Gordon Institute of Business Science
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The influence of technology readiness on technology acceptance in the South African mining industry

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A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Business Administration.

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Abstract

The South African mineral mining sector makes significant contributions to the local economy and participates in social initiatives that benefit employees and neighbouring communities. In recent years, volatile commodity prices, increased environmental and sustainability requirements, and deteriorating economic conditions have compelled global mining organisations to implement innovative technologies to address such challenges. Successful implementation of such technologies in the South African context is critical to ensure that the sector remains competitive and provides continued economic and social value. However, existing qualitative research concerning technology adoption within the sector has revealed that individuals have a resistive nature toward change and innovation. Therefore, this quantitative study investigated the influence of individuals' technology predispositions and perceptions on usage intentions in the South African mining context. These facets were examined by extending the prevalent Technology Acceptance Model (TAM) with elements from the Technology Readiness Index (TRI). The influence of individual differences relating to chronological age, education level, and organisational roles was also investigated. Primary data was collected through non-probability snowball sampling of 150 respondents, and non-parametric statistical methods were used to determine the relationships between the TRI motivators, TRI inhibitors, TAM perceived usefulness (PU), and TAM usage intention (UI) constructs. It was found that there was a positive correlation between TRI motivators concerning PU and UI, with a converse relationship for the TRI inhibitors. There was a strong positive correlation between PU and UI, which confirmed the findings of several previous studies involving the TAM. There was no significant difference between groups of different chronological ages and organisational roles concerning UI, but there was a significant difference for individuals with different levels of education. Additionally, and importantly, it was found that the respondents primarily held a positive perception and linked inclination towards adoption intentions, which contradicted the findings within the existing literature. The results also indicated a high degree of predictability concerning adoption based on individuals' perceptions. Stakeholders and managers looking to technology to solve business challenges should consider these perceptions to ensure successful implementation.

Keywords

Mining industry, technology adoption, technology acceptance model (TAM), technology readiness index (TRI)

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Vikesh Chiba

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List of Abbreviations

Table 1: List of abbreviations

Abbreviation	Explanation
4IR	Fourth Industrial Revolution
AI	Artificial Intelligence
ANOVA	Analysis of Variance
BIU	Behavioural Intention to Use
CEO	Chief Executive Officer
CSIR	Council for Scientific and Industrial Research
EFA	Exploratory Factor Analysis
GIBS	Gordon Institute of Business Science
HPGPS	High Precision Global Positioning Systems
IoT	Internet of Things
IIoT	Industrial Internet of Things
IS	Information Systems
IT	Information Technology
KMO	Kaiser-Meyer-Olkin
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
Q-Q	Quantile-Quantile
RFID	Radio Frequency Identification
TAM	Technology Acceptance Model
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
TRI	Technology Readiness Index
TRII	Technology Readiness Index Inhibitors
TRIM	Technology Readiness Index Motivators
UI	Usage Intention
USA	United States of America
UTAUT	Unified Theory of Acceptance and Use of Technology
VR	Virtual Reality

1 Chapter One: Introduction to Research Problem

1.1 Introduction

The mining sector, long regarded as one of the more conservative and conventional industries concerning innovation, currently finds itself at a crossroads due to increased industry complexities such as environmental and sustainability requirements, diminishing ore grades, competition for resources, and volatile commodity prices (Olvera, 2022). Mining companies need to effectively implement and sustainably adopt new methods of working to address these challenges while also maintaining the crucial role played in terms of providing employment, facilities, and infrastructure to the local (and often remote) communities (Aznar-Sánchez et al., 2019).

This chapter provides background to the research problem by firstly considering the contributions made by the local mining industry to the South African economy and society. Further context relating to technology and trends within mining is discussed, followed by technology adoption challenges within mining that builds toward justification of the research problem and primary research question. Finally, business and academic research aims are highlighted before providing an overview of the structure of this report.

1.2 Background to Research Problem

1.2.1 Economic and Social Contributions of South African Mining

South Africa has a rich history of mineral mining. While the nation's economic structures have diversified, mining still contributed 7.6% to GDP and provided 2.3 million jobs directly and indirectly from July 2020 to June 2021 (Pricewaterhouse Coopers, 2021). The Minerals Council of South Africa CEO Roger Baxter recently emphasised the significance of mining in terms of the contributions made toward the labour market, government fiscus, and the South African economy when referring to the mining facts and figures released by the Minerals Council for 2021 (Seccombe, 2022). In addition, the success of several other sectors within the South African economy depends on the link to the mining industry, and the mining sector also serves as a market for various sectors (Zvarivadza, 2018).

Besides the fiscal and economic contributions, mining companies often implement social programmes and supportive infrastructure to support the local communities. The local mining industry has become a leader in implementing corporate social responsibility initiatives since the 1994 democratisation, with the sector making the most significant financial contributions (Siyobi, 2015). Schools, clinics, and community centres are built to support the families of the mine employees and instil a sense of employee embeddedness. These initiatives aim to create a socially supportive environment where employees can better contribute to the mining company's operations and financial performance. Given the economic and social contributions that the mining sector provides, it becomes critical that the industry keeps pace with trends and innovations to remain globally competitive.

1.2.2 Mining and Technology

Mnwana and Bowman (2018) suggest that fluctuating commodity prices and weakened economic conditions are compelling mining companies to implement new technologies to innovate the mining value chain to address these challenges through improved productivity. Danquah (2018) suggests that countries in sub-Saharan Africa have access to a spectrum of innovations from global technology leaders. With countries such as Sweden, Canada, Australia, and Chile already successfully implementing mining technologies such as innovative logistics applications and automated mining processes (Kansake et al., 2019), it is expected that the South African mining sector will soon follow suit.

New technologies can also address environmental and sustainability challenges relating to pollution reduction, waste prevention, and cleaner production processes (Ediriweera & Wiewiora, 2021). One of the core themes of the 2022 Mining Indaba held in Cape Town was that mining in South Africa needs to evolve to focus more on implementing technologies that reduce mining operations' environmental and carbon footprints (Engineering News, 2022). This will require investment into automated equipment and software, new battery and hydrogen technologies as replacement diesel engines, digital twins and digitalisation for process optimization, and alternative energy sources, to name a few.

From an economic perspective, the CEO of the Council for Scientific Research (CSIR), Dr Thulani Dlamini, has pointed out that fourth industrial revolution (4IR) technologies are available to the sector and are seen as value drivers that can assist in unlocking up to R153 billion in value over the next four years (Mining Weekly, 2022). The urgency relating to technology implementation in the mining sector has therefore been highlighted as a priority that requires an appropriate degree of business attention. However, one of the key challenges faced is that the industry has traditionally demonstrated resistance regarding the rate of technology adoption (Kashan et al., 2022).

1.2.3 Technology Trends within the Mining Industry

Mineral mining on a large scale can be divided into the major methods of surface mining or underground mining, with each having sub-methods related to the characteristics of the mined ore. While there are differences between the mining methods, the technologies available for surface and underground mining are similar, with a small grouping of technologies specific to each technique. These technologies are fundamentally aimed at easier and more efficient ore extraction processes, which is particularly relevant to underground mines since ore extraction requires deeper mining techniques (Ranjith et al., 2017). Additional benefits include the reduction of carbon emissions and waste, creating a safer working environment for employees, and automating operational processes. Figure 1 illustrates some of the technologies that are believed to impact the mining industry significantly within the next decade.

A broad range of emerging technologies are currently available for use within mineral mining. These include mechanized and autonomous mining equipment, data analytics platforms, virtual reality (VR), industrial internet of things (IIoT), radio frequency identification (RFID), artificial intelligence (AI), advanced measurement technologies (geological measurement), machine learning, high precision global positioning systems (HPGPS), and drones (Bhattacharyya & Shah, 2021; Gruenhagen & Parker, 2020). These technologies can be categorized into systems that form part of the fourth industrial revolution and are likely to be expanded through further development.

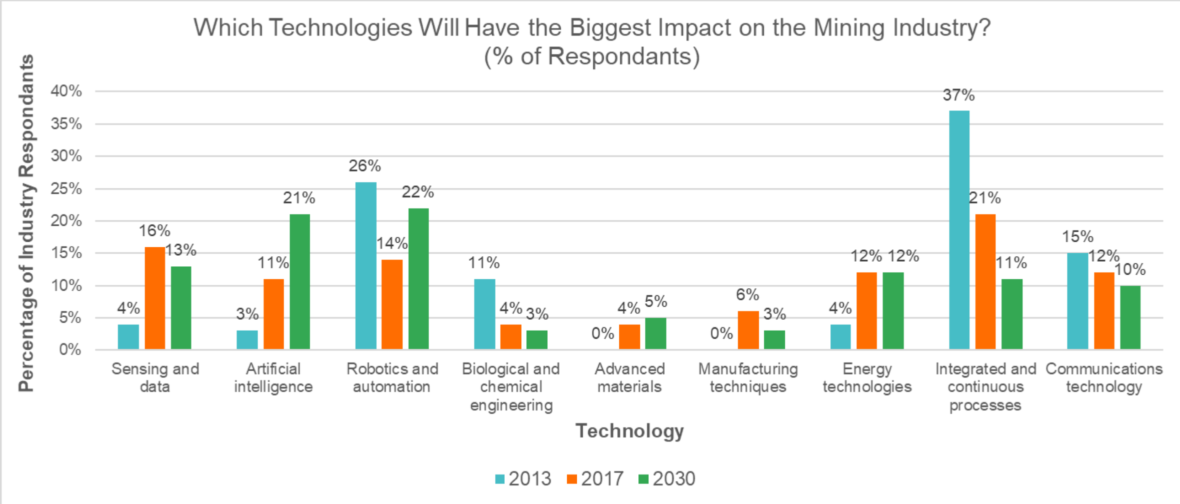

Figure 1: Technologies within mining deemed to have the most significant impact

Source: Stanway et al. (2017)

1.2.4 Technology Adoption in Mining

In general, the introduction of new technologies is either adopted slowly or resisted entirely within the mining industry (Ediriweera & Wiewiora, 2021). While several factors contribute to this, Gruenhagen and Parker (2020) argued that the industry has a conservative and change-resistant culture where individual resistance is one of the primary barriers to new technology adoption. In addition, a 2021 study on the oil and gas industry (which has also been found to be resistive to technology adoption) found that individuals' attitudes, personalities, and motivations are the primary factors that influence adoption (Roberts et al., 2021). In support of this notion, Nstoelengoe (2019) found that the perceptions and mindsets of individuals toward technology are seen to be one of four major factors that inhibit technology adoption through a qualitative study done within the South African mining industry,

Implementing technologies in an environment where it is not adopted or used correctly can result in decreased performance from the non-technology baseline, which could have catastrophic consequences for organisations that invest heavily, expecting positive operational and financial benefits. This view is supported by Althuizen (2018), who argue that organisational failures often occur through employee resistance when new technologies are implemented. Successful adoption and continued effective use of new technologies are thus dependent on the perceptions and willingness of the individuals involved (Singh et al., 2020). Coupled with this, the lack of willingness by organisational decision-makers to explore emerging technologies, potentially due to apprehension or scepticism, poses a significant barrier to gaining and sustaining competitive advantage (Bhattacharyya & Shah, 2021).

