	⇒	Attitude (ATT)	Ibili et al. (2019); Revythi and Tselios (2019); Zhong et al. (2021); Alam et al. (2021); Shen et al. (2022); Gado et al. (2022); Holdack et al. (2022); T. Huang (2023); Debasa et al. (2023); Ngoc Su et al. (2023); Karkonasasi et al. (2023); Chanda et al. (2024).
H5	Perceived Novelty (PN)	⇒	Attitude (ATT)	Wells et al. (2010); Truong (2013); Neudecker et al. (2014); Mani & Chouk (2017); Feng and Xie (2019); Sun et al. (2023).

Moreover, **Figure 2.10** presents the conceptual framework developed for this research, tailored to the context of the mining industry. Detailed theoretical insights and concepts underpinning this framework, derived from prior research, are comprehensively outlined in **Appendix C** through **H**.

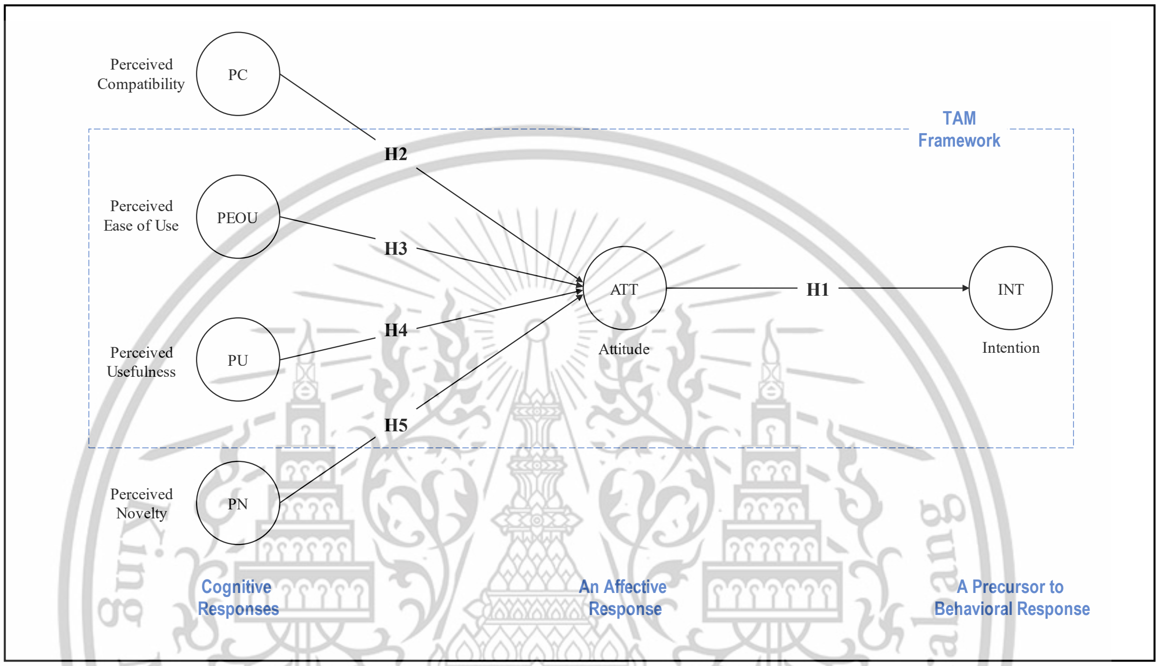

Figure 2.10 The conceptual model

Note: The conceptual model employs circles to represent each variable, thereby ensuring congruence with the analysis software (SmartPLS) and distinctly differentiating it from prior research, which utilized rectangles for each variable.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Paradigm and Methods

A paradigm, or “view of the world,” is a conceptual framework encompassing a basic set of beliefs or assumptions that act as a guide to the researchers (Creswell & Creswell, 2023). Guba and Lincoln (1994) and Perry et al. (1999) acknowledge on four fundamental paradigms for the execution of scientific research, however they held contrasting views regarding the nomenclature associated with the second paradigm. The four theoretical frameworks commonly used in research are: Positivism, Realism or Post-positivism (Guba & Lincoln, 1994; Perry et al., 1999), Critical theory, and Constructivism. Easterby-Smith et al. (2002) integrated the critical theory and constructivism paradigms to form the phenomenological paradigm, which is alternatively known as the qualitative or interpretative paradigm (Cavaye, 1996).

As this research investigates the factor that influences individuals or employees for the acceptance of i5.0 technological innovation within their organization, the positivism research paradigm is deemed suitable for addressing the research questions and objectives in the context of this research. This paradigm is extensively employed in research conducted within management and business school (Orlikowski & Baroudi, 1991). Within this paradigm, the research methodology is quantitative and requires controlled experiments on samples that represents a population. However, this paradigm has significant drawbacks, including difficulty with dynamic phenomena and inability to account for management environment's relatively unobservable facts. Moreover, while involvement and interaction is necessary to find data in many social science studies (Carson & Coviello, 1996), positivists separate themselves from the world they study (Perry et al., 1999).

3.2 Research Procedures

The research procedure shown in **Figure 3.1** began with collecting secondary data from international databases, as well as reviewing literature from conferences, journals, books and theses to identify the current trends or patterns associated with relevant topics to determine the objectives, specify the research questions and hypotheses, select research paradigm and research methodology, plus develop a conceptual framework regarding the intention to adopt i5.0 technological innovation within the context of the mining industry.

Following a thorough examination of various available methodologies, including their respective strengths and weaknesses, the quantitative approach was selected as the most suitable research methodology for addressing the research questions and objectives. Quantitative research is a systematic investigation to examine a theory by utilizing variables, measured with number and analysed with statistical procedure to determine the predictive generalization of the theory (Creswell, 2009; Creswell & Creswell, 2018, 2023). Utilizing the quantitative approach is going to provide precise measurement of variables and examination of proposed models associated with overarching casual explanations. In addition to that, the quantitative method's benefits lie in its ability to produce replicable results and generalise findings. This is achieved through the use of a rigorous research design and a suitable survey sample.

Meanwhile, the integration of sampling design considerations with all other decisions in a research study is crucial (Blair, Czaja, & Blair, 2013). The procedure of sampling design encompasses a series of five sequential processes: target population, sampling frame, sampling technique, sample size, and execution (N. K. Malhotra, 2020) as shown in **Table 3.1**. The target population comprises both male and female employees working within the mining industry in Indonesia. However, the precise population size remains unknown. To address this limitation, judgmental sampling has been employed as the sampling technique for this research. This method enables the researcher to strategically select participants based on predefined characteristics rather than relying on random selection. Judgmental sampling is widely recognized for its efficiency and applicability in exploratory research, particularly when studying specialized populations where probability-based sampling is impractical (N. K. Malhotra, 2020).

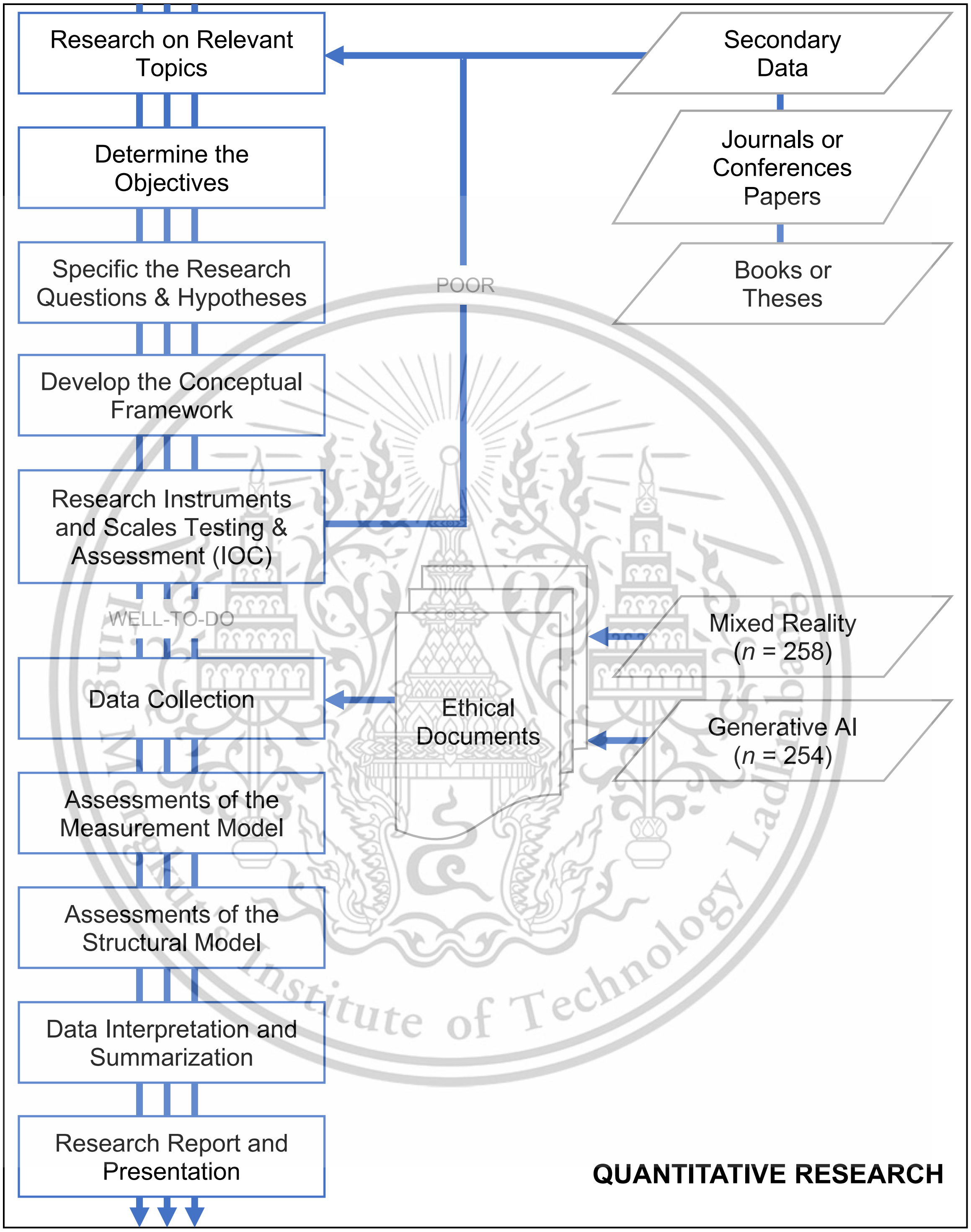

Figure 3.1 Research procedures

Table 3.1 Sampling design

SAMPLING DESIGN		DETAIL INFORMATION
Target Population	⇒	Male or female employees working within the mining industry in Indonesia.
Sampling Frame	⇒	Employees interested in participating.
Sampling Technique	⇒	A judgmental sampling
Execution	⇒	In-office survey using Laptops, Notebook, Tablet, or iPad to fill the survey with sample ratio

For determining the sample size, this research adheres to guidelines proposed by Hair et al. (2019), which emphasize the importance of dataset size, case-to-variable ratios, and robust factor analysis. According to these guidelines, a minimum of five observations per variable is required, while a more optimal ratio is 10:1. Additionally, some scholars suggest a minimum of 20 cases per variable to enhance the reliability of results. In alignment with these recommendations, this research adopts the 10:1 ratio to ensure methodological rigor and robust analytical outcomes (n = 258 for MR, and n = 254 for GenAI).

As mentioned previously, the research was conducted in Indonesia and specifically targeted employees from mining companies that meet specific criteria: being a legal entity, employing a substantial workforce, holding considerable assets, or being listed on the Indonesian stock exchange. These criteria were carefully selected to ensure that the sample aligns with the research's objectives and relevance.

The in-office survey method was chosen as the primary data collection strategy over alternatives such as telephone or mail surveys due to its distinct advantages (Bickart & Schmittlein, 1999; Colombo, 2000; De Rada, 2005; Groves, 2006; James & Bolstein, 1990; Roy & Berger, 2005; Yu & Cooper, 1983). First, personal surveys demonstrate superior response rates, with weighted averages of 81.7%, compared to 72.3% for telephone surveys and 47.3% for mail surveys. Second, this method offers optimal sample control, ensuring the survey effectively and efficiently reaches the targeted sample units.

To promote employee participation, a nominal incentive valued at less than two dollars was provided to respondents. Despite being more resource-intensive and time-consuming, in-office surveys are recognized for yielding the most representative and detailed responses (Szolnoki & Hoffmann, 2013). To further improve data collection efficiency, handheld devices such as laptops, notebooks, and tablets were employed as a modern alternative to traditional paper-based surveys.

Prior to completing the survey questionnaires, employees were provided with a comprehensive explanation of the research objectives and procedures. Participation in the study was entirely voluntary and required formal agreement to the stipulated terms and conditions. Subsequently, participants were furnished with an informational module and an instructional video elucidating the functionalities and potential applications of MR and GenAI technologies in enhancing workplace operations. To encourage engagement, respondents were offered a modest incentive, valued between one and two dollars, upon the successful completion of the survey. This study was conducted in strict compliance with the ethical standards set forth by official committees in Indonesia (KE/015/UGM/EC/2024).

3.3 Research Instruments

The research instruments were adapted from established studies on technology acceptance and related literature, which demonstrated the reliability and validity of the measurements employed. These instruments were meticulously tailored to capture the contextual and fundamental aspects of the studied factors and underwent a comprehensive validation process. Initially, industry experts from various disciplines reviewed the survey questionnaires to ensure relevance and accuracy. The questionnaires were subsequently translated from English to Indonesian by the authors, with the accuracy of the translation verified by a professional linguist. Further refinements were made following pilot testing with mining industry employees to ensure the clarity and appropriateness of the questions and responses. Then, data were collected using a 5-point Likert scale, ranging from "1" (strongly disagree) to "5" (strongly agree), to assess the key dimensions associated with the acceptance of i5.0 innovative technologies, specifically MR and GenAI.

The measurement of employees' intention to adopt MR technology was conducted using three items, such as "I intend to use it" and "I plan to use it." These items were adapted from Holdack et al. (2022), which reported a reliability coefficient of $\alpha = .84$, and George et al. (2023), with a reliability coefficient of $\alpha = .91$. that conducted the adoption of similar characteristics of technologies (i.e., augmented reality or virtual reality). Both studies explored adoption behaviours concerning technologies similar to MR, such as augmented and virtual reality. For GenAI technology, intention was assessed using four items, including "I predict to use it" and "I hope to use it." These items were adapted from Cao et al. (2021), with $\alpha = .93$, and Saif et al. (2024) , which recorded a reliability value of $\alpha = .76$. These studies focused on AI-based technologies like ChatGPT.

Employees' attitudes toward i5.0 innovations, including MR and GenAI technologies, were evaluated using four items, such as "I like the idea" and "My general opinion is favourable." These items were adapted from Holdack et al. (2022), George et al. (2023), and Cao et al. (2021) , which reported reliability coefficients of $\alpha = .84$; $\alpha = .96$; and $\alpha = .86$, respectively.

Perceived compatibility, reflecting the alignment of MR and GenAI technologies with organizational needs and infrastructure, was assessed using four items. These included statements such as "Adoption of MR/GenAI fits the needs of the company" and "MR/GenAI will be compatible with existing infrastructure in the company." The items were adapted from Ngoc Su et al. (2023), which demonstrated composite reliability of .93, and Oliveira et al. (2014) , with composite reliability of .92.

Perceived ease of use for MR technology was measured through five items, including "MR is clear and understandable" and "Adoption of MR does not require a lot of mental effort." These items were adapted from the research of Holdack et al. (2022), with $\alpha = .78$, and George et al. (2023), with $\alpha = .87$. For GenAI technology, perceived ease of use was assessed with four items, such as "I feel skilled in adopting GenAI" and "It would be easy." These items were drawn from Lai et al. (2023), with $\alpha = .90$, and Saif et al. (2024), with $\alpha = .86$.

Perceived usefulness was evaluated for both MR and GenAI technologies using four items, including "MR technology is useful" and "MR could enhance the quality of my work." These were adapted from research of Holdack et al. (2022), with reliability of $\alpha = .72$, George et al. (2023), with $\alpha = .90$, Lai et al. (2023), with $\alpha = .86$, and Saif et al. (2024), with $\alpha = .86$.

Perceived novelty was assessed for MR and GenAI technologies using three items, such as "A novel experience" and "New and refreshing." These were adapted from Wells et al. (2010), having reliability of $\alpha = .93$, and Sun et al. (2023), having reliability of $\alpha = .72$.

A comprehensive outline of the research instruments, including the survey questionnaires for both MR and GenAI adoption, is presented in **Appendix B** through **D**. These instruments were designed to ensure a robust assessment of the core constructs under investigation.

3.4 Data Analysis

The primary objective of this research is to investigate the acceptance of i5.0 innovative technologies, specifically MR and GenAI, among employees in the mining sector. To achieve this, the research extends the well-established Technology Acceptance Model (TAM) framework (Davis, 1989) and employs Partial Least Squares-Structural Equation Modelling (PLS-SEM) as the most suitable method for data analysis, given its alignment with the research objectives and its high statistical power, which is particularly beneficial for exploratory research focusing on developing or less established theories (J. Hair & Alamer, 2022; J. F. Hair, Risher, Sarstedt, & Ringle, 2019).

PLS-SEM, employing the SmartPLS program, was chosen for its ability to validate measurement models and test hypotheses in exploratory research (J. F. Hair, Risher, et al., 2019). PLS-SEM calculates optimal predictive weights through iterative processes and accommodates non-normal data distributions, offering stable and reliable estimates (J. F. Hair, Risher, et al., 2019). Additionally, PLS-SEM's relatively lower sample size requirements make it particularly suitable for exploratory research (A. Malhotra, Gosain, & Sawy, 2007; Willaby, Costa, Burns, MacCann, & Roberts, 2015). These attributes ensure robust and reliable results that align with the research's exploratory nature and objectives.

3.4.1 Measurement Model Assessment

The initial step in evaluating PLS-SEM results involves assessing the measurement models, which, in this study, are reflective. The assessment begins with examining the indicator loadings of the research instruments. Loadings exceeding .708 are recommended, as they signify that the construct accounts for more than 50% of the variance in the indicator, ensuring acceptable item reliability (J. F. Hair, Risher, et al., 2019).

The next step addresses internal consistency reliability, typically assessed using composite reliability, Cronbach's Alpha, and Rho A. Composite reliability values ranging from .60 to .70 are acceptable for exploratory research, while values between .70 and .90 indicate satisfactory to good reliability (J. F. Hair, Hult, Ringle, & Sarstedt, 2022). For Cronbach's Alpha, a minimum threshold of .70 is suggested, though it is often considered overly conservative compared to composite reliability, which can be too liberal (J. F. Hair, Risher, et al., 2019). To bridge this gap, Dijkstra and Henseler (2015) proposed Rho A as a more accurate measure of construct reliability, which generally falls between Cronbach's Alpha and composite reliability. A Rho A value above .70 is recommended.

The third step evaluates the convergent validity of each construct. Convergent validity refers to the extent to which a construct explains the variance of its items, assessed using the Average Variance Extracted (AVE). An AVE of .50 or higher indicates that the construct explains at least 50% of the variance in its indicators, denoting acceptable convergent validity (J. F. Hair et al., 2022).