Failure to make considerations toward and effectively adopt new technologies will impact mining organisations, which could have a damaging effect on the South African economy, as well as the communities that are reliant on them from a social perspective. Therefore, for mining in South Africa to remain relevant and continue to provide economic and social contributions, perceptions relating to technology adoption and implementation at the individual-level needed to be unpacked further.

1.3 Problem Statement and Primary Research Question

The mining sector in South Africa needs to effectively adopt new technologies to sustain the industry's competitiveness and continue contributing to the local economy, employees' livelihoods, and local communities' social well-being. However, existing research suggests that individuals and their inherent predispositions, perceptions, and attitudes toward new technologies could be significant barriers to initiation, implementation, and sustainable adoption. If there is a low degree of individuals' inclination toward technology to address emerging challenges within the sector, this could have potentially negative consequences for the industry and the organisations that operate within it. These factors contributed to the primary research question for this study:

To what extent do individuals' predispositions and perceptions influence their propensity towards embracing and using innovative technologies in the South African mining industry?

1.4 Research Aims: Business Contribution

The researcher aims to use the study to extend the understanding of individuals' perceptions toward technology adoption in the South African mining industry. The topic of innovation within mining has primarily been focused on the organisational-level and, as a result, important facets at the individual-level are relatively unknown (Kashan et al., 2022). Insights gained through this study will therefore contribute towards determining the appetite for innovative technologies amongst individuals within the sector. The researcher also aims to determine whether certain demographic factors influence individuals' perceptions toward technology and its adoption based on the size of the industry and the diverse range of individuals that work within it. The findings from the research will therefore provide a snapshot of the degree of technology confidence or apprehension so that organisations can effectively address potential technology discomfort or promote technological innovativeness.

The outcomes of this study will assist in developing policies, implementation strategies, and change management approaches needed for effective and successful technology adoption. Per the argument by Bhattacharyya and Shah (2021), early identification of challenges and the subsequent creation of suitable technology implementation plans can result in prompt and widespread adoption, resulting in reduced deployment costs. Consequently, this study will provide the necessary visibility to allow mining and technology supply organisations to equip themselves better to innovate the mining value chain to achieve continued economic and social value in an evolving and volatile global mining sector.

1.5 Research Aims: Theoretical and Academic Contribution

Within their literature review of factors concerning the adoption of innovation within the mining industry, Gruenhagen and Parker (2020) reported that research on technology adoption within the industry is comparably small. In particular, insufficient research considers technology adoption support or resistance at an individual-level. In support of this, Ediriweera and Wiewiora (2021) recommended that future research should be aimed at investigating individual-level perceptions and behaviours concerning technology adoption within the mining industry. Based on the research gaps identified above, the researcher seeks to extend the existing body of knowledge in the fields of innovation and technology acceptance within the mining industry at the individual-level.

This study also extends existing research done primarily from an exploratory (inductive or qualitative) approach within mining to one that is explanatory (deductive or quantitative). Most quantitative research on technology adoption at the individual level has focused on the retail sector, considering whether certain products and technologies will be accepted and adopted by consumers. Examples of these within the recent and relevant literature reviewed for this study, including the adoption of online banking by Marakarkandy et al. (2017), technology-based ride-sharing services by Y. Wang et al. (2020), self-checkout facilities by Mukerjee et al. (2019), and augmented reality by Goebert and Greenhalgh (2020), amongst several others. Therefore, the research aims to add to existing research within the mining industry and contribute towards academic literature encompassing technology adoption within an organisational context. Additionally, the current understanding of certain technology adoption models (to be discussed in Chapter 2) are extended by practical application within this study.

1.6 Structure of this Research Report

This document's structure and primary contents are presented below to serve as a roadmap for the reader. The main chapter headings and an overview of the respective content for each chapter are provided.

Chapter 1: Introduction to Research Problem

Chapter 1 begins by providing background to the economic and social contributions of the mining industry within the South African context. The relevance of technology within mining is discussed, followed by an overview of technology trends and challenges relating to adoption. This serves as the foundation for the problem statement, the need for the research, and the primary research question. Contributions to both business and academia are discussed before conclusions are drawn.

Chapter 2: Literature Review

This chapter presents a review of primarily recent and relevant literature applicable to the study. Individual-related factors and a review of the technology adoption models, and associated constructs, are presented towards the development of a conceptual model. Constructs within adoption models relevant to the study are presented, followed by a more focused review of the inter-relationships to develop hypotheses based on existing studies.

Chapter 3: Conceptual Model, Research Question, and Hypotheses

A summary of the developed conceptual model is presented based on the literature review of Chapter 2. A summary of the hypotheses generated is presented concerning the primary research question for this study.

Chapter 4: Research Methodology

This chapter presents and defends the methodological choices made for this study. The chapter encompasses the choice of research design, including the research philosophy, approach, and methodological choice. Additionally, the population considered for the study and the data-gathering processes are discussed, followed by an overview of the quality control tests and statistical analyses employed for this study. This chapter concludes with limitations relating to the research methodology.

Chapter 5: Research Results

Chapter 5 presents the study's results based on collected data and statistical analyses. The sample data and associated demographic information are presented first, followed by the quality control and hypothesis test results. Finally, relevant tables and graphical representations of the results are presented where applicable to provide a user-friendly summary and visual representation of the data respectively.

Chapter 6: Discussion of Results

This chapter presents the outcomes concerning the hypotheses developed within Chapter 2 and summarised in Chapter 3 based on the results within Chapter 5. In addition, an analysis of the descriptive statistics related to each hypothesis are also discussed concerning the hypothesis test results. Finally, the findings based on the hypothesis testing are compared against the literature reviewed in Chapter 2 from which inferences and conclusions are drawn.

Chapter 7: Conclusions and Recommendations

Chapter 7 outlines the primary conclusions based on the findings of this research study. The theoretical contributions and implications for business managers and stakeholders are also discussed. The chapter concludes with limitations applicable to this study and suggestions for future research directions.

1.7 Conclusion

This chapter provided the relevant background concerning the contributions of the South African mining industry, the need for technology within the sector, technology trends within mining, and barriers observed through existing literature toward adoption. These topics provided the platform on which the research problem statement and primary research question were framed. This study aimed to gain a further understanding of individuals' perceptions and how these perceptions may influence them toward embracing and using new technologies within the context of the South African mining sector. The research question provided direction in terms of the literature that was reviewed in the next chapter.

2 Chapter Two: Literature Review

2.1 Introduction

This chapter presents a review of the literature examined to develop a conceptual model and associated hypotheses that unpacked the research question posed for this study. As discussed within Section 1.4, there is a diverse range of individuals who work within the South African mining industry. Therefore, individual-related differences concerning technology adoption were reviewed first to gain an understanding of any demographic influences. A review of technology adoption and acceptance models follows to assess which models and associated constructs provided the investigative tools necessary to provide insights into the research problem. The chapter concludes with an examination of the applicable models and associated constructs from which hypotheses were developed based on existing literature framed by the research question. Figure 2 provides an overview of the topics discussed, the flow of logic between the topics, and the relationships assessed to develop the hypotheses.

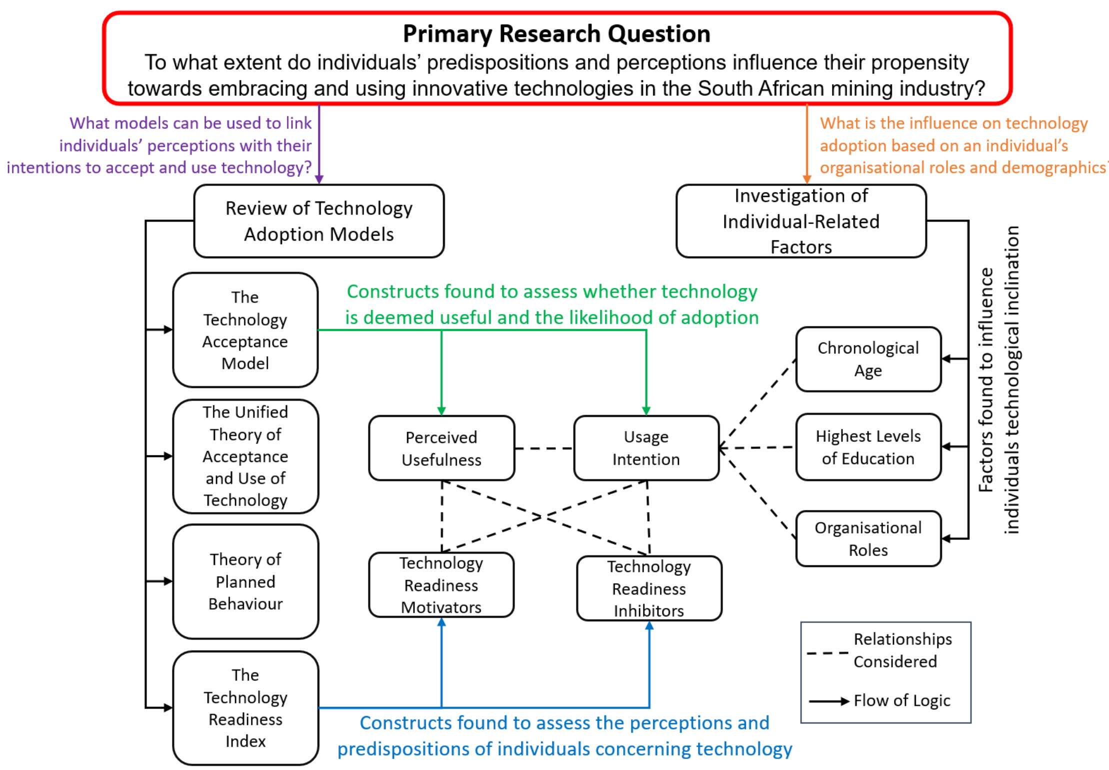

Figure 2: Roadmap of topics and logic contained within the literature review

Source: Generated by the researcher

2.2 Individual-Related Factors and Differences

Existing research supports the common perception that not every individual will be equally ready and open to adopting and accepting technology-focused innovations (Rojas-Méndez et al., 2017). Althuizen (2018) reported that individual-related factors, such as age and education, were relatively prominent in earlier technology adoption research but revealed little about an individual's motivations toward technology and were deficient from an explanatory perspective. However, since these factors are easily observed, they can help craft profiles for individuals more likely to advocate for or resist new technology implementation (Althuizen, 2018). Based on this, certain factors that could influence technology adoption were unpacked within the sub-sections to follow. These facets were deemed necessary given the mining industry's scale, the broad range of demographics encompassed within it, and the technology implementation and adoption cycle which depends on multiple stakeholders.

2.2.1 Chronological Age

The term "digital divide" refers to the gap between older and younger persons concerning technology acceptance. There is a societal notion that the younger generations tend to have a more positive attitude toward technology. However, the existing body of research provides mixed results, with certain studies showing positive correlations between age and technology acceptance, some with no significant correlation, and others with negative correlations (Hauk et al., 2018; Rojas-Méndez et al., 2017). Santini et al. (2020) supported this and ascribed the varied results to the characteristics of the studies, which include the type of technology within each study, methodological elements of the research (sample size and type of sample), cultural factors, and country settings.

Hauk et al. (2018) asserted that older individuals typically shift their focus from professional growth to social and emotionally rewarding pursuits within a work environment. This shift results in a lack of professional relevance when new technologies are introduced and, therefore, withdrawal of interest. In addition, Sundstrup et al. (2022) contended that it is generally more difficult for older employees to manage technological changes due to the fear of losing their jobs, lack of trust in technology, and a sense of being controlled. However, the perceived benefits of technology can have a positive effect on an older individual’s propensity toward adoption (Manis & Choi, 2019). Within the mining sector specifically, technologies exist that can create a safer and more comfortable work environment for employees (such as equipment and process automation discussed within Section 1.2.3), which would appeal to older employees.

2.2.2 Level of Education

Rojas-Méndez et al. (2017) argued that individuals with better education levels are more likely to be receptive to new technologies as their increased learning ability and adaptability stimulate a more optimistic view of innovation. Furthermore, this learning capability also increases their confidence to control new technology, reducing their sense of discomfort (Blut & Wang, 2020).

However, as with chronological age, there are mixed results about the role of education as a predictor of technology adoption (Cruz-Cárdenas et al., 2019). This variable becomes a critical consideration in the context of technology adoption in emerging countries and economies, especially given that technology adoption studies have focused primarily on developed countries (Cruz-Cárdenas et al., 2019; Rojas-Méndez et al., 2017). In addition, limited income and access to technology in a personal capacity could further drive individuals to use technology presented in a work environment to bolster their learning opportunities and resulting capabilities. Technology can then be used as a platform for personal development and career advancement for those individuals with previously limited education opportunities.

2.2.3 Role within the Organisation

Roberts et al. (2021) argued that an individual’s role within the organisation, who make specific decisions and enact certain behaviours on behalf of the organisation, is a significant consideration for overall successful technology adoption within the organisation. The roles within the organisation dictate if a certain technology is introduced (by decision-makers), how it is applied and monitored (through managers), and if it is used effectively (by end-users) (Roberts et al., 2021).

Hameed et al. (2012) classified innovation adoption within an organisation into three stages. The first stage is pre-adoption, which speaks to the decision-making process and comprises recognizing a need, acquiring information about potential solutions, forming an attitude toward the technology, and proposing the technology to address the need. The second stage is the adoption-decision stage, where individuals (such as managers) consider whether to accept the proposal, evaluate the technical and financial feasibility, and make decisions regarding the provision of resources for implementation. The final post-adoption phase encompasses acceptance of the technology by the end-user and subsequent use.

Based on the above, an individual's role within the organisation is a significant consideration regarding their propensity toward actively seeking innovative technologies for solutions to operational challenges and whether users effectively adopt the solutions. Furthermore, these aspects speak to individual perceptions throughout the full technology adoption process, which is critical for successful adoption and subsequent organisational benefit.

2.3 A Review of Technology Adoption and Acceptance Models

Several theoretical models and frameworks have been developed to examine technology adoption and acceptance at the individual level. It should be noted at this stage that the terms "acceptance" and "adoption" are typically used interchangeably within technology-related research (Brandon-Jones & Kauppi, 2018). Bhattacharyya and Shah (2021) summarised the primary models applicable to an individual level of analysis, which include the Theory of Planned Behaviour (TPB), the Technology Acceptance Model (TAM), and the Unified Theory of Acceptance and Use of Technology (UTAUT) which are related in terms of their roots and development. In addition to these models, Rojas-Méndez et al. (2017) purported that the Technology Readiness Index (TRI) was developed by Parasuraman (2000) as a relatively recent and independent addition which was subsequently restructured and updated to a second iteration (TRI 2.0) by Parasuraman and Colby (2015). The sections to follow highlight key aspects of each of these models and conclude to consolidate which models and associated constructs were deemed applicable to this study.

2.3.1 Theory of Planned Behaviour (TPB)

The TPB was developed by Ajzen (1991) and is a popular psychology-based theory that links an individual's behavioural intentions to their actual behaviour through the key constructs of behavioural attitude, subjective norms, and perceived behavioural control (Taherdoost, 2018a). The TPB and its constructs are illustrated in Figure 3 below. The theory speaks to one's sense of internal planning on how to behave or act given a certain scenario based on the key constructs as inputs to the person's cognitive processes. Attitude describes the degree to which a person holds negative or positive views on a topic, subjective norms describe the social influences (through family, friends, and work colleagues) that one experiences that influence their behaviour, and perceived behavioural control speaks to an individual's situational ability and the resulting perceived easiness of the activity (Roy et al., 2017).

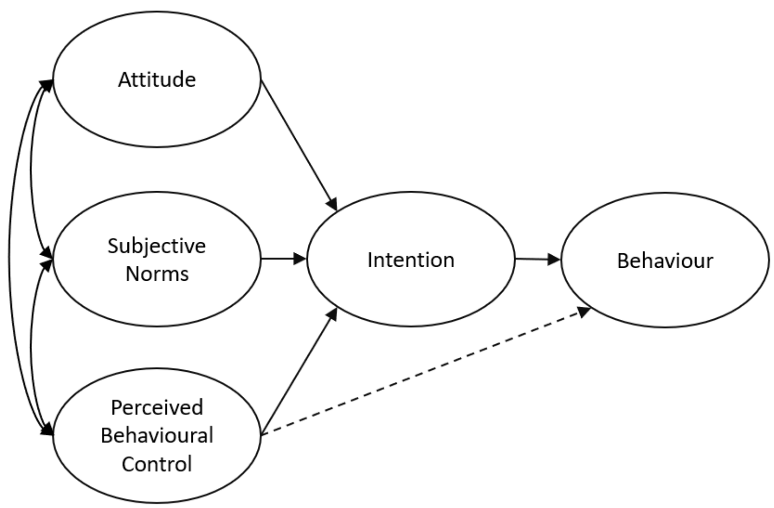

Figure 3: The Theory of Planned Behaviour (TPB)

Source: Generated by the researcher from Ajzen (1991)

Given that the TPB comprises of psychological-focused constructs, it has a broad range of applicability to different fields of study and scenarios. While it has been used to assess technology adoption in certain studies, such as consumer delivery drones (Ramadan et al., 2017) and mobile learning applications (Gómez-Ramirez et al., 2019), it's applicability falls primarily within the field of human social behaviour (Ajzen, 2011) and therefore was deemed to have limited relevance in assessing technology adoption within an organisational setting. M. M. Rahman et al. (2017) supported this notion and argued that while the TAM and UTAUT were purposefully crafted to explore technology adoption, the TPB was developed to explore generalised human behaviour. However, given that the TPB is the fundamental platform on which the TAM and subsequent UTAUT were developed, it was deemed pertinent to reflect on the TPB model.

2.3.2 The Technology Acceptance Model (TAM)

The TAM is an extension of the TPB that investigates the aspects influencing an individual's intentions toward adopting new and innovative technologies (Schmidthuber et al., 2020). It is an extensively used technology adoption model and applies to a broad range of technologies and individual profiles (Granić & Marangunić, 2019). The model was first published in a paper by Davis (1989) and is built on the constructs of perceived ease of use (PEOU) and perceived usefulness (PU) concerning an individual's attitude towards their usage intention (UI) and resulting use of the technology as illustrated in Figure 4.

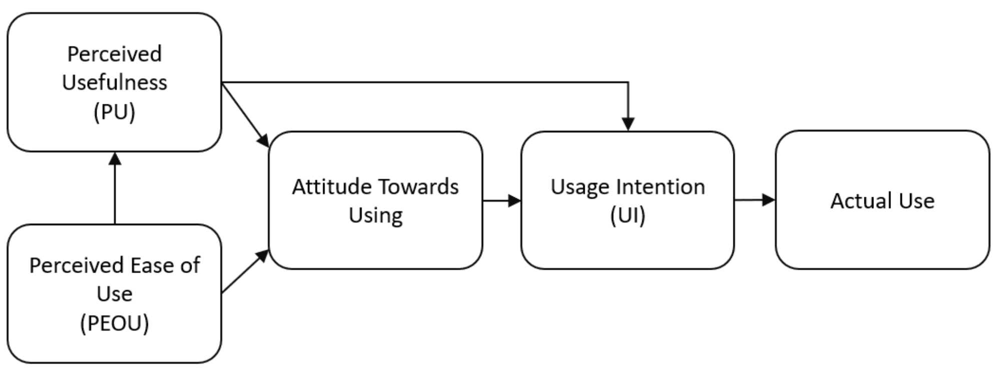

Figure 4: The Technology Acceptance Model (TAM)

Source: Generated by the researcher based on Davis (1989)

Since its inception, the model's legitimacy has been verified in several areas of technology and innovation studies (Koul & Eydgahi, 2017; Li et al., 2017; Singh et al., 2020; Yuen et al., 2021). Marakarkandy et al. (2017) also argued that the TAM constituent constructs were not affected by technological and context-specific aspects that may influence UI and therefore actual use. In addition, Manis and Choi (2019) found through existing literature and studies that the TAM is better suited to technology-related decisions with limited choices (such as those within a work environment) when compared to choices within a voluntary or social environment.

While the TAM is viewed as being one of the most prevalent and widely used technology-related acceptance and adoption models, it does not explicitly make considerations toward an individual's dispositional characteristics concerning acceptance, such as one's positive inclinations or technological fears, and was therefore not appropriate for unpacking the impacts of an individual's traits relating to acceptance (Ratchford & Ratchford, 2021). However, the model's validity, versatility, and applicability to work environments motivated the need to unpack the TAM constructs. Although, it was observed that there have been several extensions to the TAM by past researchers through the addition of independent constructs. Therefore, the primary TAM constructs and the nature of the extended models are described further in the following sections.

2.3.2.1 Perceived Usefulness (PU)

The PU construct within the TAM assesses an individual's conviction that using a certain technology will enhance their work efficacy and performance (Brandon-Jones & Kauppi, 2018). Building onto this definition, Chen and Lin (2018) stated that PU assesses a potential user's particular probability that technology use will increase his/her work performance within an organisational environment. The construct consequentially speaks to performance expectations where the user either believes that the technology will enhance or hinder his/her capabilities, which ultimately influences their attitude and intention to use. An individual must therefore have the preconceived notion that its use offers cost or time benefits (or both) and improved task efficacy for the technology to be adopted (Blut & Wang, 2020).