Finally, discriminant validity is assessed to determine whether a construct is empirically distinct from other constructs within the model. The HeteroTrait-MonoTrait (HTMT) ratio of correlations, proposed by Henseler et al. (2015) is preferred over the Fornell-Larcker criterion for this purpose. A conservative threshold for HTMT values is .85, with higher values indicating potential issues with discriminant validity (J. F. Hair et al., 2022).

3.4.2 Structural Model Assessment

Once the measurement model assessment is satisfactory, the structural model is evaluated. Key assessment criteria include the coefficient of determination (R^2), the blindfolding-based cross-validated redundancy measure (Q^2), and the significance and relevance of the path coefficients (J. F. Hair et al., 2022). This study also examines out-of-sample predictive power using the PLSpredict procedure to complement the R^2 results.

Before evaluating structural relationships, collinearity among predictor constructs must be assessed using the Variance Inflation Factor (VIF). VIF values exceeding 5 indicate potential collinearity issues, whereas values around 3 and below are ideal (Becker, Ringle, Sarstedt, & Völckner, 2015; Kock & Lynn, 2012). If collinearity is not problematic, the next step is to examine the R^2 values of the endogenous constructs, which measure the variance explained by the model. R^2 values of .75, .50, and .25 are interpreted as substantial, moderate, and weak, respectively (J. F. Hair, Risher, et al., 2019).

Predictive accuracy is further assessed using Q^2 values, with guidelines suggesting that Q^2 values greater than zero indicate predictive relevance. Thresholds for Q^2 values are 0 (low), .25 (medium), and .50 (high).

While R^2 assesses in-sample explanatory power, it does not account for out-of-sample predictive power. To address this limitation, Shmueli et al. (2016) proposed an out-of-sample prediction procedure involving a training sample and a holdout sample. Predictive performance is evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). These benchmarks are compared to a naive Linear Model (LM) benchmark (J. Hair & Alamer, 2022; J. F. Hair, Risher, et al., 2019):

1) If all dependent variable indicators show higher prediction errors compared to the LM benchmark, the model lacks predictive power.
2) If the majority of indicators exhibit higher prediction errors, the model has low predictive power.
3) If only a minority of indicators exhibit higher prediction errors, the model demonstrates medium predictive power.

4) If none of the indicators show higher prediction errors, the model exhibits high predictive power.

After obtaining substantial results from all measurement and structural assessments, comparing various model configurations with the original conceptual model enhances the robustness, validity, and practical applicability of the findings (J. F. Hair, Risher, et al., 2019; Sharma, Shmueli, Sarstedt, Danks, & Ray, 2021). Such analyses deepen the understanding of the model's predictive capabilities and its alignment with theoretical frameworks, ensuring insights are rigorous and adaptable to real-world contexts, thereby strengthening methodological integrity and providing a solid foundation for future research and practical implementation (J. F. Hair et al., 2022).

3.4.3 Statistical terminology

To enhance the readability, particularly in the context of data analysis, **Table 3.2** presents key statistical terminologies along with their definitions (J. F. Hair, Risher, et al., 2019; N. K. Malhotra, 2020). This ensures that readers, regardless of their prior statistical knowledge, can effectively comprehend and interpret the analytical methods and findings discussed in subsequent sections.

Table 3.2 Statistical terminology

STATISTICAL TERMINOLOGY		DEFINITIONS
Partial Least Squares-Structural Equation Modelling **(PLS-SEM)**	⇒	PLS-SEM is a robust statistical technique employed to analyse complex interrelations between observed and latent variables. It is particularly advantageous for exploratory research and the development of theoretical frameworks. As a causal-predictive method, PLS-SEM focuses on prediction while estimating statistical models, emphasizing structural designs that aim to deliver causal explanations.
Reflective Measurement Model		In a reflective measurement model, the latent variable (like perceived usefulness, perceived ease of use, or attitude) causes the observed indicators (questions or items on the survey). This means that any change in the latent variable will cause changes in the indicators. Since the indicators are all measuring the same concept, they are expected to be similar and highly correlated. In this type of model, arrows point from the latent variable to the indicators, showing that the underlying concept (the latent variable) determines the observed survey responses (the indicators).
Loadings	⇒	It refers to the correlations between observed indicators (items) and their corresponding latent variables (constructs). Loadings are crucial for assessing the measurement model, particularly in reflective measurement models.

Table 3.2 Statistical terminology (Continue)

STATISTICAL TERMINOLOGY		DEFINITIONS
Cronbach's Alpha **(α)**	⇒	It is a measure of internal consistency or reliability of a set of items (indicators) in a survey. A higher value (typically above .7) indicates good internal consistency, meaning the items measure the same underlying construct.
Composite Reliability **(CR)**	⇒	Another measure of internal consistency or reliability of a set of items (indicators). High values (typically above .7) indicate good internal consistency, meaning the indicators reliably measure the same construct.
Rho A **(ρA)**	⇒	Also known as Dijkstra-Henseler's rho, it is designed to provide a more accurate estimate of construct reliability compared to traditional measures like Cronbach's Alpha and Composite Reliability. Values above .7 suggest good internal consistency.
Convergent Validity	⇒	The extent to which the construct converges to explain the variance of its items.
Average Variance Extracted **(AVE)**	⇒	The metric used for evaluating a construct's convergent validity. An acceptable AVE is .50 or higher indicating that the construct explains at least 50 per cent of the variance of its items.
Discriminant Validity	⇒	The extent to which a construct is empirically distinct from other constructs in the structural model
HeteroTrait-MonoTrait **(HTMT)**	⇒	The metric used for evaluating a construct's discriminant validity. It is defined as the mean value of the item correlations across constructs relative to the (geometric) mean of the average correlations for the items measuring the same construct. A lower, more conservative, threshold value of .85 is suggested
Variance Inflation Factor **(VIF)**	⇒	It is used to assess multicollinearity among the indicators. A VIF value above 5 indicates significant multicollinearity.
R^2	⇒	R^2 represents in-sample predictive power, reflecting the proportion of variance explained in each endogenous construct. It serves as a key indicator of the model's explanatory strength. As a guideline, R^2 values of .75, .50, and .25 are interpreted as substantial, moderate, and weak, respectively.
Q^2	⇒	Another means to assess the PLS-SEM path model's predictive accuracy. As a rule of thumb, Q^2 values higher than 0, .25 and .50 depict small, medium and large predictive relevance of the PLS-path model.
PLSpredict	⇒	Another set of procedures for out-of-sample prediction that involves estimating the model on an analysis sample and evaluating its predictive performance on data other than the analysis sample, referred to as a holdout sample.
Normal Fit Index **(NFI)**	⇒	Additional measurement to assess the goodness of fit for models that provides insights into how well a specified model represents observed data relative to a baseline model.
Standardized Root Mean Square Residual **(SRMR)**	⇒	Another fit index used to assess how well a proposed model fits the observed data. It provides insights into how well a theoretical model aligns with empirical data.

CHAPTER 4

ANALYSIS RESULTS

4.1 Demographic Statistics

Comprehensive demographic statistics, detailing respondent characteristics, are presented in **Table 4.1** to offer further insight into the sample composition. In this research, a total of 258 valid survey responses for MR and 254 valid responses for GenAI were gathered from employees across four organizations within Indonesia's mining industry.

Table 4.1 Demographic statistics

		MR (*n* = 258)		**GenAI (*n* = 254)**	
		Frequency	Percentage	Frequency	Percentage
Identification of Gender	Male	148	57 %	153	60 %
	Female	110	43 %	101	40 %
	Total	**258**	**100 %**	**254**	**100 %**
Age Group	20 – 30	79	31 %	66	26 %
	31 – 40	114	44 %	113	45 %
	41 – 50	41	16 %	49	19 %
	51 – above	24	9 %	26	10 %
	Total	**258**	**100 %**	**254**	**100 %**
Level of Academic Qualification	Three-years Diploma	63	24 %	61	24 %
	Bachelor’s Degree	184	71 %	182	72 %
	Master’s Degree & Above	11	4 %	11	4 %
	Total	**258**	**100 %**	**254**	**100 %**
Employment Tenure	< 1 year	14	5 %	11	4 %
	1 – 3 years	34	13 %	32	13 %
	3 – 6 years	72	28 %	69	27 %
	6 – 9 years	29	11 %	27	11 %
	9 - 12 years	51	20 %	53	21 %
	> 12 years	58	22 %	62	24 %
	Total	**258**	**100 %**	**254**	**100 %**
Organization (*Pseudonym*)	Innovate Mining	121	47 %	134	53 %
	Ethereal Resource	109	42 %	97	38 %
	Stratum Mining	20	8 %	16	6 %
	Lapis Mining	8	3 %	7	3 %
	Total	**258**	**100 %**	**254**	**100 %**

The respondents were drawn from four diverse organizations, providing a comprehensive overview of employee perspectives across different areas and operational contexts within the industry. This diverse sample enhances the representativeness and robustness of the findings, offering valuable insights into the factors influencing the adoption of these advanced technologies.

The sample size complies with the recommended guidelines for Partial Least Squares-Structural Equation Modelling (PLS-SEM), which suggests a ratio of measurements to respondents between 1:5 and 1:20 (A. Malhotra et al., 2007; Willaby et al., 2015). By adhering to these acceptable standards, the data set is deemed sufficient for reliable and valid statistical analysis.

4.2 Measurement Model Evaluation

The psychometric properties of the scales, including the reliability and validity of the constructs, were verified by evaluating their compliance to a predetermined set of quality criteria. Construct reliability measures the reliability and internal consistency of the measured variable that represent a latent construct (J. F. Hair, Black, et al., 2019). The coefficients of Cronbach's Alpha (α), Composite Reliability (CR), and the consistent reliability coefficient of Rho A (ρA) are utilized to validate construct reliability with significant evidence.

As stated by Hair et al. (2019), Cronbach's Alpha (α) should surpass a critical value of .70, although an exploratory research level of .60 is acceptable. The findings of this research reveal that the Cronbach's Alpha (α) coefficient for all examined constructs exceeded .85, with values ranging from .87 to .91 for MR, and from .89 to .93 for GenAI. Composite Reliability (CR), defined as the ratio of true score variance to total score variance, is considered satisfactory when the values are .70 or higher (N. K. Malhotra, 2020). In this research the CR values meet the quality criteria, ranging from .91 to .94 for MR and from .90 to .92 for GenAI. The values of ρA, a good compromise between Cronbach's Alpha (α) and Composite Reliability (CR) measurement, surpassed .706, with a range of .87 to .91 for MR and .88 to .92 for GenAI. The detailed results are presented in **Table 4.2** for MR and **Table 4.3** for GenAI, with all values surpassing the recommended threshold of .70 for all constructs (J. F. Hair, Risher, et al., 2019).

Furthermore, construct validity pertains to how well a scale or collection of measures truly reflects the concept it aims to assess (J. F. Hair, Black, et al., 2019). The most widely accepted forms of validity are convergent and discriminant validity (J. F. Hair, Black, et al., 2019). Convergent validity evaluates how strongly two measures of the same concept are correlated, while discriminant validity examines how distinct a construct is from other constructs.

Table 4.2 Instruments reliability of the MR model

Factor Loadings			α	ρA	CR	AVE
INT			.913	.913	.945	.851
INT1	=	.922				
INT2	=	.924				
INT3	=	.922				
ATT			.915	.916	.940	.797
ATT1	=	.885				
ATT2	=	.900				
ATT3	=	.903				
ATT4	=	.883				
PC			.879	.883	.917	.735
PC1	=	.817				
PC2	=	.878				
PC3	=	.876				
PC4	=	.856				
PEOU			.914	.917	.936	.745
PEOU1	=	.877				
PEOU2	=	.878				
PEOU3	=	.886				
PEOU4	=	.875				
PEOU5	=	.797				
PU			.915	.915	.940	.796
PU1	=	.903				
PU2	=	.893				
PU3	=	.888				
PU4	=	.886				
PN			.904	.906	.940	.839
PN1	=	.921				
PN2	=	.927				
PN3	=	.900				

Note: INT = Intention; ATT = Attitude; PC = Perceived Compatibility; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PN = Perceived Novelty; α = Cronbach's Alpha; ρA = Rho A Reliability; CR = Composite Reliability; AVE = Average Variance Extracted.

Table 4.3 Instruments reliability of the GenAI model

Factor Loadings			α	ρA	CR	AVE
INT			.911	.912	.937	.789
INT1	=	.890				
INT2	=	.886				
INT3	=	.890				
INT4	=	.887				
ATT			.916	.916	.941	.799
ATT1	=	.897				
ATT2	=	.888				
ATT3	=	.890				
ATT4	=	.900				
PC			.914	.914	.939	.794
PC1	=	.887				
PC2	=	.894				
PC3	=	.897				
PC4	=	.887				
PEOU			.905	.910	.933	.778
PEOU1	=	.893				
PEOU2	=	.863				
PEOU3	=	.875				
PEOU4	=	.896				
PU			.916	.916	.941	.799
PU1	=	.898				
PU2	=	.892				
PU3	=	.896				
PU4	=	.890				
PN			.891	.891	.932	.821
PN1	=	.910				
PN2	=	.914				
PN3	=	.894				

Note: INT = Intention; ATT = Attitude; PC = Perceived Compatibility; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PN = Perceived Novelty; α = Cronbach's Alpha; ρA = Rho A Reliability; CR = Composite Reliability; AVE = Average Variance Extracted.

Furthermore, construct validity pertains to how well a scale or collection of measures truly reflects the concept it aims to assess (J. F. Hair, Black, et al., 2019). The most widely accepted forms of validity are convergent and discriminant validity (J. F. Hair, Black, et al., 2019). Convergent validity evaluates how strongly two measures of the same concept are correlated, while discriminant validity examines how distinct a construct is from other constructs.

To evaluate the convergent validity, an Average Variance Extracted (AVE) of .50 or greater is suggested adequate as empirical evidence (J. F. Hair, Black, et al., 2019). Meanwhile, the recommended method for assessing discriminant validity is the HeteroTrait-MonoTrait (HTMT) ratio test (Henseler et al., 2015). Henseler et al. (2015) suggests a lower, more conservative threshold value of .85 for HTMT test. The data presented in **Table 4.4** and **4.5**, which is the result of HTMT, offers sufficient support for the existence of a construct-level discriminant validation requirement. In short, the results obtained from the current research provide robust evidence that the proposed research model demonstrates sufficient levels of construct validity and reliability.

Table 4.4 HTMT discriminant validity of the MR model

	INT	ATT	PC	PEOU	PU	PN
INT						
ATT	.822					
PC	.735	.719				
PEOU	.673	.735	.583			
PU	.826	.838	.745	.821		
PN	.520	.626	.503	.466	.584	

Note: INT = Intention; ATT = Attitude; PC = Perceived Compatibility; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PN = Perceived Novelty.

Table 4.5 HTMT discriminant validity of the GenAI model

	INT	ATT	PC	PEOU	PU	PN
INT						
ATT	.830					
PC	.839	.812				
PEOU	.773	.765	.839			
PU	.841	.754	.822	.802		
PN	.754	.709	.726	.685	.682	

Note: INT = Intention; ATT = Attitude; PC = Perceived Compatibility; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PN = Perceived Novelty.

4.3 Structural Model Evaluation

When the structural model evaluation is satisfactory, the next step in evaluating PLS-SEM results is assessing the structural model. However, before assessing the structural relationship, collinearity must be examined to make sure that it does not bias the regression results. In this case, the latent variable scores of the predictor constructs in a partial regression are used to calculate the VIF values. As stated by Kock and Lynn (2012), as well as Becker et al. (2015), a Variance Inflation Factor (VIF) exceeding 5 could potentially signify the existence of a multicollinearity issue. The VIF value analysis for both models conducted in this research revealed a range of 2.0 to 3.1 for MR, as well as a range of 2.4 to 3.0 for GenAI, indicating no critical issues of collinearity in the structural models.

After collinearity is not an issue, the next step is examining the R^2 value of the endogenous construct(s). The R^2 measures the variance, which is explained in each of the endogenous constructs and is therefore a measure of the model's explanatory power (Shmueli et al., 2019). The R^2 is also referred to as in-sample predictive power (Rigdon, 2012). In terms of R^2 values, explaining a measure of the model's explanatory power, the result of the MR model shows a significant value of

.565 on intention and .665 on attitude. The Stone-Geisser Q^2 statistic (Geisser, 1975; Stone, 1974), a key measure of the structural model's predictive power, demonstrated values of .567 for intention and .615 for attitude in the MR technology model, and .628 for intention and .612 for attitude in the GenAI technology model. These results confirm the predictive relevance of the models.

Additionally, a comparison of the Root Mean Square Error (RMSE) values between the PLS-SEM model and the Logistic Regression Modelling (LM) benchmark should indicate significantly higher RMSE values for the LM benchmark for high predictive power (J. F. Hair, Risher, et al., 2019). The result shown in **Table 4.6** underscores the high predictive relevance of the MR technology model. In contrast, the GenAI technology model exhibited medium predictive relevance, highlighting the need for further investigation to enhance its predictive power. The overall model fit was also assessed, with the MR technology model achieving a Normal Fit Index (NFI) value of .905 and a Standardized Root Mean Square Residual (SRMR) of .037, and the GenAI technology model obtaining an NFI value of .901 and an SRMR of .04, confirming the robustness of both models within their respective contexts.

Having validated the model's explanatory and predictive capabilities, the final analytical step involves evaluating the statistical significance and relevance of the path coefficients. The structural model analysis, as presented in **Table 4.7**, underscores the central role of attitude as the most influential determinant in both the MR (β = .751; p < .001) and GenAI (β = .759; p < .001) models.

For the MR model, the analysis reveals that perceived compatibility (β = .201; p < .01), perceived usefulness (β = .380; p < .01), and perceived novelty (β = .191; p < .05) significantly impact attitude, while perceived ease of use (β = .202; NS) does not exhibit a substantial effect. This finding highlights the importance of aligning MR technologies with users' needs and values, demonstrating their practical benefits, and emphasizing their innovative aspects to foster positive attitudes.

Conversely, in the GenAI model, all examined factors, perceived compatibility (β = .332; p < .001), perceived ease of use (β = .200; p < .01), perceived usefulness (β = .171; p < .05), and perceived novelty (β = .191; p < .001), demonstrate a significant influence on attitude. This comprehensive effect suggests that, beyond compatibility and utility, the simplicity of use and the novelty of GenAI technologies play pivotal roles in shaping user perceptions and acceptance.

These findings provide nuanced insights into the differential factors influencing attitudes toward MR and GenAI technologies, emphasizing the need for tailored strategies to enhance user acceptance across these innovative solutions.

Table 4.6 PLSpredict results

		Q^2 Predict > 0	PLS RSME	LM RSME	PLS – LM RMSE < 0	VIF	NFI
Mixed Reality (MR) Model						**2.0** to **3.1**	**.905**
Intention	INT1	.480	.966	.980	Yes		
	INT2	.492	.951	.960	Yes		
	INT3	.475	.995	1.005	Yes		
Attitude	ATT1	.478	.878	.909	Yes		
	ATT2	.504	.823	.833	Yes		
	ATT3	.527	.855	.876	Yes		
	ATT4	.446	.896	.922	Yes		
Generative AI (GenAI) Model						**2.4** to **3.0**	**.901**
Intention	INT1	.543	.788	.746	No		
	INT2	.483	.826	.820	No		
	INT3	.474	.834	.830	No		
	INT4	.479	.832	.801	No		
Attitude	ATT1	.513	.765	.780	Yes		
	ATT2	.456	.788	.816	Yes		
	ATT3	.474	.776	.801	Yes		
	ATT4	.508	.710	.716	Yes		

Table 4.7 Significance and path coefficient results of both MR and GenAI models.