Perceived usefulness depends on the individual's perceptions of the technology, whether he or she understands the functionality and associated benefits, and whether there is an actual need for it based on the individual's circumstances and perspectives. However, Davis (1989) argued that cognitive processes are linked to a cost-benefit trade-off. Therefore, the potential benefits are considered as being subjective based on the individual's technological perceptions and their interpretation of how the technology can be used to improve work efficiency. The costs associated with the technology under consideration extend beyond financial implications and encompass the dimensions of supportive needs (infrastructure or resources), time to implement before actual use, and the effort required for use. Given that the TAM focuses on system-level adoption and is not based on the system itself, the supportive needs and time aspects are not considered within the model. However, the effort required for use is contained within the model and is discussed further below.

2.3.2.2 Perceived Ease of Use (PEOU)

A secondary influence of technology adoption within the TAM is related to an individual’s preconceived belief that using technology will have a low degree of effort, which is evaluated through the PEOU construct (Marakarkandy et al., 2017). Essentially, a piece of technology has a higher likelihood of adoption if a potential user believes that it is easy to use. Conversely, Blut and Wang (2020) found that if the technology is perceived to be complex and confusing, the individual may not believe that they can comprehend and operate it, resulting in the associated benefits being less apparent, decreasing the likelihood of adoption. Based on this, PEOU directly influences PU and attitude towards use as indicated in Figure 4.

An individual’s sense of self-efficacy and beliefs relating to the outcomes of use has an impact on his/her PEOU of the technology under consideration, where a higher degree of self-efficacy and belief concerning the ability of use positively influences their PEOU (Davis, 1989). As with PU, there is a utilitarian aspect linked to PEOU, however the utilitarianism of PEOU has a higher focus on the individual's cognitive and practical abilities rather than peripheral benefits (Luceri et al., 2022). It is important to note that an individual’s PEOU can be substantially improved through real-world demonstrations of the technology where the tangibility initiates cognitive processes that decrease uncertainty.

2.3.2.3 Attitude Toward Using

The traditional definition of attitude relates to an individual's view and subsequent position of willingness to respond, but a more updated definition in relation to technology adoption and acceptance relates to an individual's degree of positivity or negativity (liked or disliked) during evaluation (Manis & Choi, 2019; Zhao et al., 2018). Based on this definition, the attitude of a potential user is influenced by the PU and PEOU constructs, where PU and PEOU determine the individual's positive or negative position on technology. Brandon-Jones and Kauppi (2018) supported this view, however they also stated that while the PU and PEOU constructs directly influence an individual's attitude, PU directly influences UI.

In particular, consumer-focused studies were found to consider attitude since the construct may be shaped by social influences, motives, and status enhancement rather than PU and PEOU (Li et al., 2017). López-Bonilla and López-Bonilla (2017) built on this argument through a dedicated study on the influence of attitude within the TAM. They concluded that attitude should be considered within voluntary situations (retail or consumer environment) rather than compulsory situations (work environment) when considering the relationship between PU, PEOU, and UI.

2.3.2.4 Usage Intention (UI) and Actual Use

Verma et al. (2018) posited that UI persuades the actual use of technology and that the UI is determined by an individual's attitude and PU as shown in Figure 4. UI can therefore be considered as an individual's inclination toward actual use. Singh et al. (2020) supported this and argued that most research studies concentrated on examining an individual's UI to predict actual use. The UI and actual use constructs have primarily been applied to two research perspectives within existing studies, namely pre-adoption and post-adoption (Sohn, 2017). Within pre-adoption, researchers primarily considered the relationship between UI and influencing constructs (PU, PEOU, and attitude), whereas post-adoption focused on the relationship between UI and the influencing constructs concerning actual use (Sohn, 2017).

Manis and Choi (2019) argued that an individual's past use experience with a type of technology, or one that is similar, can have a dramatic impact on their PU, PEOU, attitudes toward use, and UI. Therefore, while the TAM might be robust in measuring an individual's perceptions and intentions regarding a specific type of technology, it does not consider experiences or personal predispositions concerning a system or technology. This was seen to be one of the main factors contributing to the modifications to the TAM. In addition, while the UI and actual use dimensions provide useful insights toward the likelihood of use, it requires additional contextual variables and constructs to provide a more comprehensive understanding (Y. Wang et al., 2020). The nature of the modifications to the TAM is discussed further in the following section.

2.3.2.5 Modifications to the TAM

There have been several modifications to the TAM model by past researchers through the addition of independent constructs and antecedents to explore various aspects of technology adoption (Harrigan et al., 2021; He et al., 2018). Granić and Marangunić (2019) defined these extended models as TAM++, however there have been several other naming conventions for the extended TAM, including e-TAM (Yalcin & Kutlu, 2019), TAM-TPB (Oliveira et al., 2020), VR-HAM (Manis & Choi, 2019), TAM-R (López-Bonilla & López-Bonilla, 2017), and TAM2 (Dwivedi et al., 2019).

The extensions to the TAM provided evidence to support the view of Y. Wang et al. (2020) that the TAM in its basic form is not sufficiently comprehensive for specific contextual studies. Through a meta-analysis of the TAM, King and He (2006) found that the core TAM model had four major categories of modifications comprising external precursors, elements from other theories, contextual elements, and subsequent influences. A 2015 meta-analytic review by Marangunić and Granić (2015) produced similar findings, with slight changes in the definitions of two modification categories (external precursors replaced by external predictors and subsequent influences replaced by usage measures). The major modifications and their relation to the TAM constructs proposed by Marangunić and Granić (2015) are shown in Figure 5.

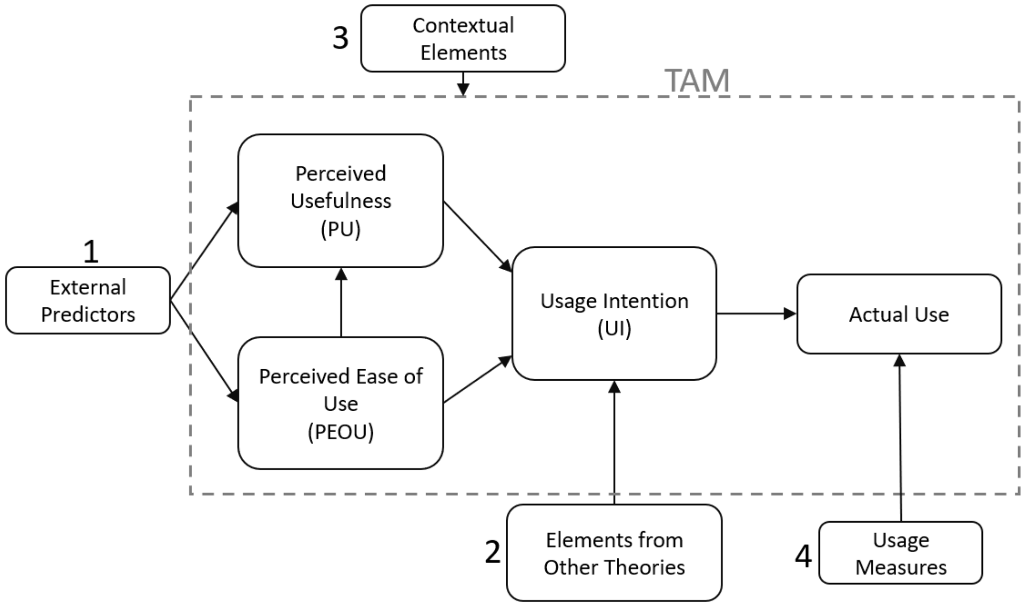

Figure 5: The four categories of TAM modifications

Source: Marangunić and Granić (2015)

The relatively unchanged nature of the TAM and associated modifications over almost a decade (2006-2015) supports the model's stability and versatility within a rapidly developing technological world. Marangunić and Granić (2015) argued that modifications to the TAM had appeared primarily through the model's enhancement by integrating supplementary constructs. Modification of the TAM, therefore, does not indicate that the model is deficient but instead provides a sound platform onto which it can be extended to suit the researcher's specific needs. Kim and Chiu (2019) supported this view and contended that, even though the TAM has proven its rigour, it must be extended and supplemented by further constructs to enhance its explanatory capabilities to provide robust insights into an individual's technology adoption behaviour for specific contexts.

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

This model was developed by Venkatesh et al. (2003) and founded on considerations made to several previous models (including the TPB and TAM) to provide a platform on which employee's acceptance and use of information systems (IS) and information technology (IT) were investigated (Dwivedi et al., 2019; Khechine et al., 2016). The model is based on the four predictor constructs of social influence, effort expectancy, performance expectancy, and facilitating conditions concerning an individual's behavioural intention and actual use of IS/IT technology (Maruping et al., 2017). In addition, an individual's voluntariness, experience, age, and gender were integrated as moderating variables between the predictor constructs and behavioural intention and use, as illustrated in Figure 6.

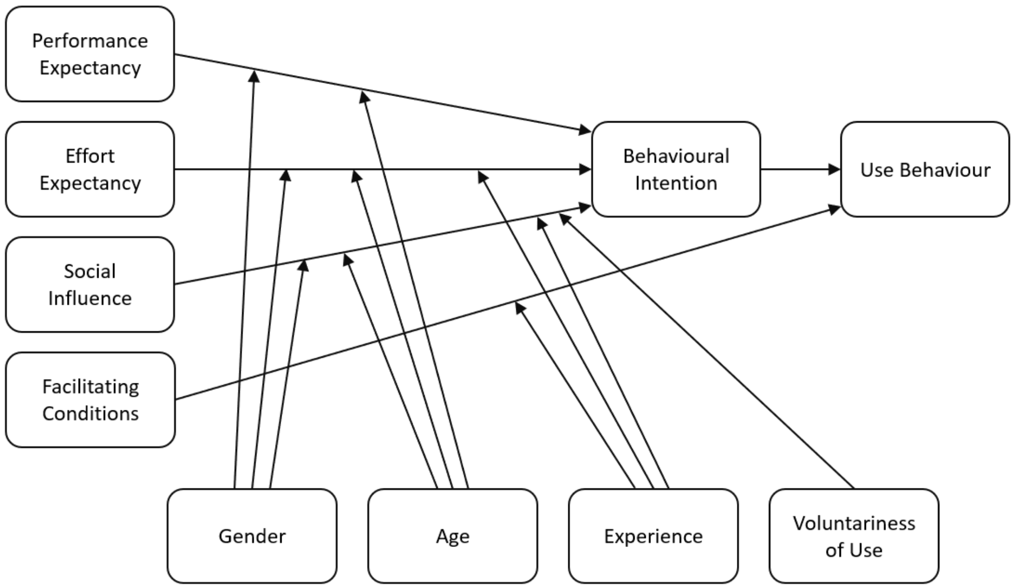

Figure 6: The Unified Theory of Acceptance and Use of Technology (UTAUT)
Source: Venkatesh et al. (2003)

The performance and effort expectancy dimensions can be likened to the TAM constructs of PU and PEOU respectively, while the social influence concept is analogous to the subjective norm construct within the TPB. M. M. Rahman et al. (2017) affirmed the similar nature of these constructs through an investigative study using the TPB, TAM, and UTAUT. They found that there was a strong correlation and a statistically significant relationship between performance expectancy and PU, effort expectancy and PEOU, as well as social influence and subjective norm. Regarding the facilitating conditions, Venkatesh et al. (2003) defined this construct as the extent to which a person perceives that their organisation has the internal and technical infrastructure to support use. However, they also acknowledged the similarity and significant theoretical commonality between facilitating conditions within UTAUT and perceived behavioural control defined within the TPB (Venkatesh et al., 2003).

Even though the UTAUT model was developed to investigate IT/IS adoption behaviour, and has primarily been used as such, it has been applied outside of the IT/IS context within several studies. Examples included the exploration of the adoption of Internet of Things (IoT) devices within the medical services industry (Arfi et al., 2021), acceptance of autonomous-driven public transport systems (Madigan et al., 2017), health-related wearable devices (H. Wang et al., 2020), and highly automated passenger vehicles (Kaye et al., 2020). Through the variety of IT/IS applications and those outside of the IT/IS context, the UTAUT model has undertaken various forms within the existing literature. However, unlike the extensions to the base TAM, there have been notable modifications to the base UTAUT model that were deemed prudent for consideration for this research study.

2.3.3.1 Modifications to the UTAUT

Using a meta-analysis approach, Blut et al. (2021) argued that while the UTAUT model is amongst the most cited models within the IT and IS literature, they also noted that it had been extensively modified through integration with other independent theoretical constructs. They also argued that the modifications bring into question the robustness of the original theory as it has not been adequately and appropriately replicated within existing research. Dwivedi et al. (2019) agreed with this view through their meta-analysis, expressing that previous studies have generally not applied the UTUAT in its form as proposed by Venkatesh et al. (2003). In addition, it was observed that the moderating constructs (gender, age, experience, and voluntariness of use) were typically removed in most studies (Dwivedi et al., 2019; Khechine et al., 2016; Mou & Benyoucef, 2021).

Both Khechine et al. (2016) and Dwivedi et al. (2019) presented revised versions of the UTAUT within their meta-analyses, excluding the moderating variables as illustrated in Figure 7. Both meta-analyses presented the same proposed version, with the only difference being the TAM attitude construct. Dwivedi et al. (2019) included this construct based on the argument that the extent of performance and effort expectancy influences an individual’s attitude and usage. It was observed that the constructs within the modified version of the UTUAT model presented in Figure 7 resembled that of the TAM model with the additional constructs of social influence and facilitating conditions. As discussed above, performance expectancy and effort expectancy can be viewed as being analogous to the TAM PU and TAM PEOU respectively.

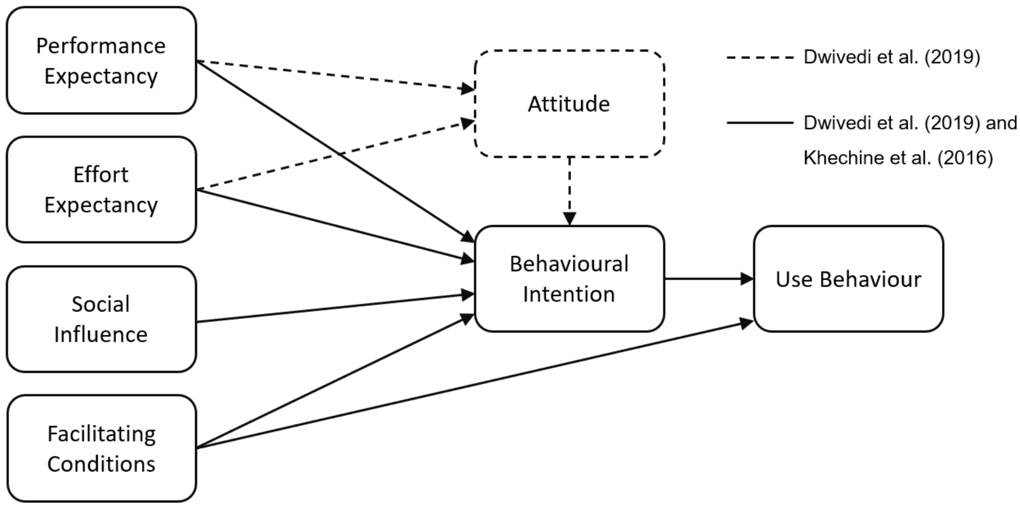

Figure 7: Proposed revision to the UTAUT model

Source: Dwivedi et al. (2019) and Khechine et al. (2016)

2.3.4 The Technology Readiness Index (TRI)

Technology readiness refers to an individual’s inclination towards embracing and using novel technologies to realize goals in both their personal and professional lives (Jafari-Sadeghi et al., 2021). The technology readiness index (TRI) was crafted and refined by Parasuraman (2000) in response to the rapid introduction of new technologies within multiple aspects of home and work life. Additionally, it was crafted to provide academic inquiry to understanding individuals' willingness to adopt and use new technology, assess the primary factors that contribute to their willingness, and unpack managerial considerations needed for segments with differing degrees of willingness (Parasuraman, 2000).

The initial model developed by Parasuraman (2000) was updated by Parasuraman and Colby (2015) and dubbed TRI 2.0. The primary aims of the update were to redefine the scale items to remove contextual elements that were no longer deemed relevant, modify the scale items to be more parsimonious, and integrate aspects relating to the evolving technological environment (Parasuraman & Colby, 2015). The TRI 2.0 model and its dimensions are expanded on below and, for simplicity, will be referred to as the TRI throughout this report.

The TRI assesses an individual's propensity to embrace technology through the meta-constructs of "motivators" and "inhibitors" (Chiu & Cho, 2020; Kim & Chiu, 2019). The motivators are represented by the sub-constructs of optimism and innovativeness, and the inhibitors by discomfort and insecurity (Parasuraman & Colby, 2015). Therefore, an individual's perceptions of technology acceptance are assessed through positive (motivators) and negative (inhibitors) facets. The TRI motivators (innovativeness and optimism) and TRI inhibitors (discomfort and insecurity) are scaled items (16-items) that measure the degree of comfort that an individual has towards technology, with a higher score on the TRI motivators indicating a high degree of comfort while a high score on the TRI inhibitors indicating a low degree of comfort (Qasem, 2021). The TRI and its constituents are presented in Figure 8 and described in the following sections.

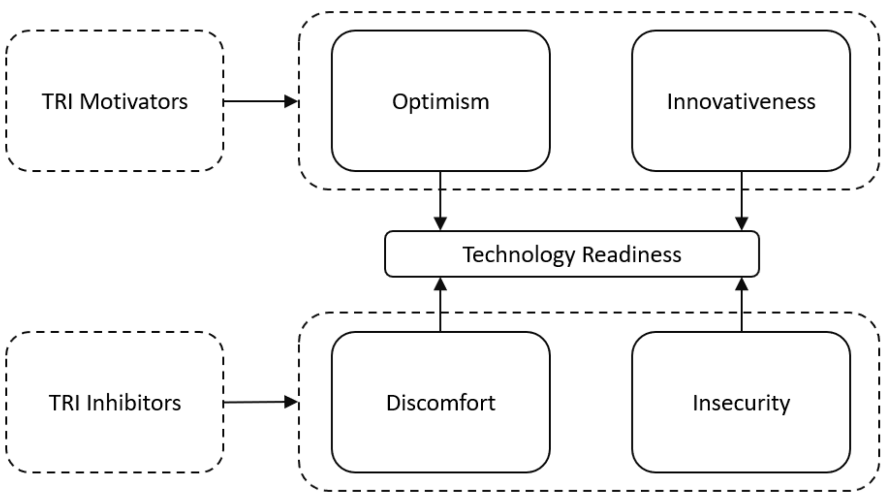

Figure 8: The Technology Readiness Index and its components

Source: Generated by the researcher based on Parasuraman and Colby (2015)

2.3.4.1 TRI Motivators: Optimism and Innovativeness

Optimism towards technology is described as "a positive view of technology and a belief that it offers people increased control, flexibility, and efficiency in their lives"

(Parasuraman & Colby, 2015, p. 60). The term optimism in itself is key in defining this construct concerning technology adoption, as optimists have a lower tendency to focus on negative aspects therefore engage with technology in a more open way (Humbani & Wiese, 2018). In addition, technology optimism has been associated with preconceived beliefs about the individual's capabilities that act as a differentiating factor when considering their outlook towards future technology-related experiences (Ramírez-Correa et al., 2020). Therefore, individuals that have an optimistic view of technology will explore and interact more enthusiastically and have a higher degree of resilience to use. In contrast, pessimists are more likely to have negative outcomes both prior to and when using technology.

Technology innovativeness refers to an individual's "tendency to be a technology pioneer and thought leader" (Parasuraman & Colby, 2015, p. 60). Technology innovators are more willing to experiment with new technologies and are highly curious regarding its capabilities and potential uses. As a result, individuals with higher degrees of technology innovativeness are more likely to try out new technologies driven towards feeding their curiosity. Innovators, therefore, see themselves as being aware of the latest trends and relish scenarios where they are consulted on new technologies and developments (Lee et al., 2020). In addition, Humbani and Wiese (2018) argued that technological innovativeness can be considered a stable signifier that is typically uninfluenced by differing environments and technology contexts.

2.3.4.2 TRI Inhibitors: Discomfort and Insecurity

Discomfort relating to technology is defined as "a perceived lack of control over technology and a feeling of being overwhelmed by it" (Parasuraman & Colby, 2015, p. 60). Discomfort can be viewed as an individual's belief that technology is too complex for them to grasp its workings and, therefore, would not be capable of using or maintaining its functionality. The sense of overwhelmingness creates a reluctance for individuals to explore technology use and is often accompanied by a sense of embarrassment relating to whether the individual has the skills for use (Lee et al., 2020). In addition, the discomfort construct is an important factor in technology adoption as the sense of lack of control can lead to mistrust in technology that can become embedded, making it challenging for individuals to overcome (Sun et al., 2019).

Insecurity is described as a sense of “distrust of technology, stemming from scepticism about its ability to work properly and concerns about its potentially harmful consequences” (Parasuraman & Colby, 2015, p. 60). Insecurity can be characterised as an individual’s sense of vulnerability regarding technology interactions, where the individual may have certain perceptions relating to poor performance, technology glitches, or even scenarios of harmful outcomes (Tavera-Mesías et al., 2022). Tavera-Mesías et al. (2022) argued that these preconceived notions implied that individuals see potential risks before making efforts toward understanding and using the technology. As with discomfort, insecurity is an essential consideration toward technology adoption based on an individual’s trust or mistrust and associated outcomes (Sun et al., 2019).

2.3.4.3 Considerations Regarding the Dimensionality of the TRI

While the TRI is simplistic in its composition, there has been some debate regarding its dimensionality. The multifaceted composition of the TRI has created variations in its conceptualization within existing research, creating ambiguity in whether it is best treated as having four dimensions (through optimism, innovativeness, discomfort, and insecurity), two dimensions (through the TRIM and TRII), or through the single dimension (the technology readiness index itself) (Blut & Wang, 2020). Parasuraman and Colby (2015) proposed that the TRI, in its original configuration, should be treated within the four dimensions of innovativeness, optimism, discomfort, and insecurity, but also purported that these can be grouped within TRI motivators and TRI inhibitors.