Hypothesis				MR			GenAI		
				β	p	Result	β	p	Result
H1	ATT	⇒	INT	.751	***	Supported	.759	***	Supported
H2	PC	⇒	ATT	.201	**	Supported	.332	***	Supported
H3	PEOU	⇒	ATT	.202	NS	Not Supported	.200	**	Supported
H4	PU	⇒	ATT	.380	**	Supported	.177	*	Supported
H5	PN	⇒	ATT	.191	*	Supported	.191	***	Supported

Note: INT = Intention; ATT = Attitude; PC = Perceived Compatibility; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PN = Perceived Novelty; β = path coefficient; p = p-Value; *** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$; NS = Non-Significance.

4.4 Configuration of Alternative Models

To adapt the theory to a new context, specifically the mining industry, alternative model configurations have been developed (J. F. Hair, Risher, et al., 2019). These configurations serve as conceptual bridges across related streams of inquiry, offering a comprehensive understanding of the phenomenon under investigation. While the focus of these alternative models remains consistent on the endogenous constructs, their structural arrangements differ (J. F. Hair et al., 2022).

In this research, the conceptual model (referred to as Model A) is systematically compared with several alternative models (Models B, C, and D) using established evaluation criteria, including R^2 values, the Bayesian Information Criterion (BIC), and Akaike weights for relative model likelihoods (Sharma, Sarstedt, Shmueli, Kim, & Thiele, 2019).

A visual representation of these models and their configurations is provided in **Figure 4.1**, illustrating the comparative framework employed in this analysis.

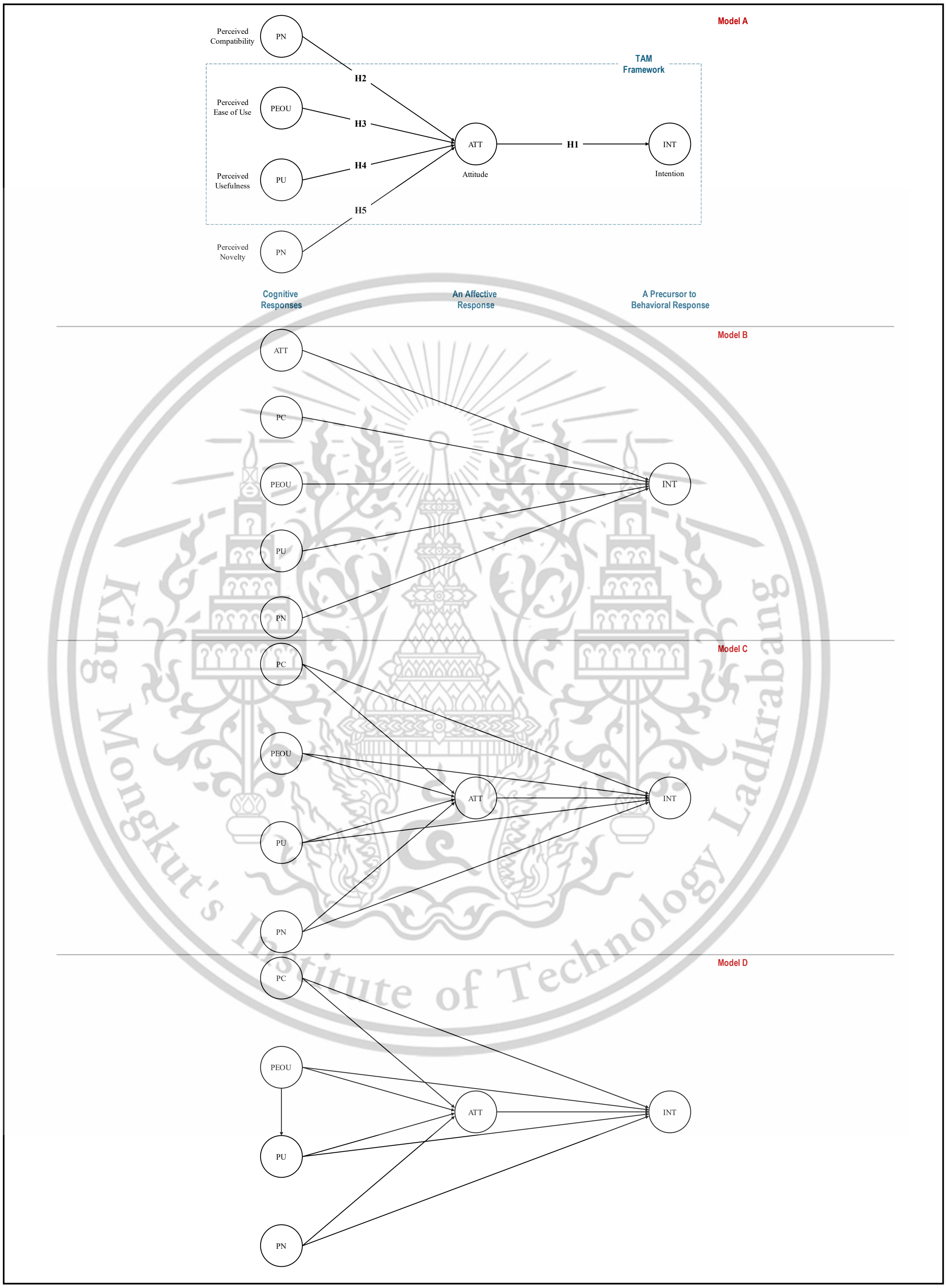

Figure 4.1 Model comparison for both i5.0 innovative technologies

As detailed in **Table 4.8**, the Akaike weights metric indicates that Model B achieves the highest values for intention, with 34.6% and 37.2% for MR and GenAI technologies, respectively. Conversely, Model A demonstrates the highest value for attitude at 34.7% for both technologies. However, Model A records the lowest values for intention, while Model B lacks predictive value for attitude, rendering it suitable only for limited explanation related to intention.

Table 4.8 Model comparison based on quality criteria for both i5.0 innovative technologies

	Model A	Model B	Model C	Model D
Mixed Reality (MR)				
R^2				
- Intention	.565	.661	.661	.661
- Attitude	.666	-	.665	.665
- Perceived Usefulness	-	-	-	.565
Bayesian Information Criterion (BIC)				
- Intention	-204.40	-246.93	-246.83	-246.81
- Attitude	-255.86	-	-255.77	-255.70
- Perceived Usefulness	-	-	-	-204.62
Akaike Weights (Relative Model Likelihoods)				
- Intention	.000	.346	.329	.325
- Attitude	.347	-	.332	.321
- Perceived Usefulness	-	-	-	-
Generative AI (GenAI)				
R^2				
- Intention	.577	.731	.731	.731
- Attitude	.632	-	.631	.631
- Perceived Usefulness	-	-	-	.536
Bayesian Information Criterion (BIC)				
- Intention	-208.19	-301.24	-300.97	-300.83
- Attitude	-227.22	-	-226.80	-226.72
- Perceived Usefulness	-	-	-	-184.713
Akaike Weights (Relative Model Likelihoods)				
- Intention	.000	.372	.325	.303
- Attitude	.387	-	.313	.301
- Perceived Usefulness	-	-	-	-

Although Model D incorporates perceived usefulness in its metrics, it exhibits lower Akaike weights compared to Model C and shows suboptimal performance in the PLSpredict results.

Consequently, Model C emerges as the most suitable model for further analysis, given its balanced performance across key evaluation criteria (R^2, BIC, and Akaike Weights).

Table 4.9 provides detailed information on the PLSpredict results for the MR and GenAI-enhanced models (referred to as Model C). The findings indicate satisfactory performance, with both models demonstrating high predictive power, further supporting their robustness and suitability for advanced analysis.

Table 4.9 PLSpredict results for MR and GenAI enhanced models

		Q^2 Predict > 0	PLS RSME	LM RSME	PLS – LM RMSE < 0	VIF	NFI
Mixed Reality (MR) Model						**2.0** to **3.1**	**.905**
Intention	INT1	.499	.948	.980	Yes		
	INT2	.511	.933	.960	Yes		
	INT3	.489	.981	1.005	Yes		
Attitude	ATT1	.478	.878	.909	Yes		
	ATT2	.504	.824	.833	Yes		
	ATT3	.527	.855	.876	Yes		
	ATT4	.446	.896	.922	Yes		
Generative AI (GenAI) Model						**2.4** to **3.0**	**.901**
Intention	INT1	.602	.735	.746	Yes		
	INT2	.526	.790	.820	Yes		
	INT3	.509	.806	.830	Yes		
	INT4	.528	.791	.801	Yes		
Attitude	ATT1	.513	.765	.780	Yes		
	ATT2	.456	.787	.816	Yes		
	ATT3	.474	.776	.801	Yes		
	ATT4	.508	.711	.716	Yes		

After confirming the model's explanatory and predictive power, the next step is to assess the statistical significance and relevance of the path coefficients. This evaluation ensures that the relationships between the constructs are not only meaningful but also empirically supported, offering valuable insights into the dynamics of the MR and GenAI-enhanced model. These results are detailed in **Table 4.10**, as well as illustrated in **Figure 4.2** and **Figure 4.3**, providing a comprehensive overview of the enhanced model's performance.

Table 4.10 Significance and path coefficient results of both MR and GenAI enhanced models.

			MR			**GenAI**		
			β	***p***	**Result**	***β***	***p***	**Result**
ATT	⇒	INT	.353	**	Supported	.264	***	Supported
PC	⇒	ATT	.201	**	Supported	.332	***	Supported
PC	⇒	INT	.195	*	Supported	.203	**	Supported
PEOU	⇒	ATT	.201	NS	Not Supported	.198	**	Supported
PEOU	⇒	INT	.022	NS	Not Supported	.042	NS	Not Supported
PU	⇒	ATT	.380	**	Supported	.179	***	Supported
PU	⇒	INT	.340	*	Supported	.298	***	Supported
PN	⇒	ATT	.191	**	Supported	.191	**	Supported
PN	⇒	INT	-.006	NS	Not Supported	.169	***	Supported

Note: INT = Intention; ATT = Attitude; PC = Perceived Compatibility; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PN = Perceived Novelty; β = path coefficient; p = p-Value; *** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$; NS = Non-Significance.

Following the evaluation of the direct relationships between variables in both enhanced models, further analysis was conducted to explore potential indirect relationships. The results, as detailed in **Table 4.11**, highlight the critical mediating role of attitude. In the MR model, attitude partially mediates the relationships between perceived compatibility and intention, as well as between perceived usefulness and intention. Additionally, it fully mediates the relationship between perceived ease of use and intention. For the GenAI model, attitude serves as a partial mediator for the relationships between perceived compatibility, perceived usefulness, and perceived novelty with intention. These findings emphasize the integral role of attitude as a bridge linking key constructs to the intention to adopt these transformative technologies, providing deeper insights into the mechanisms underlying technology acceptance.

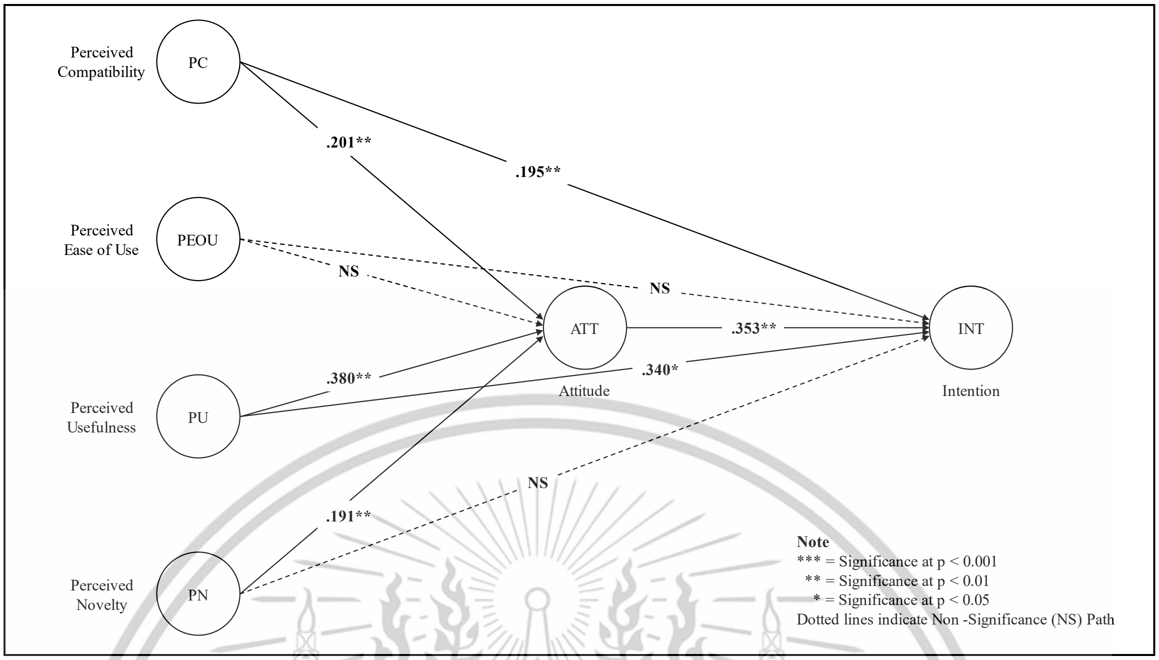

Figure 4.2 MR enhanced model

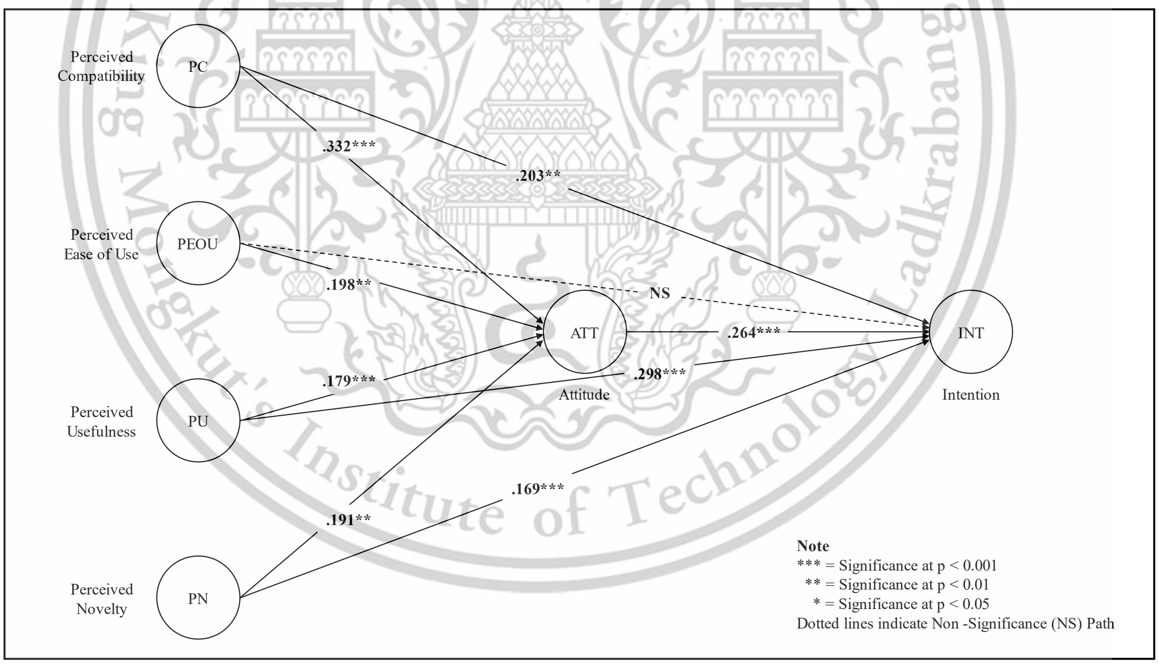

Figure 4.3 GenAI enhanced model

Table 4.11 Mediation analysis results of MR and GenAI enhanced models

	Direct Effect	*t*	*p*	Indirect Effect	*t*	*p*	Results
Mixed Reality (MR) Model							
PC ⇒ ATT ⇒ INT	.195	2.167	**	.071	2.053	*	Complementary (Partial Mediation)
PEOU ⇒ ATT ⇒ INT	.022	.179	NS	.071	1.292	NS	No Effect (No Mediation)
PU ⇒ ATT ⇒ INT	.340	2.209	**	.068	1.740	*	Complementary (Partial Mediation)
PN ⇒ ATT ⇒ INT	-.006	.097	NS	.134	1.298	NS	No Effect (No Mediation)
Generative AI (GenAI) Model							
PC ⇒ ATT ⇒ INT	.203	2.653	***	.088	2.206	*	Complementary (Partial Mediation)
PEOU ⇒ ATT ⇒ INT	.042	.669	NS	.052	2.121	*	Indirect-Only (Full Mediation)
PU ⇒ ATT ⇒ INT	.298	5.254	***	.047	2.018	*	Complementary (Partial Mediation)
PN ⇒ ATT ⇒ INT	.169	3.568	***	.050	2.212	*	Complementary (Partial Mediation)

Note: INT = Intention; ATT = Attitude; PC = Perceived Compatibility; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; PN = Perceived Novelty; β = path coefficient; p = p-Value; *** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$; NS = Non-Significance.

CHAPTER 5

CONCLUSION AND DISCUSSION

5.1 Conclusion

In summary, while both models share common factors influencing user attitudes and intentions, there are unique aspects to consider for each i5.0 innovative technology. For the MR model, it is evident that perceived usefulness and compatibility are critical factors that significantly influence both attitude and intention. Developers should focus on enhancing the practical benefits and ensuring that Mixed Reality solutions align well with users' existing values and experiences. This alignment can be achieved by creating user-friendly interfaces and functionalities that demonstrate clear utility or usefulness. Marketers should highlight the innovative aspects of MR to attract interest, while also emphasizing its practical benefits and compatibility to drive adoption. Decision-makers should prioritize investments in features that enhance perceived usefulness and compatibility, supporting initiatives that demonstrate tangible benefits and seamless integration with existing systems in organizations. Other stakeholders, such as educators and trainers, should focus on demonstrating the practical applications and benefits of MR to ensure users understand how it can enhance their tasks and fit into their routines.

In contrast, the GenAI model shows that perceived ease of use and novelty play significant roles in shaping user attitudes and intentions. Developers should prioritize creating intuitive and user-friendly GenAI solutions, as perceived ease of use significantly impacts attitude. Emphasizing the practical benefits and utility of GenAI is also crucial. Marketers should highlight the innovative aspects of GenAI, showcasing its potential to revolutionize tasks while emphasizing ease of use and practical benefits. Decision-makers should invest in features that enhance ease of use, usefulness, and novelty, supporting initiatives that demonstrate the innovative potential of GenAI. Other stakeholders should focus on demonstrating the ease of use and innovative aspects of GenAI, ensuring users understand its practical applications and benefits.