Recent studies utilizing the TRI were mixed regarding the dimensions used for the model. Sinha et al. (2019), Lee et al. (2020), Peng and Yan (2022), Goebert and Greenhalgh (2020) employed a one-dimensional approach to studies within mobile payments, wearable payments, media kiosks, and augmented reality respectively. Mishra et al. (2018) and Humbani and Wiese (2018) utilized a two-dimensional approach for culture socialisation and mobile payments, while Phung et al. (2022) used both two-dimensional and four-dimensional for unpacking technology adoption amongst

Vietnamese college students. However, most studies using the TRI have adopted the four-dimensional configuration. These include those by Chen and Lin (2018) (health-related mobile applications), Kaushik and Agrawal (2021) (e-learning adoption), Aboelmaged et al. (2021) (health-related mobile applications), Rojas-Méndez et al. (2017) (cultural assessment of technology readiness), and Tavera-Mesías et al. (2022) (mobile payments with gender considerations).

The dimensionality for the application of TRI was considered for this study based on the above findings. Blut and Wang (2020) argued that TRI should be conceptualised as two-dimensional (through the TRI motivator and TRI inhibitor elements) as a compromise between model precision and parsimony in depicting the model's facets which was confirmed through their meta-analysis concerning TRI. However, the researcher also resolved that the four-dimensional composition, as proposed by Parasuraman and Colby (2015), should not be ignored. Therefore, consideration was made at the two-dimensional level with the optimism and innovativeness dimensions contained within the TRI motivators, while the TRI inhibitor dimensions encompassed discomfort and insecurity.

2.3.5 Relevance and Applicability of the Technology Adoption Models and Constructs

The key aspects of the TPB, TAM, UTAUT, and TRI were assessed to determine which adoption models and model constructs were applicable for use within this study. The criteria used for the assessment were based on the primary research question, namely which models and associated constructs provided the necessary insights into the propensity of individuals toward embracing and using new and innovative technologies in the South African mining industry.

The TPB was developed to explore more generalised human behaviour when compared to the technology-focused TAM and UTAUT (M. M. Rahman et al., 2017), and as discussed in Section 2.3.1, it was primarily reviewed as a precursor to the TAM and UTAUT models. The UTAUT model was developed for use within the IT/IS context, and while there have been studies done outside of this context, it was argued that the model had not been adequately used it its original form (Dwivedi et al., 2019). In addition, most studies have excluded the moderating constructs of age, gender, experience, and voluntariness (Dwivedi et al., 2019; Khechine et al., 2016; Mou & Benyoucef, 2021), reducing the model to one that was comparable to the TAM.

Like the UTAUT model, the TAM has also undergone several modifications. However, these modifications have served to expand and enhance the model through the addition of supplementary constructs (Marangunić & Granić, 2015). Additionally, the model was proven useful for studies with different technologies and contexts (Marakarkandy et al., 2017) and was found to be better suited to technology decisions within an organisational environment (Manis & Choi, 2019). Based on these aspects, the TAM was deemed suitable for this study.

However, as Y. Wang et al. (2020) proposed, the TAM should be modified and extended to meet specific research needs within different contexts. Therefore, the researcher deemed it prudent to extend the TAM by incorporating the TRI dimensions of motivators and inhibitors to assess an individual's outlook and beliefs. Therefore, the personality constructs of the TRI were treated as external predictors and coalesced with the TAM perception-related and UI constructs providing a more insightful understanding of the mental processes involved in the propensity toward technology adoption (Chiu & Cho, 2020). In support of this, Tavera-Mesías et al. (2022) argued that integrating the TRI dimensions with the TAM constructs provided the benefit of understanding the predispositions and beliefs of an individual. In contrast, the TAM only made consideration towards a particular system or technology.

Apart from the addition of the TRI dimensions, three constructs within the TAM were not considered for the study based on the nature of the primary research question and the study's context. The TAM constructs excluded were PEOU, attitude, and actual use. Figure 9 illustrates the TRI and TAM constructs deemed suitable for this study, with the motivation for the TAM modifications discussed below.

Verma et al. (2018) argued that PU was more significant than PEOU, specifically within organisational-context studies. Sun et al. (2019) stated that PU can be viewed as an instrumental construct regarding technology adoption, while PEOU speaks to an individual's hedonic encounters when using a specific technology. Given that PU is a more robust indicator of UI, is more relevant within an organisational setting, and this study considered technology as a generalised concept (non-specific type of technology), PEOU was excluded from the study.

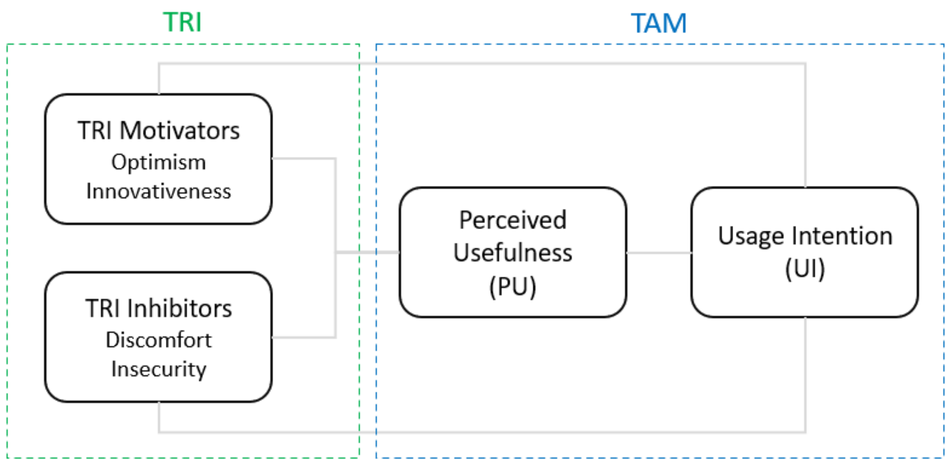

Figure 9: TAM and TRI constructs used for the study toward a conceptual model

Source: Generated by the researcher

As discussed in Section 2.3.2, an individual's attitude toward technology adoption is shaped by social influences, motives, and status enhancement (Li et al., 2017). These attitude factors were deemed more applicable to technology adoption in a voluntary situation (such as consumer-focused studies) rather than within an organisational setting when considering the relationship between PU and UI (López-Bonilla & López-Bonilla, 2017). Given that this study focused on the technology adoption of individuals within mining organisations, the TAM attitude construct was not considered.

The TAM construct of actual use was excluded from the conceptual model based on the study's aim to assess individuals' propensity towards adopting new and innovative technologies rather than their inclination towards existing technologies. Therefore, assessing the propensity towards technology adoption focused on UI rather than the TAM actual use construct.

2.4 Examination of the TAM and TRI Constructs

Existing literature was reviewed to assess the relationship between the TRI and TAM constructs used for this study and unpack associations to the organisational context. Understanding these relationships provided a platform from which hypotheses were developed toward crafting an appropriate research methodology for the study.

2.4.1 TRI Motivators, Perceived Usefulness, and Usage Intention

Blut and Wang (2020) argued that the TRI motivators encompass the positive dimensions of the TRI and that individuals who demonstrate a high degree of technology optimism and innovativeness are more likely to adopt new technologies. It has been argued that innovative individuals feel that not using new technologies makes them feel that they are missing out on possible personal benefits, and that these individuals tend to be more optimistic about new technology based on the perceived personal benefits (Qasem, 2021).

Within an organisational setting, individuals who demonstrate positivity toward technology adoption typically consider it as means of achieving ongoing competitive advantages for their organisations through increased efficiency, reduced long-run costs, and improved customer experiences (Sun et al., 2020). A critical distinction of those individuals who are more technologically motivated is their drive toward actively searching for new technologies to address organisational challenges, whereas those individuals who are not motivated will avoid using a new technology until it becomes a necessity (Goebert & Greenhalgh, 2020). Based on these aspects, it was deduced that individuals who seek out new technologies have a preconceived notion that new technologies will increase their work efficacy.

S. A. Rahman et al. (2017) argued that while the TRI motivator dimension of optimism has been found to positively influence PU withing studies of varying contexts, the impact of innovation on PU has produced mixed results. For example, contrary to their argument on the relationship between PU and technology adoption, Blut and Wang (2020) found that the TRI motivators did not significantly affect PU within their meta-analysis. However, within real-world studies considering technologies within different contexts, a positive relationship was found by Chiu and Cho (2020), Rejikumar et al. (2020), and Lee et al. (2020). Nevertheless, one can draw an intuitive deduction that if an individual has an optimist view towards technology and he/she is innovative in terms of its applications, then there is a higher likelihood that the individual will have a higher degree of PU. In line with this, S. A. Rahman et al. (2017) argued that the TRI motivators had a positive effect on usefulness such that:

H_1: TRI motivators have a positive relationship with PU.

Individuals who demonstrate a high degree of technological motivation (relating to the TRI motivators) tend to be drawn towards the novelty associated with new technology, and there is typically no significant distinction in their stance between technologies used personally versus within their organisation (Blut & Wang, 2020). This speaks to both the innovativeness and optimism dimensions, where the individual demonstrates creativity through linking innovative solutions with a personal or organisational need and has an optimistic view that the outcome will be beneficial. Rejikumar et al. (2020) reported that individuals with high UI perceive that technology assists in addressing future challenges and enhances an organisation's ability to compete, while simultaneously making their work more meaningful and easier to execute.

Sun et al. (2019) posited that an individual’s UI of a system is based on their preconceived notions and beliefs. However, Blut and Wang (2020) argued that the TRI is a more generalised concept that assesses differences between individuals, whereas technology-related expertise and self-efficacy are more appropriate for measuring one's beliefs. Contrary to this, Tavera-Mesías et al. (2022) found that the positive TRI dimensions were a significant indicator towards an individual’s UI beliefs. Aligned with this, Chen and Lin (2018) argued that personality traits related to the positive TRI motivators dimension can directly impact the individual’s intentions toward technology adoption and therefore influence UI positively.

Regarding previous research on the relationship between the TRI and UI, Flavián et al. (2021) found that the TRI optimism construct had a significant positive relationship with UI concerning AI-based financial investment services, but surprisingly, the innovativeness dimension had no effect on UI. On the other hand, Lee et al. (2020) found that the constructs within the TRI contributed significantly to their study encompassing wearable payment devices and that the TRI motivators had a significant and positive influence on UI, which was aligned with the findings of Chang and Chen (2021) and Phung et al. (2022). Therefore, based on most recent studies finding that TRI had a positive effect on UI, it was hypothesised that:

H_2: TRI motivators have a positive relationship with UI.

2.4.2 TRI Inhibitors, Perceived Usefulness, and Usage Intention

The negative inhibitor dimensions of TRI (discomfort and insecurity) can be linked to an individual's sense of trust and risk concerning technology. Individuals who rank highly on TRI inhibitors exhibit fear and doubt towards using innovative technologies (Kamble et al., 2019), which reduces their ability to see and explore potential benefits. Therefore, technology is seen as a barrier towards enhancing their capabilities, and they are less willing to detach themselves from their known experiences. However, Acheampong et al. (2017) argued that certain individuals might overcome their insecurity and discomfort if the benefits associated with the innovative technology are significant. While this may be true within certain environments and contexts, there were limited studies that support this notion.

Blut and Wang (2020) argued that individuals who score highly on the TRI inhibitors scale are more sceptical about the potential benefits and less likely to relish the realised benefits. Scepticism naturally generates a sense of negativity through doubt and fear, which introduces perceived risk with innovative technologies. Additionally, the negative perceptions create mental barriers that restrict individuals from fully appreciating the utilitarian value that new technologies can provide. These views were aligned with the significant negative relationship found between the TRI inhibitors and PU by Kim and Chiu (2019), Acheampong et al. (2017), and Chang and Chen (2021). However, Kamble et al. (2019) found that both insecurity and discomfort had no effect on PU, while S. A. Rahman et al. (2017) found a significant relationship for the insecurity dimension with no effect for discomfort. Nevertheless, based on the definition of H_1 and the significant negative relationships found by the mentioned authors, it was hypothesised that:

H_3: TRI inhibitors have a negative relationship with PU.

Individuals who do not perceive usefulness in innovative technologies are less likely to have a high degree of UI. Blut and Wang (2020) contended that individuals who portray technology inhibition anticipate an outcome of failure rather than benefit, even without any practical exposure or attempts at usage. These individuals perceive a higher degree of risk associated with the technologies use when compared to their beliefs regarding benefits from its use (Tavera-Mesías et al., 2022). Apart from the risk aspect, some individuals may perceive that using the technology may result in embarrassing situations and reputational damage through misuse (Lee et al., 2020).

As was discussed in Section 2.3.4, trust in technology has a significant role in one's inclination towards adoption. Schaefer et al. (2016) posited that human trust in technology is determined by the personality and nature of the individual, and that trust is one of the most important factors in determining whether the technology will be used or not. Cognitive factors regarding understanding the system's workings and self-efficacy in the individual's ability to use the system affect their perceptions of its use (Schaefer et al., 2016). It was therefore expected that an individual's insecurity and discomfort would impact his/her trust in the technology, which ultimately determines their UI. Blut and Wang (2020) supported this notion based on research within the field of IS and found that TRI inhibitors had a negative impact on technology UI. Corresponding relationships were found within studies done by Phung et al. (2022) and Lee et al. (2020) that assessed technology readiness amongst college students and adoption of wearable payment technology respectively. These findings were partially supported by Flavián et al. (2021) and Pham et al. (2020), who found significant negative relationships for discomfort and insecurity separately. It was therefore hypothesised that:

H_4: TRI inhibitors have a negative relationship with UI.

2.4.3 Perceived Usefulness and Usage Intention

Brandon-Jones and Kauppi (2018) argued that when an individual appreciates the usefulness of innovative technology in enhancing their work efficiency, it will positively impact their UI. This is attributed to individuals' willingness to adopt and use new technology if they expect it to provide distinct advantages over existing methods (Schmidthuber et al., 2020). Marakarkandy et al. (2017) claimed that PU has been one of the most robust indicators of UI and adoption within the field of internet banking, however, also argued that several different factors within different contexts influence PU. Nevertheless, Marangunić and Granić (2015) contended, based on their meta-analysis of the TAM, that PU was consistently found to be a key determinant for UI. This meta-analytic finding was supported by recent studies done by Verma et al. (2018) Schmidthuber et al. (2020), and Singh et al. (2020). As a result, it was hypothesised that:

H5: PU has a positive relationship with UI.

As an important supplement to the above in relation to this study, Razmak and Bélanger (2018) argued that UI is significantly correlated with actual use of technology, which implies that UI is a strong indicator of technology acceptance. In support of this, Taherdoost (2018b) found a direct relationship between UI and technology adoption in a study exploring the acceptance of e-services. Therefore, whilst this study did not consider actual use of technology, it was argued that UI provides key insights into sustainable adoption through UI.

2.4.4 Usage Intention and Individual-Related Factors

Given the relevance and importance of UI concerning technology adoption, the relationship between UI and the individual-related factors discussed in Section 2.2 were considered for this study. A review of relevant literature was done to gain an understanding of the expected relationships between UI in terms of chronological age, education levels, and organisational roles.

2.4.4.1 Chronological Age and UI

Manis and Choi (2019) stated that younger individuals have a higher PU than older individuals concerning UI since older generations believe their technological skills are inferior due to higher anxiety levels and low self-efficacy. However, Mariano et al. (2022) argued that age-related stereotypes often pose a threat to older individuals creating fabricated anxiety that forms a barrier to UI. As discussed in Section 2.2.1, there were mixed results with little consensus within existing research concerning the influence of age on technology acceptance (Cruz-Cárdenas et al., 2019).

Althuizen (2018) stated that misrepresentation of chronological age could present itself through biases toward older individuals with low levels of education (increased reluctance) or younger individuals with high levels of education (increased acceptance). Nevertheless, Hauk et al. (2018) found that chronological age had a negative relationship with usage intention within their meta-analysis that investigated the relationship between age and the TAM constructs. Therefore, within the context of this study, it was hypothesised that:

> **H_6:** There is a significant difference within distinct chronological age groups in terms of UI.

2.4.4.2 Level of Education and UI

Rojas-Méndez et al. (2017) argued that individuals with higher education levels have more complex cognitive structures that enhance their learning abilities when encountering new challenges or environments. Furthermore, more educated people are typically aware of these abilities, which improves their sense of self-efficacy. As a result, individuals with a higher perception of self-efficacy have reduced anxiety when encountering new challenges, which influences their PU and therefore UI concerning innovative technology (Santini et al., 2020).

In contrast to the above, Sundstrup et al. (2022) purported that appropriate training in the skills required for the use of technology can improve adoption and implementation, and therefore shortcomings through the lack of formal education can be compensated by this. Harrigan et al. (2021), in a study concerning trust linked to online purchase intentions using TAM, found that individuals' education levels did not significantly influence their PU or UI. Yuen et al. (2021) also found that levels of education were not a significant determinant of UI based on a study of the adoption of autonomous vehicles. It was therefore hypothesised that:

> **H_7:** There is no significant difference within distinct groups of educational levels in terms of UI.

2.4.4.3 Organisational Role and UI

There is limited research within existing recent and relevant literature that explores the predispositions and perceptions relating to technology usage for different roles within an organisational setting. Damanpour and Schneider (2006) argued that decision-makers (concerning organisational strategy) and managers significantly influence the organisation's capabilities by promoting organisational culture, providing the resources and motivation, and building the necessary capacity for innovative change. Therefore, the role of decision-makers and managers in enabling and promoting the appropriate organisational culture and technologies to address business and operational challenges is critical to ensure sustained competitive advantage. Cruz-Cárdenas et al. (2019) stated that culture impacted the PU and UI of individuals. While this argument was made at a country level, comparisons can also be drawn to the organisational level.

Within the context of this study, Gruenhagen and Parker (2020) contended that the mining industry is viewed as having a change-resistant, traditionalist culture. The fear of job loss through the introduction of innovative technologies places pressure on decision-makers to carefully strategise which technologies to implement to improve competitive advantage while maintaining employment. Silva and Lima (2017) argued that introducing new technologies elevates concerns about the potential rise in unemployment of lower-skilled workers, which could influence the perceptions of potential users concerning PU and UI. Based on the innovation drive by decision-makers and managers, as well as potential concerns about technological unemployment by users within the context of the mining industry, it was hypothesised that:

H_8: There is a significant difference within distinct groups of organisational roles in terms of UI.

2.5 Conclusion

This chapter presented the relevant literature based on this study's primary research question. Within the considerations made to individual-related differences, it was found that an individual's chronological age and level of education influenced their perceptions regarding technology. Additionally, an individual's organisational role was found to contribute to whether technology is effectively adopted within an organisational setting based on the different phases of technology implementation.

The chapter also presented a review of technology acceptance and adoption models. The constructs within these models and modifications within previous studies were examined to determine their applicability. It was found that modification of the TAM to integrate constructs from the TRI provided the means to unpack the primary research question. TRI motivators and inhibitors were integrated with the PU and UI constructs from the TAM to examine individuals' perceptions and the associated relationship with their inclination toward adoption. Based on previous studies, hypotheses were developed based on relationships between the TRI and TAM constructs. The individual-related factors discussed above were examined concerning the UI construct, and hypotheses were developed between these aspects and UI. The constructs and hypotheses provided the structure for developing the conceptual model for this study.

3 Chapter Three: Conceptual Model, Research Question, and Hypotheses

3.1 Introduction

The foundation for the conceptual model developed for this study was formed from the literature reviewed in Chapter 2, where the TRI inhibitors and motivators were integrated with the TAM PU and UI and hypotheses were established based on previously studied relationships. This chapter presents the conceptual model and consolidates the hypotheses.

3.2 Conceptual Model

Figure 10 illustrates the conceptual model used for this study based on the integration of the TAM constructs of PU and UI with the TRI dimensions of inhibitors and motivators. The model and its representation were adapted from a study encompassing similar constructs by Kim and Chiu (2019). The conceptual model illustrates the hypotheses developed within Section 2.4 based on the relationships found between the TRI and TAM constructs from previous studies within the existing literature. In addition, the individual-related factors have been integrated into the conceptual model as control variables with associated hypotheses assessing their relationship with UI as discussed in Section 2.4.

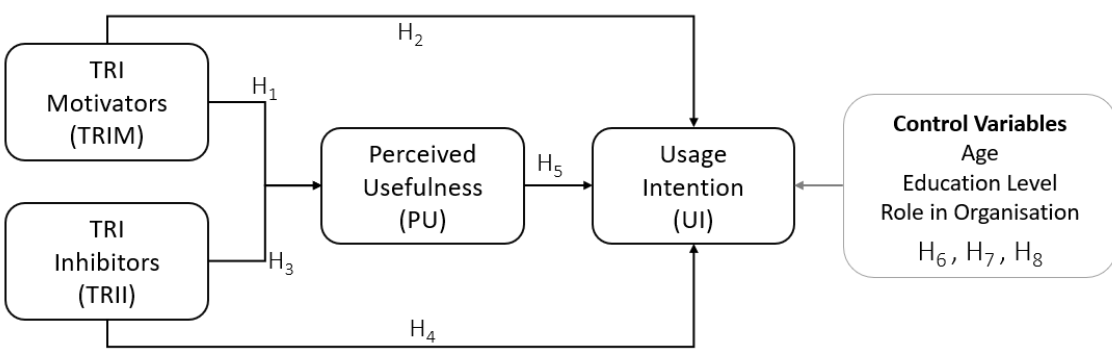

Figure 10: The conceptual framework for the research study

Source: Adapted from Kim and Chiu (2019)

3.3 Research Question and Hypotheses

The primary research question posed in Section 1.3 in response to the identified research problem states:

To what extent do individuals' predispositions and perceptions influence their propensity towards embracing and using innovative technologies in the South African mining industry?