5.2 Discussion

This research presents a comprehensive conceptual model designed to investigate the adoption of i5.0 innovative technologies, specifically Mixed Reality (MR) and Generative AI

(GenAI) technologies, among mining industry employees in a developing country, as well as specifically providing in-depth answer to the research questions regarding:

1) What are the fundamental determinants influencing employee acceptance of i5.0 technologies, specifically MR and GenAI, within the Indonesian mining industry?
2) To what extend do those fundamental determinants influencing employee acceptance of i5.0 technologies, specifically MR and GenAI, within the Indonesian mining industry?
3) How can the findings be applied in real-world settings, particularly in terms of practical implications and theoretical contributions?

A thorough review of the literature identified five critical constructs (attitude, perceived compatibility, perceived ease of use, perceived usefulness, and perceived novelty) as the primary factors shaping employees' acceptance of MR and GenAI technologies. Despite the transformative potential of these innovations, empirical research investigating their adoption within the mining industry in developing countries remains notably scarce.

This research addresses this gap by offering pivotal theoretical and practical insights into the acceptance of MR and GenAI technologies in the mining sector. To evaluate the proposed conceptual model, nine hypotheses were tested using data from a robust total sample of 512 respondents. The data were gathered through an office-intercept survey employing technology-assisted methods and analysed using advanced multivariate statistical techniques, ensuring a comprehensive understanding of the underlying adoption dynamics.

The results of this research underscore the pivotal role of attitude in driving the intention to adopt i5.0 innovative technologies, specifically MR (β = .353; p < .01) and GenAI (β = .264; p < .001). Attitude was empirically deemed to be the greatest significant criterion in positively shaping the acceptance of both MR and GenAI innovative technologies. This indicates that mining industry workers would be extremely motivated to embrace MR technology innovation when they hold favourable attitudes towards it. These results are consistent with previous research examining behavioural intentions to adopt various technologies (Acikgoz et al., 2023; Buranelli de Oliveira et al., 2022; Chanda et al., 2024), including extended reality technologies (Holdack et al., 2022; Jiang et al., 2021; Sun et al., 2023) and other similar AI technologies (Cao et al., 2021; Saif et al., 2024).

Beyond its direct effect, attitude emerged as a critical mediator within the enhanced models for both MR and GenAI adoption. In the enhanced MR model, attitude partially mediates the relationships between perceived compatibility and intention (β = .071; t = 2.503; p < 0.05), as well as between perceived usefulness and intention (β = .134; t = 1.740; p < 0.05). In the enhanced GenAI model, its mediating role is even more extensive, bridging perceived compatibility (β =

.088; $t = 2.503$; $p < 0.05$), perceived ease of use ($\beta = .0.52$; $t = 2.121$; $p < 0.05$), perceived usefulness ($\beta = .0.47$; $t = 2.018$; $p < 0.05$), and perceived novelty ($\beta = .050$; $t = 2.212$; $p < 0.05$) with the intention to adopt. These findings highlight the central role of attitude in fostering technology acceptance, providing critical insights into how positive perceptions can translate into actionable intentions. The results emphasize the importance of fostering favourable attitudes toward i5.0 technologies, specifically MR and GenAI, through targeted interventions, such as employee engagement and communication strategies. These efforts will be essential to accelerate the adoption of both technological innovations, thereby enhancing operational efficiency and competitive advantage within the mining sector.

Furthermore, the empirical findings of this research further highlight the critical role of perceived compatibility in fostering both positive attitudes and intentions to adopt both i5.0 innovative technologies. For MR, a significant positive relationship was identified between perceived compatibility and attitude ($\beta = .201$; $p < .01$), as well as between perceived compatibility and intention ($\beta = .195$; $p < .05$). Similarly, for GenAI, the relationship between perceived compatibility and attitude ($\beta = .332$; $p < .001$) and between perceived compatibility and intention ($\beta = .203$; $p < .01$) was also significant. These results are consistent with prior research in various domains, further validating the importance of compatibility in shaping technology acceptance. Mining industry workers are more likely to adopt MR and GenAI technologies when they perceive these innovations as compatible with their organization's values, their professional responsibilities, and their personal needs. This alignment fosters a favourable attitude toward the technology and a stronger intention to integrate it into their work processes. The findings indicate that perceived compatibility has both direct and indirect effects on intention through attitude, as evidenced by the partial mediation of attitude in the relationship between perceived compatibility and intention for both MR ($\beta = .071$; $t = 2.503$; $p < 0.05$) and GenAI ($\beta = .088$; $t = 2.503$; $p < 0.05$). These results underscore the dual importance of ensuring that technological innovations align with organizational goals and employees' needs, while also emphasizing the role of cultivating positive attitudes. By addressing both compatibility and attitude, organizations can significantly enhance the likelihood of successful technology adoption. This approach not only maximizes acceptance but also facilitates smoother integration of MR and GenAI technologies, driving operational efficiencies and advancing the mining industry's technological evolution.

In addition, the influence of perceived ease of use on attitude and intentions reveals significant distinctions between the MR and GenAI models, offering critical insights into the nuances of technology adoption in the mining sector. In the MR model, the relationship between PEOU and attitude was found to be statistically non-significant ($\beta = 0.201$; NS) indicating that perceived ease of use does not significantly affect mining industry employee's attitude towards MR. suggesting that employees' perceptions of MR technology's ease of use do not substantially impact their attitudes toward its adoption. This result diverges from prior research, which has frequently highlighted the pivotal role of ease of use in shaping attitudes toward technological adoptions. Conversely, in the GenAI model, perceived ease of use significantly influences attitude ($\beta = .198$; $p < 0.01$), aligning with established theoretical perspectives and empirical findings. This indicates that mining employees who perceive GenAI as user-friendly are more likely to develop positive attitudes toward its adoption, thus reinforcing the relevance of ease of use in this context.

Regarding the direct effect of perceived ease of use on intention, both models yield non-significant results, with the MR model ($\beta = .022$; NS) and the GenAI model ($\beta = .042$; NS). These findings contradict prevailing literature, which often posits ease of use as a direct antecedent to behavioural intention. Such deviations underscore the distinct contextual and technological factors influencing adoption decisions in the mining industry. Notably, the GenAI model demonstrates a fully mediated relationship between PEOU and intention via attitude ($\beta = .0.52$; $t = 2.121$; $p < 0.05$). This suggests that while perceived ease of use does not exert a direct effect on intention, it indirectly influences intention by positively shaping attitudes. Specifically, employees who find GenAI easy to use are more likely to form favourable attitudes, which subsequently enhance their intention to adopt the technology.

In contrast, the MR model shows no significant direct or indirect effects of perceived ease of use on intention ($\beta = .0.71$; $t = 1.292$; NS). This finding indicates that perceived ease of use is not a critical determinant of intention in the MR context. Instead, other influential factors, such as the technology's perceived usefulness, alignment with organizational goals, and its ability to address employees' specific needs, play a more pivotal role in shaping adoption intentions. These results have significant implications for strategies aimed at fostering technology adoption in the mining industry. For GenAI, initiatives should prioritize enhancing usability and simplifying user interactions, as these efforts directly contribute to shaping favourable attitudes and, consequently, increasing adoption intentions. In the case of MR, adoption strategies should focus less on ease of use and more on demonstrating the technology's practical benefits, ensuring its compatibility with existing workflows, and fostering a positive perception of its utility in addressing industry-specific challenges.

Strong evidence also highlights the critical role of perceived usefulness in shaping attitudes and intentions toward the adoption of MR and GenAI technologies within the mining industry. The empirical results demonstrate that perceived usefulness significantly influences attitudes toward both MR ($\beta = .198$; $p < .01$) and GenAI ($\beta = .198$; $p < .01$) technologies, as well as intentions to adopt MR (β = .198; p < .01) and GenAI (β = .198; p < .01) innovations. These findings indicate that mining employees are more likely to develop a positive attitude toward MR technology when they perceive it as beneficial for enhancing productivity, improving information accessibility, fostering collaborative efforts, and streamlining operational efficiency through automation. Similarly, employees' intentions to adopt MR technology are bolstered when they view it as a highly useful tool for their work processes. These patterns are consistent with prior research on extended reality (XR) technologies, including augmented reality (AR), MR, and virtual reality (VR), as well as studies on AI technologies across diverse industrial contexts.

Additionally, the results reveal that attitude partially mediates the relationship between perceived usefulness and intention for both MR (β = .134; t = 1.740; p < 0.05) and GenAI models (β = .0.47; t = 2.018; p < 0.05). This mediation underscores the dual significance of perceived usefulness that not only does it directly influence the intention to adopt these technologies, but it also shapes attitudes, which further enhance adoption intentions. These findings emphasize the necessity of demonstrating the practical value of technological innovations, ensuring that they align with workers' needs and industry demands. For organizations aiming to promote the adoption of MR and GenAI technologies, highlighting their usefulness in achieving specific organizational goals, such as productivity gains, operational efficiency, and enhanced collaboration, is imperative. By doing so, organizations can foster favorable attitudes and drive stronger intentions among employees to embrace these i5.0 innovations.

The findings also demonstrate a robust empirical association between perceived novelty and attitudes toward both MR and GenAI technologies. However, the direct influence of perceived novelty on the intention to adopt these technologies varies significantly between the two models. In the GenAI model, the effect is statistically significant (β = .198; p < 0.01), whereas it is non-significant in the MR model (β = .198; NS). These results underscore the differentiated impact of perceived novelty on adoption behaviours across technological contexts. Perceived novelty in MR technology appears to evoke heightened curiosity and interest among mining industry employees, thereby fostering more favourable attitudes. This observation is consistent with earlier studies emphasizing the pivotal role of novelty in shaping attitudes toward technological innovations (Truong, 2013; Wells et al., 2010), including Virtual Reality (VR) technologies (Sun et al., 2023). By offering innovative features and novel experiences, MR technology stimulates an emotional response that translates into a positive attitudinal shift, even if it does not directly influence the intention to adopt.

In addition to its direct impact, perceived novelty also interacts with attitudes to influence the intention to adopt. The mediating role of attitude, however, varies across the two models. In the

MR model, no mediation effect is observed (β = .144; t = 1.298; NS), suggesting that the appeal of novelty does not sufficiently translate into actionable adoption intentions via attitudinal pathways. Conversely, in the GenAI model, attitude partially mediates the relationship between perceived novelty and intention to adopt (β = .050; t = 2.212; $p < 0.05$), indicating that novelty enhances attitudes, which in turn contribute to adoption decisions. These findings highlight the nuanced interplay between perceived novelty, attitudes, and behavioural intentions, emphasizing the importance of tailoring strategies to the unique characteristics of each technological innovation. For GenAI technologies, leveraging their novel attributes can effectively drive adoption intentions through both direct and attitudinal mechanisms. For MR technologies, however, additional factors beyond novelty and attitude may need to be addressed to strengthen adoption intentions among mining industry employees.

5.2.1 Theoretical Contribution

The innovation of Mixed Reality (MR) technology, which seamlessly integrates the physical and digital worlds, facilitates natural and intuitive 3D interactions among humans, technology, and their environment in real-time. MR has immense potential to revolutionize the mining industry by enhancing both work experiences and productivity. By providing immersive solutions that blend real-world operations with digital enhancements, MR enables greater efficiency and effectiveness (Sánchez & Hartlieb, 2020). Similarly, the innovation of GenAI is projected to significantly enhance productivity in these sectors by automating complex tasks and optimizing resource management (Dwivedi et al., 2023). GenAI is expected to contribute to global productivity growth, with potential annual increases of 0.2% to 3.3% from 2023 to 2040, contingent on effective redeployment of labour hours (Chui et al., 2023). the integration of AI, particularly GenAI, represents a pivotal advancement for the mining sector within the i5.0 framework, promising enhanced efficiency, sustainability, and human-technology collaboration.

Given the limited research on the adoption of technological innovation within the mining industry (Gruenhagen & Parker, 2020), particularly in the context of MR and GenAI in developing Southeast Asian countries, this research makes a substantial contribution to scientific knowledge. Through the rigorous application of established theoretical frameworks to the largely unexplored context of the mining sector, this research thoroughly examines the factors influencing employee acceptance of both MR and GenAI technologies.

This research challenges prevailing assumptions in technology adoption research by presenting robust quantitative insights into the determinants of MR and GenAI technology acceptance. It critically examines the relationships between perceived compatibility, perceived usefulness, and perceived novelty with the intention to adopt these technologies, offering a nuanced perspective on adoption dynamics. Contrary to findings in other contexts, the research reveals that perceived ease of use does not significantly influence the acceptance of either MR or GenAI technologies. This departure from established theories underscores the importance of contextual factors in shaping technology adoption behaviours.

A key theoretical contribution of this research lies in its emphasis on the mediating role of attitude in the relationship between perceived ease of use and the intention to adopt GenAI technologies. This finding strongly supports and extends the theoretical foundations of the Technology Acceptance Model (TAM) and its derivatives, which consistently position attitude as a critical mediating construct in the process of technology acceptance. Conversely, the findings related to MR technologies indicate the absence of both a mediating effect and a direct influence of perceived ease of use on intention to adopt. This divergence suggests that alternative determinants may exert a more pronounced impact on MR adoption, necessitating further exploration and theoretical refinement. These findings underscore the importance of investigating additional constructs or reconfiguring existing theoretical models to better accommodate the unique factors driving MR adoption. The research further enriches the discourse by providing deeper insights into the evolution of user attitudes toward emerging technologies, offering an opportunity to enhance the theoretical frameworks that guide our understanding of technology acceptance. By addressing the nuances specific to MR and GenAI technologies, this research advances the broader theoretical landscape and highlights the complex and dynamic nature of user attitudes in response to technological innovations, particularly in the context of i5.0.

Moreover, this research advances the discourse on the cultural and contextual specificity of technology adoption models. While TAM and other established frameworks have been extensively validated in Western contexts, this research provides a theory-driven model tailored to the unique cultural and operational characteristics of Indonesia's mining industry. By addressing the distinctive challenges and opportunities within this critical sector, the research bridges a significant gap in the literature, offering a more comprehensive understanding of technology adoption in non-Western and industry-specific settings.

The research also enriches the broader field of Business and Management Information Systems by extending existing theories to account for the socio-cultural and industrial complexities of the mining sector. It underscores the necessity of incorporating cultural and operational variables into technology adoption models to enhance their applicability and relevance in diverse contexts. These findings have significant implications for both scholars and practitioners, as they provide actionable insights for developing strategies to promote the adoption of MR and GenAI technologies in sectors characterized by unique cultural and operational challenges. In conclusion, this research not only reaffirms the relevance of established theories in technology adoption but also highlights the critical need for contextual adaptations. By offering a tailored approach to understanding technology adoption in Indonesia's mining industry, the research contributes valuable theoretical insights, paving the way for future research and informed decision-making in the adoption of technological innovations within the context of i5.0.

5.2.2 Practical Implications

The practical implications of this research can be significant for developers, marketers, decision makers, and related other stakeholders with several key points to consider. Since perceived ease of use is not a significant factor, the focus should on the other significant factors, such as fostering positive attitude, demonstrating both I.50 innovative technology's usefulness, aligning it with employees' needs, and creating engaging experiences. Since attitude is the most influential factor in the acceptance of both MR and GenAI. In this case, efforts should be made to foster positive attitudes towards MR. This can be achieved through engaging and immersive experiences, showcasing the unique benefits of MR, and providing positive testimonials and case studies. Similarly, for GenAI, marketing and user engagement strategies should focus on building a positive perception of GenAI by highlighting its innovative capabilities, ease of use, and successful applications.

Related to the MR model, the significant impact of perceived usefulness and compatibility on both attitude and intention suggests that efforts should focus on enhancing the practical benefits and ensuring that Mixed Reality solutions align well with users' existing values and experiences. Developers should prioritize creating user-friendly interfaces and functionalities that demonstrate clear utility. The positive influence of perceived novelty on attitude indicates that marketing strategies for marketers should highlight the innovative and cutting-edge aspects of Mixed Reality. However, since novelty does not significantly drive intention, marketing campaigns should also emphasize the practical benefits and compatibility of Mixed Reality with users' needs. The findings also suggest decision makers that investments in Mixed Reality should prioritize features that enhance perceived usefulness and compatibility. Decision-makers should support initiatives that demonstrate the tangible benefits of Mixed Reality and ensure that it integrates seamlessly with existing systems and workflows. Other stakeholders, such as educators and trainers, the emphasis on perceived usefulness and compatibility implies that training programs should focus on demonstrating the practical applications and benefits of Mixed Reality. Ensuring that users understand how Mixed Reality can enhance their tasks and fit into their routines will be crucial for adoption.

Meanwhile, related to the GenAI model, the significant impact of perceived ease of use on attitude suggests that efforts should focus on creating intuitive and user-friendly GenAI solutions. Enhancing the ease of use can positively shape user attitudes and facilitate adoption. Additionally, developers should continue to emphasize the practical benefits and utility of GenAI. The significant influence of perceived novelty on both attitude and intention indicates that marketing strategies for marketers should highlight the innovative aspects of GenAI. Campaigns should showcase how GenAI can revolutionize tasks and provide unique solutions, while also emphasizing its ease of use and practical benefits. The findings suggest that investments in GenAI should prioritize features that enhance ease of use, usefulness, and novelty. Decision-makers should support initiatives that demonstrate the innovative potential of GenAI and ensure that it is accessible and beneficial to users. Other stakeholders, such as educators and trainers, the emphasis on perceived ease of use and novelty implies that training programs should focus on demonstrating how easy and innovative GenAI solutions are. Ensuring that users understand the practical applications and benefits of GenAI will be crucial for adoption.

The practical implications of this research can be significant for developers, marketers, decision-makers, and other related stakeholders, offering several critical considerations for fostering the adoption of i5.0 innovative technologies. Since perceived ease of use does not emerge as a significant determinant of acceptance, strategic efforts should prioritize other impactful factors, such as fostering positive attitudes, demonstrating the usefulness of these technologies, aligning them with employees' needs, and creating engaging and meaningful user experiences. Given that attitude is the most influential factor in the acceptance of both MR and GenAI technologies, targeted initiatives to cultivate positive attitudes are essential. For MR, this can be achieved by providing engaging and immersive experiences that effectively highlight the unique benefits of MR technology. Demonstrations, case studies, and testimonials highlighting the practical applications of MR can help to build confidence and positive perceptions. Similarly, for GenAI, marketing strategies should emphasize its innovative capabilities, ease of use, and successful applications, fostering a favorable perception among potential users. The emphasis on attitude as a mediator also underscores the need for communication strategies that highlight how these technologies can address specific user needs and challenges.

Furthermore, for the MR model, the findings underscore the critical role of perceived usefulness and compatibility in shaping both attitudes and intentions. Efforts to enhance the practical benefits of MR should focus on aligning the technology with users' values and experiences. Developers should prioritize designing user-friendly interfaces and functionalities that clearly demonstrate utility and relevance to mining industry applications. Additionally, the significant impact of perceived novelty on attitude indicates that marketing strategies should highlight the innovative and cutting-edge features of MR. However, as novelty does not directly influence intention, campaigns must also emphasize the practical benefits and compatibility of MR with users' existing workflows and infrastructure. Decision-makers are encouraged to support initiatives that prioritize these factors, ensuring that MR technology integrates seamlessly into current systems and enhances overall efficiency. For educators and trainers, the focus should be on developing programs that clearly communicate the practical applications and benefits of MR, ensuring that employees understand its potential to enhance their tasks and routines.

In the GenAI model, the significant impact of perceived ease of use on attitude highlights the importance of creating intuitive and user-friendly solutions. Developers should focus on designing GenAI applications that are accessible and minimize complexity, as this can positively influence attitudes and facilitate adoption. The findings also emphasize the importance of perceived novelty, which significantly affects both attitude and intention to adopt GenAI. Marketing campaigns should underscore the innovative aspects of GenAI, demonstrating how it can revolutionize tasks, address challenges, and offer unique solutions. At the same time, practical benefits and ease of use should be clearly communicated to reinforce its value proposition. Decision-makers should prioritize investments that enhance these attributes, supporting initiatives that demonstrate the practical and innovative potential of GenAI in real-world scenarios. For educators and trainers, programs should be developed to highlight the ease of use and novel features of GenAI while providing clear examples of its practical applications, ensuring that users can effectively integrate it into their workflows.

Overall, this research provides actionable insights for all stakeholders aiming to promote the adoption of i5.0 technologies in the mining sector. By addressing the key determinants of acceptance and tailoring strategies to the specific contexts of MR and GenAI technologies, all the stakeholders can drive meaningful progress in the adoption of these transformative innovations. All the practical implications are summarized in **Table 5.1** as follows.

Table 5.1 Practical implication of both i5.0 innovative technologies in mining industry

	Mixed Reality (MR)	Generative AI (GenAI)
Developers	The pronounced impact of perceived usefulness and compatibility on attitudes and intentions underscores the imperative for developers to prioritize the creation of intuitive interfaces and functionalities that not only demonstrate clear practical benefits but also align seamlessly with users' existing values and experiences.	The significant influence of perceived ease of use on attitudes underscores the need for developers to prioritize the creation of intuitive and user-friendly GenAI solutions while simultaneously emphasizing their practical benefits and utility to positively shape user attitudes and facilitate adoption.
Marketers	The positive influence of perceived novelty on attitude highlights the importance of marketing strategies that showcase the innovative and cutting-edge aspects of MR, while also emphasizing its practical benefits and compatibility with users' needs, given its limited direct impact on intention.	The significant influence of perceived novelty on both attitude and intention underscores the need for marketing strategies to highlight the innovative aspects of GenAI, showcasing its potential to revolutionize tasks and provide unique solutions, while also emphasizing its ease of use and practical benefits.
Decision-makers	Investments in MR should prioritize enhancing perceived usefulness and compatibility by supporting initiatives that demonstrate its tangible benefits and ensuring seamless integration with existing systems and workflows.	Investments in GenAI should prioritize enhancing ease of use, usefulness, and novelty by supporting initiatives that showcase its innovative potential while ensuring it remains accessible and beneficial to users.
Other stakeholders	Such as educators and trainers, the emphasis on perceived usefulness and compatibility implies that training programs should focus on demonstrating the practical applications and benefits of MR. Ensuring that users understand how MR can enhance their tasks and fit into their routines will be crucial for adoption.	Such as educators and trainers, the emphasis on perceived ease of use and novelty implies that training programs should focus on demonstrating how easy and innovative GenAI solutions are. Ensuring that users understand the practical applications and benefits of GenAI will be crucial for adoption.

5.3 Limitation and Future Research Agenda

The exclusive reliance on a quantitative approach to investigate the acceptance of i5.0 innovative technologies in Indonesia's mining industry highlights several methodological constraints. While quantitative methods are effective in identifying patterns and relationships, they often fail to capture the intricate and unstructured factors influencing technology adoption. The complexity of interactive and interrelated variables demands a qualitative dimension to uncover deeper, more nuanced insights. Future studies should incorporate qualitative methods alongside quantitative approaches to provide a more holistic understanding of the dynamics underlying technology acceptance. Such mixed-method research would enable a richer exploration of factors that numerical analyses alone cannot address, offering a more comprehensive perspective on the interplay of adoption drivers.

The research's limitations also extend to its sample size, which may hinder the generalizability of its findings. Future research should aim to include larger and more diverse samples to ensure broader applicability across various contexts and demographics. Moreover, the cross-sectional design employed in this research captures data at a single point in time, which restricts the ability to observe changes in user attitudes, perceptions, and intentions over time. Longitudinal research is recommended to explore the temporal dynamics of technology adoption, offering valuable insights into the factors that contribute to sustained acceptance and long-term integration of i5.0 technologies in the mining sector.

The scope of this research primarily focuses on specific variables such as perceived compatibility, ease of use, usefulness, and novelty. However, other influential factors, such as trust, privacy, and security, have not been examined. Future research should investigate these additional dimensions to develop a more comprehensive understanding of the challenges and opportunities associated with adopting MR and GenAI technologies. Furthermore, a comprehensive examination of regulatory frameworks and their influence on technology adoption could yield valuable insights into the development of policies that effectively balance innovation, user protection, and ethical considerations within the mining industry. Additionally, future research should explore the role of top management support in fostering positive attitudes toward the adoption of MR and GenAI technologies, as leadership commitment is often a critical determinant of successful technological integration. Moreover, given that demographic variables were not incorporated into the present study's analysis, future research could address this limitation by investigating the extent to which demographic factors shape technology acceptance, thereby enabling comparative analyses that offer a more nuanced understanding of adoption patterns across diverse employee segments within the mining sector.

Another promising area for future research is the impact of user experience (UX) design elements on attitudes and intentions toward MR and GenAI technologies. Investigating how interface design, interactivity, and usability influence user engagement could lead to the development of more intuitive and user-friendly solutions. Additionally, examining the integration of MR and GenAI with other emerging technologies, such as the Internet of Things (IoT) and blockchain, could reveal how these synergies influence user attitudes and technology adoption. Such studies would provide a holistic perspective on the broader technological ecosystem.

The adoption of MR and GenAI technologies also has significant implications for the workforce, particularly in terms of job displacement, changes in skill requirements, and employee attitudes. Research in this area could guide strategies for workforce development and the design of training programs that facilitate technology acceptance. Experimental or quasi-experimental studies would be particularly beneficial in identifying effective interventions to prepare employees for technological transitions, ensuring the successful integration of MR and GenAI within industrial workflows.

Given the cultural specificity of this research, which focuses on Indonesia's mining industry, future research should investigate how cultural differences influence technology adoption drivers. Replicating similar studies in diverse cultural and geographic contexts could provide insights into the universality or variability of the identified factors. Moreover, sector-specific research, such as those in healthcare, education, manufacturing, construction, or oil and gas could help tailor MR and GenAI technologies to meet the unique demands of different industries. Such research would enable the development of targeted solutions that maximize the utility and relevance of these technologies.

Finally, the broader societal and ethical implications of MR and GenAI adoption warrant further exploration. Future research should examine how these technologies impact collaboration, decision-making, and trust within organizations and society at large. Investigating these aspects through experimental designs could provide actionable insights into the mechanisms that drive or hinder technology adoption. By addressing these areas, future studies can advance the understanding of MR and GenAI technologies, supporting their effective implementation and contributing to the broader discourse on technological innovation and its integration into society.

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APPENDIX

APPENDIX A

LEGAL ENVIRONMENT AND RESEARCH ETHICS APPROVAL

1. Dissertation Approval

Announcement
KMITL Business School
King Mongkut's Institute of Technology Ladkrabang
Result of Dissertation Outline Approval (Mr. Wecka Imam Yudhistyra)

KMITL Business School, King Mongkut's Institute of Technology Ladkrabang, with the approval of the Dissertation Proposal Committee, would like to announce the research topic and approve the Dissertation outline of the Doctor of Philosophy Program in Industrial Business Administration (International Program), which was approved on 9 August 2023 to proceed as follows:

Mr. Wecka Imam Yudhistyra, Student ID 65106046, is allowed to do a Dissertation on the topic of " ADOPTION OF INDUSTRY 5.0 TECHNOLOGICAL INNOVATION: A PERSPECTIVE FROM MINING INDUSTRY IN TECHNOLOGY ACCEPTANCE AMONG EMPLOYEES" with Assoc. Prof. Dr. Chalita Srinuan as a main advisor.

In this regard, the student is required to research and write a Dissertation by consulting with his advisor to complete it within the stipulated time in the regulations of King Mongkut's Institute of Technology Ladkrabang.

Announced on November 16, 2023

(Associate Professor Dr.Singha Chaveesuk)
KMITL Business School
2023/11/16 Time 05:02:34 Non-PKI Server Sign-LN
Signature Code : NgBBA-EYAOA-AyADM-AOAA2

2. Ethical Certifications (National Science and Technology Development Agency)

– Human Research Ethic A

NSTDA

Certificate of Achievement

This is to certify that

Mr. WECKA IMAM YUDHISTYRA

has successfully completed

หลักสูตร จริยธรรมการวิจัยในมนุษย์ (Human Research Ethics) (e-Learning)

awarded on October 7, 2022.

เอกสารรับรองการฝึกอบรมทางอิเล็กทรอนิกส์ (e-Certificate)

ผ่านเว็บไซต์ https://elearn.career4future.com

e-Certificate ฉบับนี้ เป็นหลักสูตรระดับพื้นฐานเท่านั้น ไม่สามารถนำไปใช้ประกอบการยื่นขอรับรองจริยธรรมการวิจัยในมนุษย์ นอก สวทช. ได้

Certificate No. O-2022015775

Date of Expire October 6, 2023

Paving The Way for Practical S&T Knowledge

– Research Integrity

NSTDA

Certificate of Achievement

This is to certify that

Mr. WECKA IMAM YUDHISTYRA

has successfully completed

หลักสูตร จริยธรรมการวิจัย (Research Integrity) (e-Learning)

awarded on October 10, 2022.

เอกสารรับรองการฝึกอบรมทางอิเล็กทรอนิกส์ (e-Certificate)

ผ่านเว็บไซต์ https://elearn.career4future.com

Certificate No. O-2022015834

Date of Expire October 9, 2025

Paving The Way for Practical S&T Knowledge

– Research Integrity (Part 2)

– Data Recording

– Naming in Academic Publication

สวทช
NSTDA

Certificate of Achievement

This is to certify that

Mr. WECKA IMAM YUDHISTYRA

has successfully completed

หลักสูตร การมีชื่อในเอกสารเผยแพร่ทางวิชาการ (e-Learning)

awarded on October 10, 2022.

เอกสารรับรองการฝึกอบรมทางอิเล็กทรอนิกส์ (e-Certificate)

ผ่านเว็บไซต์ https://elearn.career4future.com

Certificate No. O-2022015835

Date of Expire October 9, 2024

Paving The Way for Practical S&T Knowledge

3. Ethical Approval

UNIVERSITAS GADJAH MADA
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PERSETUJUAN KOMISI ETIK

No: KE/UGM/015/EC/2024

Judul Protokol Penelitian	:	Adopsi Inovasi Teknologi Industri 5.0: Sebuah Perspektif dari Industri Pertambangan dalam Penerimaan Teknologi di Kalangan Karyawan (*Adoption of Industry 5.0 Technology Innovation: A Perspective from The Mining Industry on The Technology Acceptance Among Employees*)
Dokumen yang telah disetujui	:	Proposal Penelitian versi 02 2024 Penjelasan kepada Calon Subyek dan *Informed Consent Form* versi 02 2024
Peneliti utama	:	Wecka Imam Yudhistyra
Peneliti yang berpartisipasi	:	Chalita Srinuan
Tanggal disetujui	:	19 Februari 2024 (valid selama 1 tahun sejak tanggal disetujui)
Institusi/tempat penelitian	:	Perusahaan tambang di Jakarta, Indonesia

Komisi Etik Penelitian Universitas Gadjah Mada menyatakan bahwa dokumen tersebut di atas telah memenuhi standar prinsip-prinsip etika penelitian.

Komisi Etik Penelitian Universitas Gadjah Mada memiliki wewenang untuk mengawasi aktivitas penelitian kapanpun.

Peneliti Utama diwajibkan untuk menyerahkan:

- ☐ Laporan kemajuan penelitian
- ☐ Laporan khusus jika ada kejadian serius
- ☑ Laporan akhir ketika penelitian telah selesai.

Ketua Panel

Dra. Sri Kusrohmaniah, M.Si., Ph.D.

Sekretaris Panel

Ario Wicaksono, M.Si., Ph.D.

APPENDIX B

INFORMED CONSENT FORM

Informed Consent Form
Formulir Penjelasan dan Persetujuan

KMITL Business School, Lat Krabang, Bangkok, Thailand 10520

KEY INFORMATION
You are being asked for consent to participate in this research. The aim of this research is to examine the factors that influence the acceptance of industry 5.0 technology innovations (i.e., Mixed Reality – MR and Generative Artificial Intelligence – GenAI) among mining industry employees. Participation is voluntary. There is no penalty if you decide not to participate or withdraw from the study, and your relationship with Mr. Wecka Imam Yudhistyra (Principal Investigator) and the KMITL Business School will not be affected by this decision. The estimated time of participation in this research is approximately 30 minutes. There are no potential risks of participating included.

QUALIFICATIONS TO PARTICIPATE
You are being asked to participate because of your status as an employee in a company operating in the mining industry.

PROCEDURE
Surveys must adhere to the health protocols (i.e., using a mask and providing hand sanitizer and cleaning wipes), including following the rules implemented by the company. If you agree to participate in this research, you will be informed about the MR and GenAI technology innovations that have the potential to improve your experience and productivity at work. After that, you will be asked to answer survey questionnaires (which could be filled in with the help of field workers). If you successfully complete the survey, you are awarded a benefit of approximately 1-2 USD for your participation.

PARTICIPANT CONFIDENTIALITY
To maintain data privacy, your name will not be associated with any publications or presentations. Researchers will use anonymization methods, such as numbering or pseudonyms, to identify participants, not your name. Your identifying information will only be shared if required by law or you provide written permission. Upon the completion of the research, all collected data will be promptly destroyed to ensure the prevention of any potential data leakage and to uphold strict confidentiality and ethical standards.

DETAIL PENTING
Anda dimintai persetujuan untuk berpartisipasi dalam penelitian ini. Tujuan dari penelitian ini adalah untuk menguji faktor-faktor yang mempengaruhi adopsi sitem ERP di kalangan karyawan industri pertambangan. Partisipasi bersifat sukarela. Tidak ada penalti jika Anda memutuskan untuk tidak berpartisipasi atau menarik diri dari penelitian, dan hubungan Anda dengan Tuan Wecka Imam Yudhistyra (Penyelidik Utama) dan Sekolah Bisnis KMITL tidak akan terpengaruh oleh keputusan ini. Perkiraan waktu keikutsertaan dalam penelitian ini kurang lebih 30 menit. Tidak ada potensi risiko untuk berpartisipasi.

KUALIFIKASI UNTUK BERPARTISIPASI
Anda sedang dimintai untuk berpartisipasi karena status Anda sebagai karyawan di perusahaan yang bergerak industry pertambangan.

PROSEDUR
Survei harus mematuhi protokol kesehatan (seperti menggunakan masker serta menyediakan hand sanitizer dan tisu pembersih), termasuk mengikuti aturan yang diterapkan perusahaan. Jika Anda setuju untuk berpartisipasi dalam penelitian ini, Anda akan diminta menjawab pertanyaan survei (yang bisa diisi dengan bantuan staf lapangan). Jika Anda berhasil menyelesaikan survei, Anda diberikan keuntungan kurang lebih 1-2 USD atas partisipasi Anda.

KERAHASIAAN PESERTA
Untuk menjaga privasi data, nama Anda tidak akan dihubungkan dengan publikasi atau presentasi apa pun. Peneliti akan menggunakan metode anonimisasi, seperti penomoran atau nama samaran, untuk mengidentifikasi partisipan, bukan nama Anda. Informasi identitas Anda hanya akan dibagikan jika diwajibkan oleh hukum atau Anda memberikan izin tertulis. Setelah penelitian selesai, semua data yang dikumpulkan akan segera dimusnahkan untuk memastikan pencegahan potensi kebocoran data dan untuk menegakkan kerahasiaan dan standar etika yang ketat.

DISCLAIMER
The risk of participating is generally nothing. If you have health concerns that impact your ability to participate, however, you may want to consult a healthcare professional before agreeing to participate in this study. The researchers and KMITL Business School are not responsible for any medical or mental health expenses.

PENAFIAN
Risiko berpartisipasi umumnya tidak ada apa-apanya. Namun, jika Anda memiliki masalah kesehatan yang memengaruhi kemampuan Anda untuk berpartisipasi, Anda mungkin ingin berkonsultasi dengan profesional kesehatan sebelum menyetujui untuk berpartisipasi dalam penelitian ini. Para peneliti dan KMITL Business School tidak bertanggung jawab atas biaya medis atau kesehatan mental apa pun.

REFUSAL TO SIGN CONSENT
You are not required to participate in this study and have the right to refuse signing this form. Refusal to participate in this research or to sign the form will not affect anything. If you refuse to sign this form, you cannot participate in the study.

PENOLAKAN TANDA TANGAN PERSETUJUAN
Anda tidak diwajibkan untuk berpartisipasi dalam penelitian ini dan berhak menolak menandatangani formulir ini. Penolakan untuk berpartisipasi dalam penelitian ini atau menandatangani formulir tidak akan mempengaruhi apapun. Jika Anda menolak untuk menandatangani formulir ini, Anda tidak dapat berpartisipasi dalam penelitian ini.

CANCELLING THIS CONSENT
At any time during the study, you have the right to withdraw your consent to participate in this study. To withdraw from the study, we ask you to contact the researcher. If you withdraw from the study, the researcher will stop collecting additional information and data about you.

MEMBATALKAN PERSETUJUAN INI
Kapan pun selama penelitian, Anda berhak menarik persetujuan Anda untuk berpartisipasi dalam penelitian ini. Untuk mengundurkan diri dari penelitian, kami meminta Anda untuk menghubungi peneliti. Jika Anda menarik diri dari penelitian, peneliti akan berhenti mengumpulkan informasi dan data tambahan tentang Anda.

PARTICIPANT CERTIFICATION
I have read this Informed Consent form. I have been given the opportunity to ask questions regarding the study, and I have received answers to any questions I had regarding the study. I understand that if I have any additional questions about the study or my rights as a participant, I may contact Mr. Wecka Imam Yudhistyra by email:
- weckayudhistyra@gmail.com

KETERANGAN PESERTA
Saya telah membaca formulir Informed Consent ini. Saya telah diberi kesempatan untuk mengajukan pertanyaan mengenai penelitian ini, dan saya telah menerima jawaban atas setiap pertanyaan yang saya miliki mengenai penelitian ini. Saya memahami bahwa jika saya memiliki pertanyaan tambahan mengenai penelitian atau hak saya sebagai peserta, saya dapat menghubungi Bapak Wecka Imam Yudhistyra melalui email:
- weckayudhistyra@gmail.com

By filling in the survey questionnaire, I agree to be a participant in this research. I acknowledge that I am aware of what this research involves.
Dengan mengisikan kuesioner survey ini, Saya setuju untuk menjadi partisipan dalam penelitian ini. Saya mengakui bahwa saya mengetahui apa saja yang tercakup dalam penelitian ini.

APPENDIX C

PREVIOUS RELATED LITERATURE ON THE CONCEPTUAL MODEL

1. Previous literature regarding the concept of Intention

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Intention	The degree to which a consumer is willing to buy a product through an online store.	▪ If the opportunity arises, I intend to buy from online stores ▪ If given the chance, I can predict what I should buy from an online store in the future ▪ I am likely to transact with an online store soon	Retail	Peña-García et al. (2020)
Intention	Willingness to perform a particular action	▪ I will use the HoloLens in the future. ▪ I will recommend using the HoloLens. ▪ Using the HoloLens in the future is important to me.	Retail	Holdack et al. (2022);
Intention	An indicator describing how much effort an individual is willing to put in order to perform desired behaviour	▪ I intend to take Augmented Reality (AR) and Virtual Reality (VR) in the next term. ▪ I am willing to take AR/VR ▪ I would like to recommend AR/VR	Education	Jang et al. (2021)
Intention	User's intention to use a technology	▪ I plan to use m-AR in the future. ▪ If possible, I will try to use m-AR. ▪ I will try to use m-AR of necessary in teaching business ethics.	Education	Hadi et al. (2022)
Intention	Individual's readiness to perform a given behaviour	▪ I intend to use AR applications in my future teaching. ▪ I plan to use AR applications in my future teaching. ▪ I predict I will use AR applications in my future teaching.	Education	George et al. (2023)

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Intention	Person’s readiness to perform an action	▪ Next time if I buy a car, I will consider buying an electric car. ▪ I expect to drive an electric car in the near future. ▪ Spending money on buying electric car is right choice.	Automobile or Automotive Industry	Chanda et al. (2024);
Behavioural Intention	Individual’s willingness to perform a particular action.	▪ I intend to use Chat-GPT as often as necessary. ▪ I hope to use Chat-GPT in the coming months. ▪ I will recommend the use Chat-GPT to my family and friends.	Education	Saif et al. (2024)
Intention to Use	An individual's intention to use a technology.	▪ I intend to use AI in the future. ▪ I will always try to use AI in my workplace. ▪ I plan to use AI frequently.	Construction, Retail, Manufacture, and Finance	Cao et al. (2021)
Intention to Use	An individual's intention to use a technology.	▪ I intend to use AI in the future. ▪ I will always try to use AI in my workplace. ▪ I plan to use AI frequently.	Information Technology, Finance, and Manufacture	Baabdullah (2024)
Behavioural Intention	A measure of the likelihood a person will use the technology.	▪ I intend to use AR/VR applications for my studies in the future. ▪ I predict I would use AR/VR applications for my learning experiences. ▪ I plan to use AR/VR applications frequently.	Education	Shen et al. (2022)
Intention to Use	Consumers’ intention	▪ The next time I buy online, I plan to use AR shopping application for shopping. ▪ Using AR shopping application is my first choice when shopping online. ▪ I would recommend AR shopping application to my friend. ▪ I have positive things to say about AR shopping application to my friend	Retail	Jiang et al. (2021)

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Intention	An individual’s intention to use AI for decision making.	▪ I intend to use Artificial Intelligence (AI) in the future. ▪ I will always try to use AI in my workplace. ▪ I plan to use AI frequently	Construction, Retail, Manufacture, and Finance	Cao et al. (2021)

2. Previous literature regarding the concept of attitude

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Attitude	Consumers who may develop favourable and unfavourable beliefs towards the use of smartwatches.	▪ Using a smartwatch would be a positive decision. ▪ Using a smartwatch would be a smart decision to make. ▪ I have a positive impression of using a smartwatch for work. ▪ I would feel excited to purchase a smartwatch I would be happy to use a smartwatch.	Consumer Products	Acikgoz et al. (2023)
Attitude	User’s evaluation of a technology.	▪ In my opinion, using the HoloLens is a good idea. ▪ Altogether, I like shopping with the HoloLens.	Retail	Holdack et al. (2022);
Attitude	An individual's positive or negative feelings about using a specific technology.	▪ Using ChatGPT is positive. ▪ Using ChatGPT increases my productivity at work. ▪ Using ChatGPT my effectiveness at work.	Education	Saif et al. (2024)
Attitude	An individual's positive or negative feelings about using a specific technology.	▪ It's a good idea to use VR to create nature-themed oil paintings. ▪ It is a wise idea to use VR to create nature-themed oil paintings. ▪ I like the idea of using VR for nature-themed oil painting. ▪ It is a pleasure to use VR to create nature-themed oil paintings.	Technology and Digital Media	Sun et al. (2023)

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Attitude	User's evaluation of the desirability of employing a specific technology.	▪ I like the idea of using AR/VR applications in my studies/learning. ▪ AR/VR applications make my learning more interesting. ▪ I like learning with AR/VR applications. ▪ My general opinion regarding AR/VR applications is positive.	Education	Shen et al. (2022);
Attitude	A consumer's willingness to embrace EVs to reduce hazardous air pollution from exhaust emissions.	▪ For me, adopting an EV is extremely good. ▪ For me, adopting an EV is extremely wise. ▪ I am interested in EVs.	Automobile or Automotive Industry	Chanda et al. (2024)
Attitude	Consumers' positive attitude.	▪ I think using AR shopping application is a good idea. ▪ I think other people should also use AR shopping application. ▪ I think AR shopping application is a good experiential online shopping technology. ▪ I think I will be filled with affection and satisfaction for AR shopping application. ▪ I think AR shopping applications are so interesting that it makes you want to know more.	Retail	Jiang et al. (2021)
Attitude	Degree to which the adoption of a behaviour is evaluated in a favourable or unfavourable way.	▪ In my opinion, using an electric car is a good attitude. ▪ In my opinion, using an electric car is a wise attitude. ▪ In my opinion, using an electric car is a favourable attitude. ▪ In my opinion, using an electric car is a positive attitude.	Automobile or Automotive Industry	Buranelli de Oliveira et al. (2022)

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Attitude	individual's favourable or unfavourable feelings towards a given behaviour	▪ In my opinion, it is desirable for every customer to use Mobile Payment Services (MPS). ▪ Using MP gives me pleasure. ▪ Using MP is a good idea for me. ▪ Using MP provides convenience in transactions used by traders in my business. ▪ Using MP makes it easier for me to check transactions that occur in my business.	Finance	Gunnoo et al. (2023)
Attitude	Positive feeling working with the systems	▪ Using VHC is a good idea. ▪ Working with VHC is pleasant. ▪ Using VHC is beneficial for us. ▪ Overall, our attitude toward using VHC is positive.	Healthcare	Karkonasasi et al. (2023)
Attitude	An individual's positive or negative feelings about using AI for organizational decision-making.	▪ Using AI is a good idea. ▪ I like the idea of using AI. ▪ Using AI would be pleasant.	Construction, Retail, Manufacture, and Finance	Cao et al. (2021)
Attitude	The individual's positive or negative evaluation of performing the behaviours.	▪ Using AR applications is a good idea. ▪ I plan to use AR applications in my future teaching. ▪ I predict I will use AR applications in my future teaching.	Education	George et al. (2023)

3. Previous literature regarding the concept of perceived compatibility

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Perceived Compatibility	A positive perception and belief in the compatibility of a technology.	Online shopping using AR shopping application would be compatible with: ▪ my lifestyle. ▪ my actual needs. ▪ the way I like online shopping.	Retail	Jiang et al. (2021)
Compatibility	Degree to which an innovation is perceived as compatible with existing values, former experiences, and the needs of potential adopters.	▪ I believe that driving an electric car would fit my lifestyle. ▪ I believe that driving an electric car would fit what I need. ▪ I believe that driving an electric car would fit into my routine.	Automobile or Automotive Industry	Buranelli de Oliveira et al. (2022)
Compatibility	The extent to which an innovation is judged to be matched with a person's values, past experiences, and requirements	▪ Mobile Payment Services (MPS) fits well with the way I manage my finances. ▪ I like to try and adopt new technology. ▪ MPS is compatible with my lifestyle. ▪ MPS is suitable to integrate with banking services.	Finance	Gunnoo et al. (2023)
Perceived Compatibility	An indicator of how willing consumers are to embrace new products or services and is consistent with innovation and the values, experiences and needs of potential adopters (Arvidsson,	▪ Mobile payment would fit my transaction style. ▪ Mobile payment would fit well with the way I like to spend. ▪ Mobile payment would be compatible with most aspects of my transactions.	Finance	Arli and Bakpayev (2023)

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Perceived Compatibility	the extent to which the system is perceived to be compatible with the current values and prior experiences of nurses, and their requirements in the workplace in administrating childhood vaccinations	▪ Using Virtual Health Connect (VHC) is compatible with all aspects of our work. ▪ Using VHC is entirely compatible with our current situation. ▪ We think using VHC fits adequately with the way we like to work. ▪ We think using VHC fits into our work style.	Healthcare	Karkonasasi et al. (2023)
Perceived Compatibility	Compatibility refers to using a smartwatch that would be consistent with the individual current state of my daily life, habits and preferences.	▪ Using a smartwatch would be consistent with my current preference. ▪ Using a smartwatch would be consistent with my current habits. ▪ Using a smartwatch would be consistent with the current state of my daily life. ▪ Using a smartwatch would match my living experience.	Consumer Products	Acikgoz et al. (2023)
Compatibility	The extent to which new technology usage befits an organization	▪ Not Available	Various Industry	Chatterjee et al. (2023)
Compatibility	The suitability between the use of Electric Motorcycles (EMs) and the lifestyle and current situation of their users	▪ Using Electric Motorcycles (EMs) will fit well with the way I like to travel. ▪ Using EMs will fit well with my lifestyle. ▪ Using EMs is completely compatible with my current situation.	Automobile or Automotive Industry	Ngoc Su et al. (2023)

4. Previous literature regarding the concept of perceived ease of use

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Perceived Ease of Use	The degree to which a person believes that using a particular system would be free of effort	▪ I find that driving an Electric Vehicle is easy and comfortable. ▪ Learning to drive an Electric vehicle will be/is easy. ▪ I find that handling an Electric Vehicle will be/is easy.	Automobile or Automotive Industry	Chanda et al. (2024)
Perceived Ease of Use	The degree to which nurses believe that using the systems would be effortless.	▪ Our interaction with Virtual Health Connect (VHC) would be clear and understandable. ▪ Interacting with VHC would not demand a lot of our mental effort. ▪ We would find it easy to get VHC to do what we want it to do. ▪ We would find VHC to be easy to use.	Healthcare	Karkonasasi et al. (2023)
Perceived Ease of Use	The extent to which a person has a belief that using a new system or a new technology would be free of effort.	▪ The process of using an AI based system is easily understandable by me. ▪ It is easy for our organization to operate an AI based manufacturing and production system. ▪ I will be able to use the AI based manufacturing and production system in our organization. ▪ I agree that all the related employees can quickly learn about the usage of AI based technology.	Manufacture and Production	Chatterjee, Rana, et al. (2021)
Perceived Ease of Use	The degree to which an individual believes that a particular technology can be easily understood or operated.	▪ The use of facial recognition payment is easy for me. ▪ The use of facial recognition payment is understandable and clear for me. ▪ It won’t be hard for me to become skilful at using facial recognition payment	Finance	Zhong et al. (2021)

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Perceived Ease of Use	The degree to which a user does not find it complex to learn, realize, and operate a system.	▪ Users will use the AI-CRM system if it is simple to use. ▪ Everyone would like to use AI-CRM system if it is felt compatible. ▪ AI-CRM system can address all our organizational needs. ▪ Operating AI-integrated CRM system is easy. ▪ Training will help to use the AI-integrated CRM system easily. ▪ Transition from legacy CRM system to AI-CRM system will be easy.	Manufacture and Service	Chatterjee, Chaudhuri, et al. (2021)
Perceived Ease of Use	Pertains to the perceived ability, autonomy, and control when using AI	▪ I would find AI-based applications easy to use. ▪ Interacting with artificial intelligence would not require a lot of effort.	Education	Gado et al. (2022)
Perceived Ease of Use	Ease of use of a systems or technology.	▪ Learning to operate AR welding simulator is easy for me. ▪ I find it easy to get AR welding simulator to do what I want to do. ▪ AR welding simulator is rigid and reliable to interact with. ▪ Overall, I find AR welding simulator easy to use.	Education	Papakostas et al. (2022)
Perceived Ease of Use	The degree to which Autonomous Vehicles (Avs) can be easily used in an individual's opinion.	▪ Learning to operate driverless cars would be easy for me. ▪ I would find it easy to get driverless cars to do what I want to do. ▪ I will find driverless cars easy to use.	Automobile or Automotive Industry	T. Huang (2023)
Perceived Ease of Use	The extent to which an individual has a belief that using a new system or a new technology would be free of effort.	▪ I think it is easy to learn how to drive Electric Motorcycles (EMs). ▪ It would be simple to control Ems. ▪ I will have no problems if I use Ems. ▪ Overall, I think EMs is easy to use	Automobile or Automotive Industry	Ngoc Su et al. (2023)

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Perceived Ease of Use	The degree to which a person believes that using a particular system would be free of effort.	▪ Learning to use mobile apps to make restaurant reservations is easy for me. ▪ Interaction with mobile apps for restaurant reservations is clear and understandable. ▪ I find the mobile apps for restaurant reservations flexible to interface with them. ▪ I find mobile apps for restaurant reservations easy to use. ▪ Interacting with mobile apps to make restaurant reservations requires no mental effort.	Hospitality	Debasa et al. (2023)
Perceived Ease of Use	The degree to which a person believes that using a particular system is free of effort	▪ Learning how to use ChatGPT is easy for me. ▪ I find ChatGPT easy to address academic inquiries. ▪ I find it easy for me to become skilful at asking ChatGPT to address my academic inquiries. ▪ My interaction with ChatGPT is clear and understandable when it addresses my academic inquiries.	Education	Lai et al. (2023)

5. Previous literature regarding the concept of perceived usefulness

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Perceived Usefulness	An individual's perception of how valuable a new technology is in meeting their driving expectations.	▪ EVs are useful to reduce my household expenditures on transportation. ▪ EVs can improve my travel efficiency and improve my living quality.	Automobile or Automotive Industry	Chanda et al. (2024)
Perceived Usefulness	The degrees to which nurses believe that using the system would improve their job routine	▪ Using VHC would improve our effectiveness in our job. ▪ Using VHC would improve our job performance. ▪ Using VHC would make it easier to perform our job. ▪ We would find VHC to be useful in our job.	Healthcare	Karkonasasi et al. (2023)
Perceived Usefulness	The potential users' subjective possibility that using a system or the application of a system will enhance the job performance of the users within the context of the firm.	▪ I agree that using an AI based manufacturing and production system makes our firm more efficient. ▪ I believe that the use of an AI based manufacturing and production system increases productivity in our organization. ▪ I can achieve things in a quicker way using an AI based manufacturing and production system. ▪ AI based systems reduce production costs.	Manufacture and Production	Chatterjee, Rana, et al. (2021)
Perceived Usefulness	The degree to which an individual believes that the performance of a task may be improved by using a particular technology.	▪ Facial recognition payment can help me pay quickly. ▪ It is useful to use facial recognition payment. ▪ The use of facial recognition payment is beneficial to me.	Finance	Zhong et al. (2021)

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Perceived Usefulness	The degree to which a user believes that using a particular technology or system would effectively enhance job performance	▪ I hope that AI-CRM system will benefit the organizations. ▪ CRM is useful and if AI is embedded to it, organization would flourish much more. ▪ AI-CRM System is deemed to be useful in any business organization. ▪ Employee would feel comfortable using new AI-integrated CRM system. ▪ In developed countries AI-CRM has brought in grand success. ▪ AI-CRM system will be acceptable if its benefits are perceived.	Manufacture and Service	Chatterjee, Chaudhuri, et al. (2021)
Perceived Usefulness	The degree to which an individual believes that using AI will help and benefit him or her	▪ Using the system would increase my productivity, effectivity, efficiency, as well as expected benefits of using AI.	Education	Gado et al. (2022)
Perceived Usefulness	A form of extrinsic motivation as users engage in an activity to earn a reward or avoid a punishment.	▪ Using AR welding simulator increases my productivity. ▪ Using AR welding simulator increases my training performance. ▪ Using AR welding simulator enhances my effectiveness on the job. ▪ Overall, I find AR welding simulator useful in my job.	Education	Papakostas et al. (2022)
Perceived Usefulness	The function and advantage that can be achieved through use of technologies.	▪ Using a driverless car can improve my driving efficiency. ▪ Using a driverless car can improve my travel efficiency. ▪ Using a driverless car can reduce my driving stress.	Automobile or Automotive Industry	T. Huang (2023)

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Perceived Usefulness	The degree to which a person believes that the performance of a task may be improved by using a particular technology.	▪ I think using Electric Motorcycles (EMs) can save me money (e.g., fuel cost, maintenance cost). ▪ I think using EMs can make my driving easier. ▪ I think using EMs can improve my driving safety performance. ▪ I think using EMs can provide me a better driving experience. ▪ I think using EMs can offer me a comfortable, relaxing driving experience.	Automobile or Automotive Industry	Ngoc Su et al. (2023)
Perceived Usefulness	Using an app taking into account whether such use will help people to perform their job better.	▪ Using apps to make restaurant reservations improves my day-to-day performance. ▪ Using mobile apps to make reservations in restaurants allows me to better organize my day-to-day activities. ▪ Using mobile apps to make restaurant reservations would increase my productivity in my daily task. ▪ Using mobile apps to make restaurant reservations increases my work efficiency.	Hospitality	Debasa et al. (2023)
Perceived Usefulness	It indicates whether technology can be used for successful task accomplishment	▪ I find ChatGPT useful for answering academic inquiries. ▪ Using ChatGPT addresses my academic inquiries more quickly. ▪ Using ChatGPT to address my academic inquiries would increase my academic performance. ▪ Using ChatGPT to address my academic inquiries would enhance my effectiveness of learning.	Education	Lai et al. (2023)

6. Previous literature regarding the concept of perceived novelty

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Perceived Novelty	How users perceive technology, for instance, as something new, intriguing, and different from what they have previously encountered or understood	▪ I found it a novel experience to create nature-themed oil paintings in VR. ▪ Using VR to create nature-themed oil paintings is refreshing to me. ▪ Using VR to create natural-themed oil paintings represents a simple and novel way of painting natural-themed oil paintings.	Technology and Digital Media	Sun et al. (2023)
Novelty	The extent to which the novel ad execution differs from consumers' expectations	▪ The video ad is original. ▪ This video ad is different from my expectations of a car commercial. ▪ This video ad is memorable.	Digital Media	Feng and Xie (2019)
Perceived Novelty	Perceived to be unique or different and/or recent or new.	▪ This smartwatch is unique. ▪ This smartwatch is different compared to the other watches.	Consumer Products	Mani & Chouk (2017)
Perceived Novelty	A new and different perspective	The ad is … ▪ Unconventional ▪ Original ▪ New ▪ Moder	Digital Media	Neudecker et al. (2014)
Perceived Novelty	The degree to which a user perceives an innovation to be a new and exciting alternative to an existing technology.	▪ I found using the hand-scanner to be a novel experience. ▪ Using the hand-scanner is new and refreshing. ▪ The hand-scanner represents a neat and novel way of making a [payment card brand] payment	Finance	Wells et al. (2010)

VARIABLE	DEFINITION	QUESTIONNAIRE ITEMS	INDUSTRY	AUTHOR(S)
Perceived Novelty	The degree to which a product or service is perceived as unusual, different, or unique compared with other products	How novel this service to you? ▪ Not Novel ⇔ Very Novel How original this service to you? ▪ Not Original ⇔ Very Original How innovative this service to you? ▪ Not Innovative ⇔ Very Innovative	Digital Media	Truong (2013);

APPENDIX D

RESEARCH INSTRUMENTS

1. Research instruments: Item of Congruence (IOC)

Although the measurement of research instruments utilized in this research have been extensively employed and validated in prior research, an additional layer of scrutiny was applied to ensure their suitability and alignment with the research objectives. Specifically, the items were evaluated using the Item of Congruence (IOC) metric, a widely recognized method for assessing the consistency between test items and the specific objectives they are intended to measure (Turner & Carlson, 2003). This evaluation was conducted to ensure the research instrument's robustness and theoretical rigor. A panel of three subject matter experts was engaged to rate each test item based on its relevance and clarity in measuring the intended objective of the associated construct. The rating system employed consists of three categories: 1 (clearly measures the objective), 0 (unclear whether it measures the objective), and -1 (does not measure the objective at all). These ratings reflect the degree to which each item aligns with the theoretical and practical aspects of the construct it seeks to measure. The feedback provided by the experts was integral to refining the measurement instrument. It ensured that each item was not only contextually appropriate but also theoretically aligned with the conceptual framework of the study. This rigorous validation process helps minimize ambiguity and enhances the precision of the measurement tool. The Item of Congruence (IOC) metric is calculated using the following formula:

$$\text{IOC} = \frac{\textit{Sum of expert ratings for each item}}{\textit{Number of experts}}$$

This formula provides a numerical value that indicates the degree of alignment between the item and the intended objective. Items with an IOC score of 0.8 or higher are generally considered acceptable, while items falling below this threshold may require revision or exclusion. The table below summarizes the results of the IOC analysis following multiple iterations of modifications informed by expert feedback to enhance the theoretical robustness and practical applicability of the research instrument.

	Exp. 1	Exp. 2	Exp. 3
Generative AI (GenAI)			
Intention			
If my company were to adopt Generative AI technology innovation, I intend to use it.	1	1	1
If my company were to adopt Generative AI technology innovation, I predict that I would use it.	1	1	1
If my company were to adopt Generative AI technology innovation, I plan to use it for working activities.	1	1	1
If my company were to adopt Generative AI technology innovation, I hope to use it.	1	1	1
Attitude			
I like the idea of adopting Generative AI technology innovation for work.	1	1	1
Generative AI technology innovation makes my job even more interesting.	1	1	1
I like working with Generative AI technology innovation.	1	1	1
My general opinion regarding Generative AI technology innovation is favourable.	1	1	1
Perceived Compatibility			
I perceive that the adoption of Generative AI technology innovation fits the needs of the company.	1	1	1
I perceive that the adoption of Generative AI technology innovation is fully compatible with current business operation.	1	1	1
I perceive that adopting Generative AI technology innovation is compatible with our company corporate culture and value system.	1	1	1
I perceive that the adoption of Generative AI technology innovation will be compatible with existing infrastructure in the company.	1	1	1
Perceived Ease of Use			
I perceive that adopting Generative AI technology innovation for work would be easy.	1	1	1
I perceive skilful in adopting Generative AI technology innovation.	1	1	1
I perceive that the adoption of Generative AI technology innovation is not complicated or does not require a lot of mental effort.	1	1	1
I perceive that Generative AI technology innovation is clear and understandable.	1	1	1

	Exp. 1	Exp. 2	Exp. 3
Perceived Usefulness			
I perceive that Generative AI technology innovation is useful. For instance, I can make well-informed decisions faster and consistently enhance my performance with assistance from the Generative AI technology innovation.	1	1	1
I perceive that Generative AI technology innovation could enhance the quality of my work.	1	1	1
I perceive that Generative AI technology innovation could enhance my work effectiveness.	1	1	1
I perceive that Generative AI technology innovation could enhance the productivity of my work.	1	1	1
Perceived Novelty			
I perceive that adopting the Generative AI technology innovation to be a novel experience.	1	1	1
I perceive that adopting the Generative AI technology innovation is new and refreshing.	1	1	1
I perceive that adopting the Generative AI technology innovation represents a neat and novel way of working in the company.	1	1	1
Mixed Reality (MR)			
Intention			
If my company were to adopt MR technology innovation, I intend to use it.	1	1	1
If my company were to adopt MR technology innovation, I predict that I would use it.	1	1	1
If my company were to adopt MR technology innovation, I plan to use it for working activities.	1	1	1
Attitude			
I like the idea of adopting MR technology for work.	1	1	1
MR technology innovation makes my job even more interesting.	1	1	1
I like working with MR technology innovation.	1	1	1
My general opinion regarding MR technology innovation is favourable.	1	1	1
Perceived Compatibility			
I perceive that the adoption of MR technology innovation fits the needs of the company.	1	1	1

	Exp. 1	Exp. 2	Exp. 3
I perceive that the adoption of MR technology innovation is fully compatible with current business operation.	1	1	1
I perceive that adopting MR technology innovation is compatible with our company corporate culture and value system.	1	1	1
I perceive that the adoption of MR technology innovation will be compatible with existing infrastructure in the company.	1	1	1
Perceived Ease of Use			
I perceive that adopting MR technology innovation for work would be easy.	1	1	1
I perceive skilful in adopting MR technology innovation.	1	1	1
I perceive that the adoption of MR technology innovation is not complicated or does not require a lot of mental effort.	1	1	1
I perceive that MR technology innovation is clear and understandable.	1	1	1
I perceive that the innovation of MR technology for work to be flexible and conducive to interfacing with it.	1	1	1
Perceived Usefulness			
I perceive that MR technology innovation is useful. For instance, I am able to conduct seamless virtual communication or collaboration with co-workers in different locations (i.e., coworkers in border locations/overseas); or provision remote expert support, diagnostics, and real-time guidance to repair faulty or malfunctioning equipment.	1	1	1
I perceive that MR technology innovation could enhance the quality of my work.	1	1	1
I perceive that MR technology innovation enables me to accomplish works more quickly.	1	1	1
I perceive that MR technology innovation could enhance my work effectiveness.	1	1	1
Perceived Novelty			
I perceive that adopting the MR technology innovation to be a novel experience.	1	1	1
I perceive that adopting the MR technology innovation is new and refreshing.	1	1	1
I perceive that adopting the MR technology innovation represents a neat and novel way of working in the company.	1	1	1

The three experts who validated the Item of Congruence (IOC) in this research meet the minimum standard criteria for expertise and qualifications (Turner & Carlson, 2003). Their profiles are as follows.

☑ **Expert (1st)**

A highly experienced civil servant in Directorate General Energy and Mineral Resources Republic of Indonesia who also serves as the Head of the Geologist Association of Indonesia (IAGI), Maluku Branch. with extensive research related to mineral resources. With extensive research and professional expertise in the field of mineral resources, this expert brings invaluable practical perspectives. His input was critical in ensuring that the research items are applicable and relevant to the real-world contexts and operational dynamics of the mining industry.

Dr. Herfien Samlehu, M.Eng.

☑ **Expert (2nd)**

A seasoned professional with extensive expertise in industrial operations and technological applications, particularly in the domains of project management and estimation. He holds the position of Asset Management Manager at PT. Pertamina Indonesia, a leading state-owned enterprise renowned for its integrated operations in the upstream and downstream sectors of energy and petrochemicals. Drawing on his profound industry knowledge, this expert provided critical evaluations of the research items, focusing on their clarity, precision, and theoretical alignment with the research's objectives. His insights were instrumental in ensuring the research instrument's relevance and applicability to real-world industrial settings.

Evri Marta Risal, S.T., M.Sc.

☑ **Expert (3rd)**

The third expert is a highly accomplished academic affiliated with the Ho Chi Minh University of Economics and Finance. With an extensive portfolio of research publications and significant professional experience in relevant fields, this expert brought a wealth of theoretical expertise to the study. Her contributions were crucial in critically assessing the research items, ensuring their theoretical alignment with the constructs, and enhancing the overall rigor of the conceptual framework.

Luu Thi Mai Vy, PhD.

2. Research instruments: Translation into Bahasa Indonesia

This section delineates the research instruments employed in this research, alongside their corresponding translations from English to Indonesian. The translations were initially drafted by the author and subsequently validated by an official linguist, with further refinements made by the author to ensure linguistic accuracy and conceptual equivalence.

EKO TJAHYADI
PENERJEMAH TERSUMPAH

DEMOGRAPHY

(DEMOGRAFIS)

What is your gender?
(Apa jenis kelamin Anda?)

○ **Male**
(Pria)

○ **Female**
(Wanita)

How old are you?
Berapa usia Anda?

○ **20 – 30 years old**
(20 – 30 years old)

○ **31 – 40 years old**
(31 – 40 years old)

○ **41 – 50 years old**
(41 – 50 years old)

○ **51 years old, and above**
(51 tahun dan diatasnya)

What is the highest academic qualification you have completed?
Apa kualifikasi akademis tertinggi yang pernah Anda selesaikan?

○ **Diploma**
(Diploma)

○ **Bachelor's Degree**
(Sarjana)

○ **Master's Degree**
(Magister)

○ **Doctoral Degree**
(Doktor)

How long have you been with the current company?
Sudah berapa lama Anda bekerja di perusahaan saat ini?

○ **< 1 year**
(< 1 tahun)

○ **> 1 year – < 3 years**
(> 1 tahun – < 3 tahun)

○ **> 3 years – < 6 years**
(> 3 tahun – < 6 tahun)

○ **> 6 years – < 9 years**
(> 6 tahun – < 9 tahun)

○ **> 9 years – < 12 years**
(> 9 tahun – < 12 tahun)

○ **> 12 years**
(> 12 tahun)

GENERATIVE AI TECHNOLOGY INNOVATION

(INOVASI TEKNOLOGI AI GENERATIF)

INTENTION (NIAT)

	Strongly Disagree Sangat Tidak Setuju	**Disagree** Tidak Setuju	**Neutral** Netral	**Agree** Setuju	**Strongly Agree** Sangat Setuju
1. **If my company were to adopt Generative AI technology innovation, I intend to use it.** (Jika perusahaan saya mengadopsi inovasi teknologi AI Generatif, saya berniat menggunakannya.)	○	○	○	○	○
2. **If my company were to adopt Generative AI technology innovation, I predict that I would use it.** (Jika perusahaan saya mengadopsi inovasi teknologi AI Generatif, saya memperkirakan saya akan menggunakannya.)	○	○	○	○	○
3. **If my company were to adopt Generative AI technology innovation, I plan to use it for working activities.** (Jika perusahaan saya mengadopsi inovasi teknologi AI Generatif, saya berencana menggunakannya untuk aktivitas kerja.)	○	○	○	○	○

4. **If my company were to adopt Generative AI technology innovation, I hope to use it.** (Jika perusahaan saya mengadopsi inovasi teknologi AI Generatif, saya berharap untuk menggunakannya.)	○	○	○	○	○

ATTITUDE (SIKAP)

	Strongly Disagree Sangat Tidak Setuju	**Disagree** Tidak Setuju	**Neutral** Netral	**Agree** Setuju	**Strongly Agree** Sangat Setuju
1. I like the idea of adopting Generative AI technology innovation for work. (Saya menyukai gagasan mengadopsi inovasi teknologi AI Generatif untuk pekerjaan.)	○	○	○	○	○
2. Generative AI technology innovation makes my job even more interesting. (Inovasi teknologi AI Generatif membuat pekerjaan saya semakin menarik.)	○	○	○	○	○
3. I like working with Generative AI technology innovation. (Saya suka bekerja dengan inovasi teknologi AI Generatif.)	○	○	○	○	○
4. My general opinion regarding Generative AI technology innovation is favorable. (Pendapat umum saya mengenai inovasi teknologi AI Generatif adalah baik.)	○	○	○	○	○

PERCEIVED USEFULNESS (PERSEPSI KEBERGUNAAN)

	Strongly Disagree Sangat Tidak Setuju	**Disagree** Tidak Setuju	**Neutral** Netral	**Agree** Setuju	**Strongly Agree** Sangat Setuju
1. **I perceive that Generative AI technology innovation is useful. For instance, I can make well-informed decisions faster and consistently enhance my performance with assistance from the Generative AI technology innovation.** (Saya merasa bahwa inovasi teknologi AI Generatif berguna. Misalnya, saya dapat mengambil keputusan yang tepat dengan lebih cepat dan secara konsisten meningkatkan kinerja saya dengan bantuan inovasi teknologi AI Generatif.)	○	○	○	○	○
2. **I perceive that Generative AI technology innovation could enhance the quality of my work.** (Saya merasa bahwa inovasi teknologi AI Generatif dapat meningkatkan kualitas pekerjaan saya.)	○	○	○	○	○
3. **I perceive that Generative AI technology innovation could enhance my work effectiveness.** (Saya merasa bahwa inovasi teknologi AI Generatif dapat meningkatkan efektivitas kerja saya.)	○	○	○	○	○
4. **I perceive that Generative AI technology innovation could enhance the productivity of my work.** (Saya merasa bahwa inovasi teknologi AI Generatif dapat meningkatkan produktivitas pekerjaan saya.)	○	○	○	○	○

PERCEIVED EASE OF USE (PERSEPSI KEMUDAHAN PENGGUNAAN)

	Strongly Disagree Sangat Tidak Setuju	**Disagree** Tidak Setuju	**Neutral** Netral	**Agree** Setuju	**Strongly Agree** Sangat Setuju
1. I perceive that adopting Generative AI technology innovation for work would be easy. (Saya merasa bahwa mengadopsi inovasi teknologi AI Generatif untuk bekerja adalah hal yang mudah.)	○	○	○	○	○
2. I perceive skillful in adopting Generative AI technology innovation. (Saya merasa terampil dalam mengadopsi inovasi teknologi AI Generatif.)	○	○	○	○	○
3. I perceive that the adoption of Generative AI technology innovation is not complicated or does not require a lot of mental effort. (Saya merasa inovasi pengadopsian teknologi AI Generatif tidak rumit dan tidak memerlukan banyak usaha mental.)	○	○	○	○	○
4. I perceive that Generative AI technology innovation is clear and understandable. (Saya merasa inovasi teknologi Generative AI jelas dan dapat dimengerti.)	○	○	○	○	○

PERCEIVED COMPATIBILITY (PERSEPSI KOMPATIBILITAS)

	Strongly Disagree Sangat Tidak Setuju	**Disagree** Tidak Setuju	**Neutral** Netral	**Agree** Setuju	**Strongly Agree** Sangat Setuju
1. **I perceive that the adoption of Generative AI technology innovation fits the needs of the company.** (Saya merasa penerapan inovasi teknologi AI Generatif sesuai dengan kebutuhan perusahaan.)	○	○	○	○	○
2. **I perceive that the adoption of Generative AI technology innovation is fully compatible with current business operation.** (Saya merasa penerapan inovasi teknologi AI Generatif sepenuhnya sesuai dengan operasional bisnis saat ini.)	○	○	○	○	○
3. **I perceive that adopting Generative AI technology innovation is compatible with our company corporate culture and value system.** (Saya merasa bahwa penerapan inovasi teknologi AI Generatif sejalan dengan budaya perusahaan dan sistem nilai perusahaan kita.)	○	○	○	○	○
4. **I perceive that the adoption of Generative AI technology innovation will be compatible with existing infrastructure in the company.** (Saya merasa bahwa adopsi inovasi teknologi AI Generatif akan kompatibel dengan infrastruktur yang ada di perusahaan.)	○	○	○	○	○

PERCEIVED NOVELTY (PERSEPSI KEBARUAN)

	Strongly Disagree Sangat Tidak Setuju	**Disagree** Tidak Setuju	**Neutral** Netral	**Agree** Setuju	**Strongly Agree** Sangat Setuju
1. **I perceive that adopting the Generative AI technology innovation to be a novel experience.** (Saya merasa bahwa mengadopsi inovasi teknologi AI Generatif merupakan sebuah pengalaman baru.)	○	○	○	○	○
2. **I perceive that adopting the Generative AI technology innovation is new and refreshing.** (Saya merasa bahwa mengadopsi inovasi teknologi AI Generatif adalah hal baru dan menyegarkan.)	○	○	○	○	○
3. **I perceive that adopting the Generative AI technology innovation represents a neat and novel way of working in the company.** (Saya merasa bahwa penerapan inovasi teknologi AI Generatif mewakili cara kerja yang rapi dan baru di perusahaan.)	○	○	○	○	○

MIXED TECHNOLOGY INNOVATION

(INOVASI TEKNOLOGI MIXED REALITY)

INTENTION (NIAT)

	Strongly Disagree Sangat Tidak Setuju	**Disagree** Tidak Setuju	**Neutral** Netral	**Agree** Setuju	**Strongly Agree** Sangat Setuju
1. **If my company were to adopt MR technology innovation, I intend to use it.** (Jika perusahaan saya mengadopsi inovasi teknologi MR, saya berniat menggunakannya.)	○	○	○	○	○
2. **If my company were to adopt MR technology innovation, I predict that I would use it.** (Jika perusahaan saya mengadopsi inovasi teknologi MR, saya memperkirakan saya akan menggunakannya.)	○	○	○	○	○
3. **If my company were to adopt MR technology innovation, I plan to use it for working activities.** (Jika perusahaan saya mengadopsi inovasi teknologi MR, saya berencana menggunakannya untuk aktivitas kerja.)	○	○	○	○	○

ATTITUDE (SIKAP)

	Strongly Disagree Sangat Tidak Setuju	**Disagree** Tidak Setuju	**Neutral** Netral	**Agree** Setuju	**Strongly Agree** Sangat Setuju
1. **I like the idea of adopting MR technology innovation for work.** (Saya menyukai gagasan mengadopsi inovasi teknologi MR untuk pekerjaan.)	○	○	○	○	○
2. **MR technology innovation makes my job even more interesting.** (Inovasi teknologi MR membuat pekerjaan saya semakin menarik.)	○	○	○	○	○
3. **I like working with MR technology innovation.** (Saya suka bekerja dengan inovasi teknologi MR.)	○	○	○	○	○
4. **My general opinion regarding MR technology innovation is favorable.** (Pendapat umum saya mengenai inovasi teknologi MR adalah baik.)	○	○	○	○	○

PERCEIVED USEFULNESS (PERSEPSI KEBERGUNAAN)

	Strongly Disagree Sangat Tidak Setuju	**Disagree** Tidak Setuju	**Neutral** Netral	**Agree** Setuju	**Strongly Agree** Sangat Setuju
1. **I perceive that MR technology innovation is useful. For instance, I am able to conduct seamless virtual communication or collaboration with co-workers in different locations (i.e., coworkers in border locations/overseas); or provision remote expert support, diagnostics, and real-time guidance to repair faulty or malfunctioning equipment.** (Saya merasa bahwa inovasi teknologi MR berguna. Misalnya, saya dapat melakukan komunikasi atau kolaborasi virtual yang lancar dengan rekan kerja di lokasi berbeda (yaitu rekan kerja di lokasi perbatasan/luar negeri); atau menyediakan dukungan ahli jarak jauh, diagnostik, dan panduan waktu nyata untuk memperbaiki peralatan yang rusak atau tidak berfungsi.)	○	○	○	○	○
2. **I perceive that MR technology innovation could enhance the quality of my work.** (Saya merasa bahwa inovasi teknologi MR dapat meningkatkan kualitas pekerjaan saya.)	○	○	○	○	○
3. **I perceive that MR technology innovation enables me to accomplish works more quickly.** (Saya merasa	○	○	○	○	○

bahwa inovasi teknologi MR memungkinkan saya menyelesaikan pekerjaan dengan lebih cepat.)					
4. **I perceive that MR technology innovation could enhance my work effectiveness**. (Saya merasa bahwa inovasi teknologi MR dapat meningkatkan efektivitas kerja saya.)	○	○	○	○	○

PERCEIVED EASE OF USE (PERSEPSI KEMUDAHAN PENGGUNAAN)

	Strongly Disagree Sangat Tidak Setuju	**Disagree** Tidak Setuju	**Neutral** Netral	**Agree** Setuju	**Strongly Agree** Sangat Setuju
1. **I perceive that adopting MR technology innovation for work would be easy.** (Saya merasa bahwa mengadopsi inovasi teknologi MR untuk bekerja adalah hal yang mudah.)	○	○	○	○	○
2. **I perceive skillful in adopting MR technology innovation.** (Saya merasa terampil dalam mengadopsi inovasi teknologi MR.)	○	○	○	○	○
3. **I perceive that the adoption of MR technology innovation is not complicated or does not require a lot of mental effort.** (Saya merasa pengadopsian teknologi MR tidak rumit dan tidak memerlukan banyak usaha mental.)	○	○	○	○	○
4. **I perceive that MR technology innovation is clear and understandable.** (Saya merasa inovasi teknologi MR jelas dan dapat dimengerti.)	○	○	○	○	○
5. **I perceive that the innovation of MR technology for work to be flexible and conducive to interfacing with it.** (Saya merasa inovasi teknologi MR untuk pekerjaan bersifat fleksibel dan kondusif untuk berinteraksi dengannya.)	○	○	○	○	○

PERCEIVED COMPATIBILITY (PERSEPSI KOMPATIBILITAS)

	Strongly Disagree Sangat Tidak Setuju	**Disagree** Tidak Setuju	**Neutral** Netral	**Agree** Setuju	**Strongly Agree** Sangat Setuju
1. **I perceive that the adoption of MR technology innovation fits the needs of the company.** (Saya merasa penerapan inovasi teknologi MR sesuai dengan kebutuhan perusahaan.)	○	○	○	○	○
2. **I perceive that the adoption of MR technology innovation is fully compatible with current business operation.** (Saya merasa penerapan inovasi teknologi MR sepenuhnya sesuai dengan operasional bisnis saat ini.)	○	○	○	○	○
3. **I perceive that adopting MR technology innovation is compatible with our company corporate culture and value system.** (Saya merasa bahwa penerapan inovasi teknologi MR sejalan dengan budaya perusahaan dan sistem nilai perusahaan kita.)	○	○	○	○	○
4. **I perceive that the adoption of MR technology innovation will be compatible with existing infrastructure in the company.** (Saya merasa bahwa adopsi inovasi teknologi MR akan kompatibel dengan infrastruktur yang ada di perusahaan.)	○	○	○	○	○

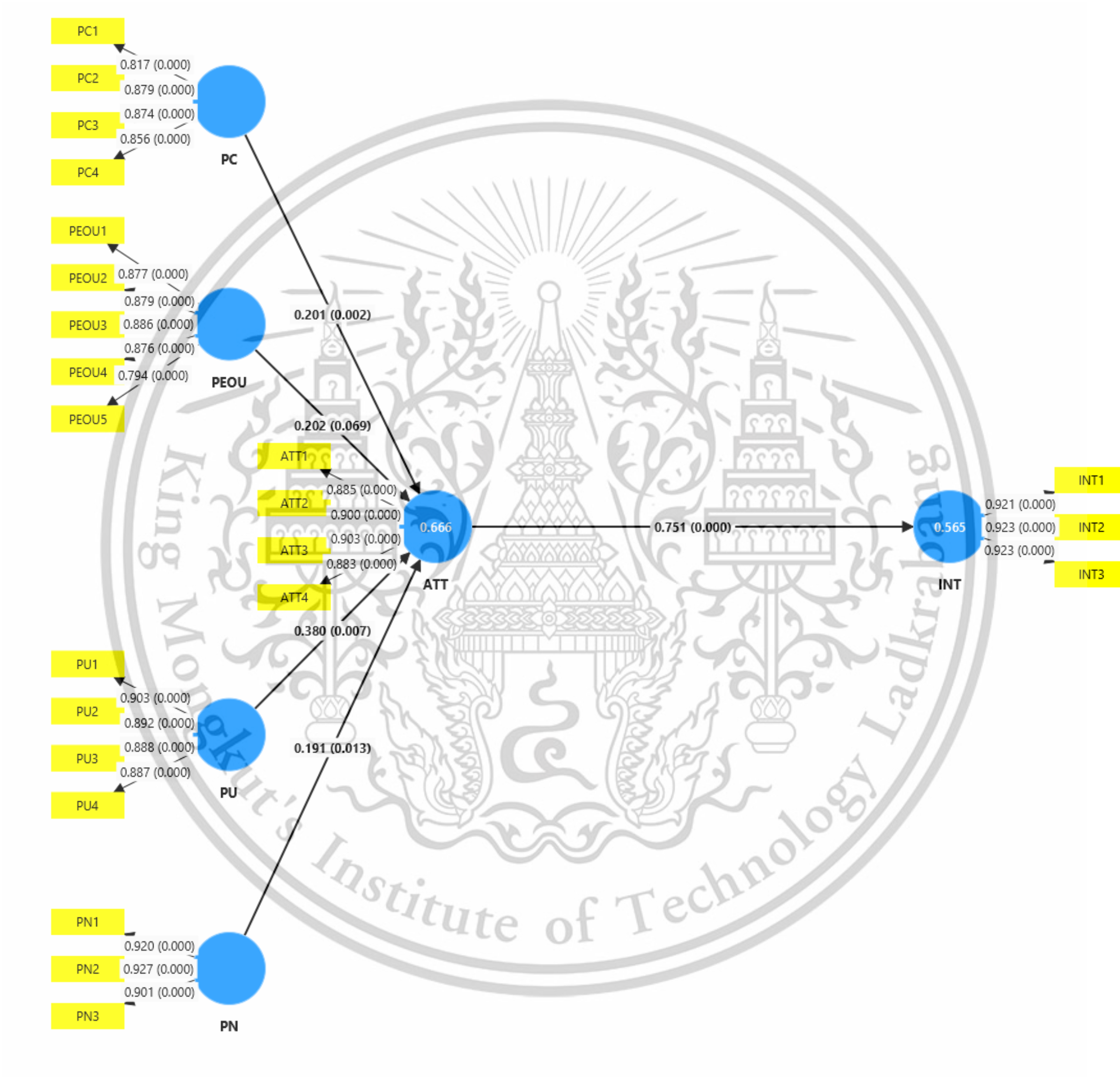
PERCEIVED NOVELTY (PERSEPSI KEBARUAN)

	Strongly Disagree Sangat Tidak Setuju	**Disagree** Tidak Setuju	**Neutral** Netral	**Agree** Setuju	**Strongly Agree** Sangat Setuju
1. **I perceive that adopting the MR technology innovation to be a novel experience.** (Saya merasa bahwa mengadopsi inovasi teknologi MR merupakan sebuah pengalaman baru.)	○	○	○	○	○
2. **I perceive that adopting the MR technology innovation is new and refreshing.** (Saya merasa bahwa mengadopsi inovasi teknologi MR adalah hal baru dan menyegarkan.)	○	○	○	○	○
3. **I perceive that adopting the MR technology innovation represents a neat and novel way of working in the company.** (Saya merasa bahwa penerapan inovasi teknologi MR mewakili cara kerja yang rapi dan baru di perusahaan.)	○	○	○	○	○

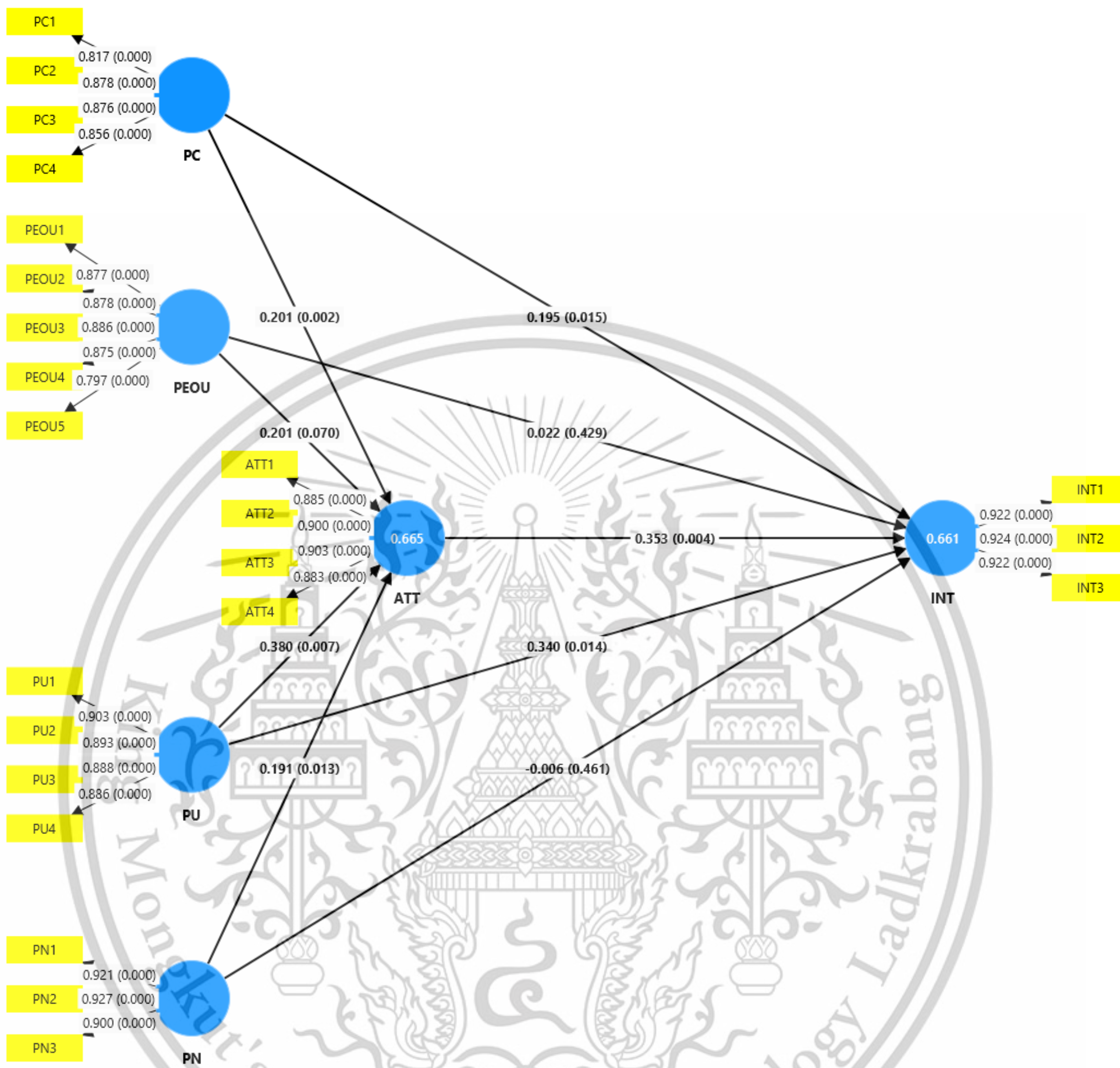
APPENDIX E

SMARTPLS RESULTS

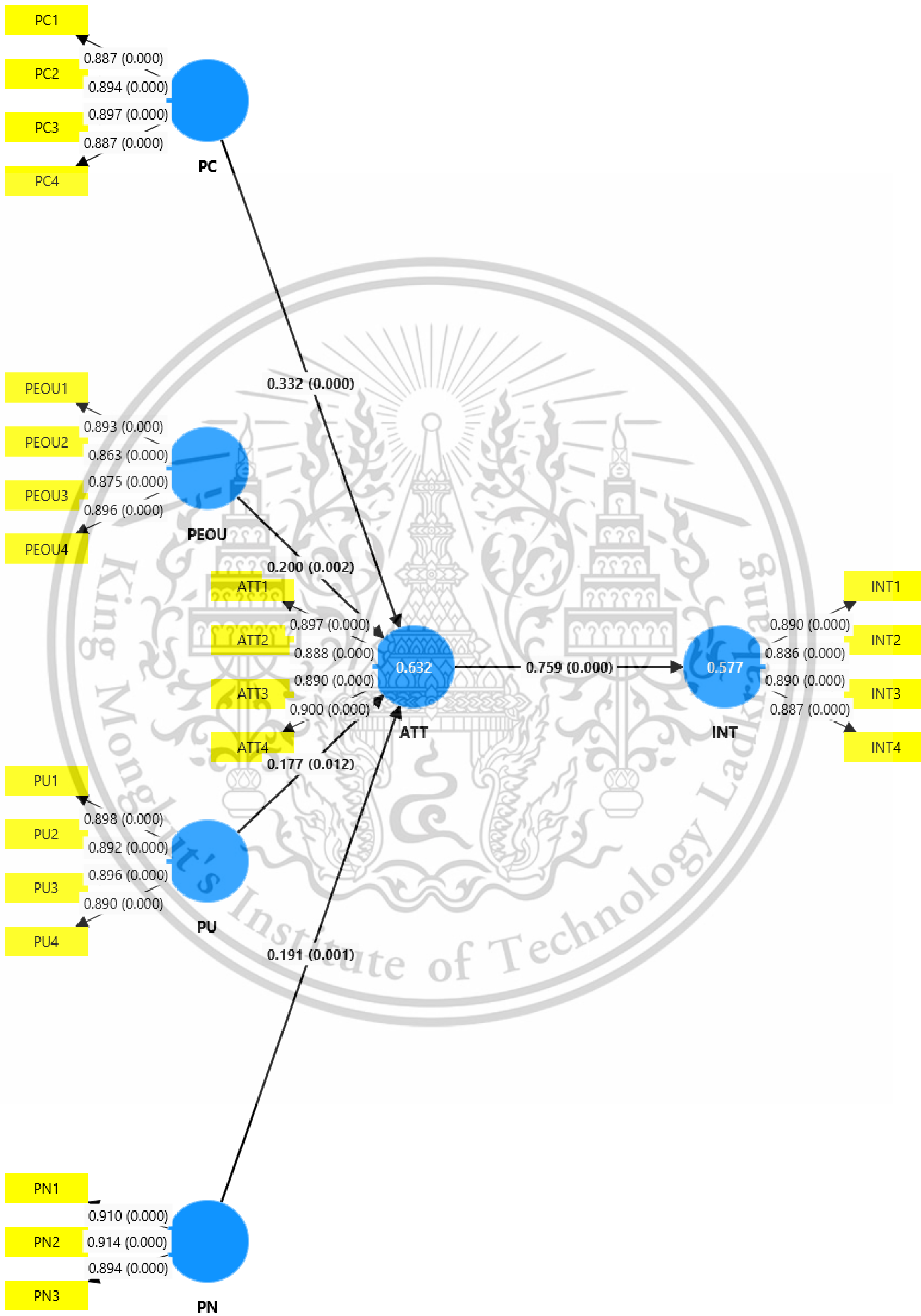
1. The conceptual model of MR



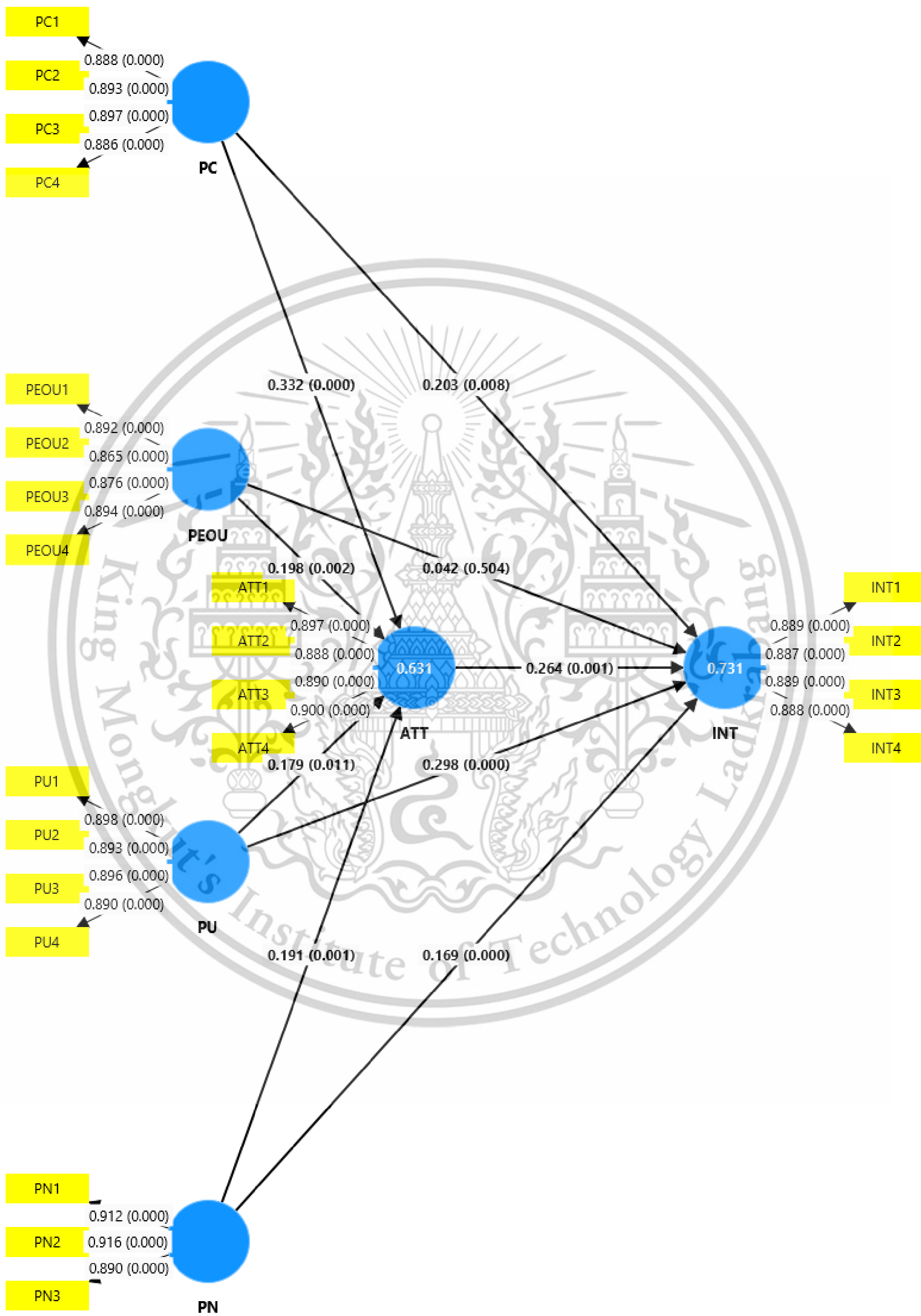
2. The enhanced model of MR



3. The conceptual model of GenAI



4. The enhanced model of GenAI



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Work Experience	▪ Research and Teaching Assistant, 2022 – *present* KMITL, Kingdom of Thailand ▪ Government Employee, 2020 – 2021 Ministry of Education and Culture, Republic of Indonesia