The above research question was framed as an inquisitive examination of the problem statement. Through the literature reviewed and the conceptual model developed, the researcher deconstructed the research question into hypotheses from which relationships were tested in a quantifiable manner. This approach allowed the researcher to use the scientific method to gather evidence which was then used to derive an objective answer to the inquisitive real-world research question (Zikmund et al., 2009). The hypotheses developed within Section 2.4 based on existing research were consolidated and are presented below.

H_1: TRI motivators (TRIM) have a positive relationship with PU.

H_2: TRI motivators (TRIM) have a positive relationship with UI.

H_3: TRI inhibitors (TRII) have a negative relationship with PU.

H_4: TRI inhibitors (TRII) have a negative relationship with UI.

H_5: PU has a positive relationship with UI.

H_6: There is a significant difference within distinct chronological age groups in terms of UI.

H_7: There is no significant difference within distinct groups of educational levels in terms of UI.

H_8: There is a significant difference within distinct groups of organisational roles in terms of UI.

3.4 Conclusion

The conceptual model and related hypotheses for this study were presented in this chapter. The research methodology adopted for the study was designed in a manner to test whether the hypotheses proposed were supported and is discussed in the following chapter.

4 Chapter Four: Research Methodology

4.1 Introduction

Chapter 4 describes the research methodology for this study based on the hypotheses and conceptual model derived from existing literature. The choice of research design is described first, followed by details regarding the target population, sampling method adopted, and data gathering process using the derived measurement instrument. The later sections described the data processing and analysis techniques used to perform quality assessments and statistical methods used to test the hypotheses generated in Chapter 2 and consolidated in Chapter 3. Finally, this section concludes with the limitations of the adopted research methodology.

4.2 Choice of Research Design

The research design was aimed at providing improved clarity around the research problem through precise demonstration of the views of individuals within the study, and was therefore a descriptive approach (Saunders & Lewis, 2018). However, the conceptual model and hypotheses were crafted to understand the relationships between the defined variables within the conceptual model constructs. Based on these two aspects of the study, the research design was descripto-explanatory based on theory testing of the conceptual model. The following sections describe the research design in further detail, with Figure 11 providing an overview of the elements of the design.

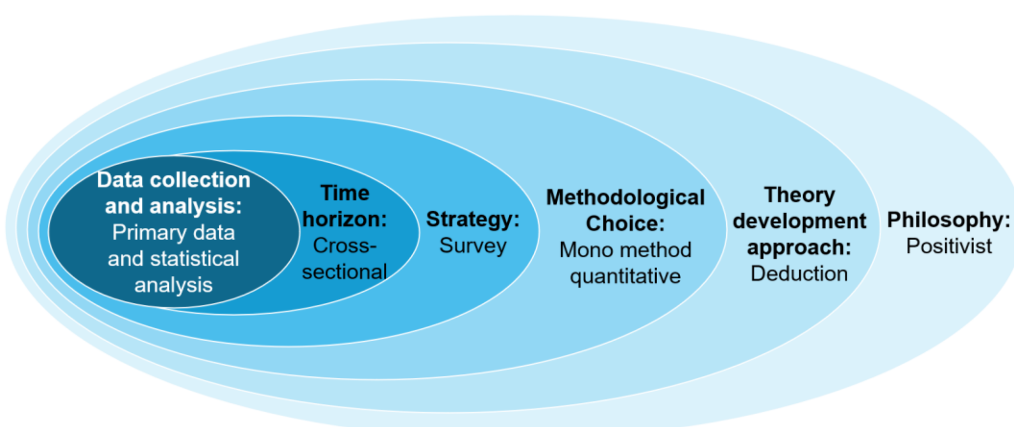

Figure 11: Overview of the research design using the research onion

Source: Adapted from Saunders and Lewis (2018)

4.2.1 Philosophy

Differences in research philosophy paradigms are related to the philosophical preferences of the researcher concerning the nature of reality, how knowledge was developed and deemed valid, and the ethics related to the research process (Saunders & Lewis, 2018). In addition, the researcher aimed to conduct the study in an objective, structured, and independent manner so that the data collected was free of bias. The researcher’s approach and associated philosophy were therefore viewed as being positivist. Kock et al. (2017) described the properties of positivist studies as having constructs that are sound in definition and hypotheses that aim to describe the underlying relationships between the constructs. These properties were aligned with the research design described and therefore corroborated the positivist view of the researcher.

4.2.2 Approach Selected

The two approaches possible, given the study's time constraints, were deduction or induction. Gottfredson and Aguinis (2017) defined deductive research as being reliant on sound theoretical rationale upon which hypotheses are created and tested, whereas inductive research is directed towards finding meaning and incongruity from which theory is developed and then tested. The researcher developed a conceptual model based on the reviewed literature, specifically TAM, TR and relevant control variables, and testing was done based on this model (therefore theory testing). Based on this, a deductive approach was therefore adopted for the study.

4.2.3 Methodological Choices

The study was conducted using a mono-method quantitative methodology and was therefore a single-technique approach to data collection. This approach was deemed to be appropriate given the time available for the study and that the hypothesis testing primarily required the collection of numeric data.

4.2.4 Strategy

The study relied on data collection using a survey as the primary source. This strategy facilitated standardised questions and associated responses from the sample population to support the hypothesis testing. Additionally, surveys were deemed appropriate given that the analysis was done at the individual level and the limitations regarding the availability of secondary data on the research topic (Crane et al., 2018).

4.2.5 Time Horizon

The study was based on data collected at a particular point in time. The time horizon was therefore cross-sectional. This choice was based on practical considerations toward the time limitations of the study (Saunders & Lewis, 2018).

4.3 Population

The primary research question focused on two areas of an individual's propensity towards technology adoption: whether it is embraced and will ultimately be used. Embracing technology speaks to whether an individual feels that it is a viable solution that can provide improvement value, while the use of technology occurs post-implementation. Therefore, the adoption of innovative technologies relies not only on individuals using the technology, but also on whether the opportunity for innovative technology is introduced by decision-makers and effectively administered by managers (Roberts et al., 2021). In addition, the research problem was centred around innovative technologies that can benefit the mining value chain from an operational productivity perspective. Based on these factors, the target population was made up of individual decision-makers, managers, and prospective users of all ages and education levels working in the operational environment of South African mining companies.

4.4 Unit of Analysis

The study aimed to understand the perceptions of innovative technology adoption based on the research problem. The proposed conceptual model focused on the TRI motivators and inhibitors concerning PU within the TAM to understand the impact on an individual's intention to use technology through the defined hypotheses. The unit of analysis was therefore perceptions of technology at the individual level. While the researcher saw value in this approach, given the context of the research problem and the purpose of the study, the possibility of extended value to the research field was also deemed a motivating factor. This was based on the argument by Meyer et al. (2017), who stated that the individual-level unit of analysis provides valuable contributions where cogency of theory is required for certain geographical contexts compared to an organisation or country-level units of analyses.

4.5 Sampling Method and Size

The sample selected was a representation of the target population and was deemed to be a critical step in the research process. Köhler et al. (2017) stated that the sample characteristics and size concerning the study must be appropriately aligned to the research problem and question. Zyphur and Pierides (2017) also argued that for effective inferential statistics of the population through quantitative methods, the sample selected must be adequately representative of the population. However, at the same time, the practicality of the sampling method was considered. Given that the acquisition of a complete list of individuals working within the operational environment of South African mining companies (target population) was not feasible due to the sheer size and nature of the industry, a non-probability sampling approach was adopted (Saunders & Lewis, 2018).

In terms of the non-probability sampling technique adopted for this study, the researcher initially accessed respondents through known contacts who were then requested to share with other individuals who met the criteria of the target population. Therefore, the researcher adopted a snowball sampling technique to increase the probability of accessing individuals to participate in the study (Saunders & Lewis, 2018). The overall sampling method was, therefore, non-probability snowball sampling.

As with the sampling method, the number of samples was important to collect sufficient data to perform an effective inferential statistical study. Köhler et al. (2017) argued that if the number of samples is insufficient, then the statistical analysis will not produce results that provide the required insights, reducing the analysis to that of a simple coin toss. Hair et al. (2019) built on this and stated that the sample size considerably impacts achieving meaningful results, with too small a sample resulting in diminished statistical power and results that cannot be generalised. Hair et al. (2019) proposed a minimum sample size of 100 responses as a rule of thumb (to be done for hypothesis testing). However, to improve the sample generalisability by increasing the degrees of freedom through a larger sample (Hair et al., 2019), a minimum sample size of 120 responses was targeted for the study.

4.6 Measurement Instrument

Primary data collection was done through a structured questionnaire in the form of a survey with close-ended responses as the measurement instrument as shown in Appendix A. This selection was based on the research approach, strategy, and the time horizon elements of the research design. All surveys were structured so that all respondents were requested to answer identical questions in the same sequence (Saunders & Lewis, 2018). The survey was not designed but rather drawn from existing literature based on the constructs within the conceptual model to collect data in relation to the defined hypotheses.

The cover letter contained examples of technologies relevant to the mining industry for context based on the technology trends outlined in Section 1.2.3. Entries for basic role and demographic information were placed in the initial sections, followed by the items relating to the constructs within the conceptual model. A screening question was placed at the beginning of the survey to verify that the respondent worked with or for the operational section of a mining company.

The survey comprised of the following four sections (detailed in Appendix A):

- Section 1: Questions on the individual's role within their organisation (confirming that the respondent worked with or for the mining section of the organisation and role in terms of technology adoption)
- Section 2: Demographic information (chronological age, level of education, and years of work experience)
- Section 3: Items relating to individuals' views on technology. These were based on the 16-item TRI scale as defined by Parasuraman and Colby (2015)

- Section 4: Items relating to individual’s stance on technology. These were based on the TAM constructs of PU and UI and were adapted from Manis and Choi (2019)

The items comprising the TRI motivators and inhibitors were part of a proprietary test instrument developed and copyrighted by Parasuraman and Colby (2015). Therefore, written permission needed to be obtained from the authors prior to the instrument being used for data collection. A copy of the permission letter received from the authors has been placed in Appendix B for reference. In addition, the authors advised that the items making up TRI inhibitors and motivators be randomised so that the inhibitor questions do not necessarily follow the motivator questions. The survey was therefore setup in this manner. However, the items relating to PU preceded those for UI.

Data collected from the survey was a combination of nominal and interval data, with sections one and two being nominal (role and demographic information) and construct-related items in sections three (TRI) and four (TAM) being interval (Wegner, 2016). A five-point Likert scale was used for responses to the TRI and TAM items, with one allocated to “strongly disagree” and five allocated to “strongly agree”. The five-point Likert scale was used to limit the variation in results and was chosen based on existing studies encompassing both TAM and TRI by Kim and Chiu (2019), Sun et al. (2019), and S. A. Rahman et al. (2017).

A pilot study was done on the survey in both formats (online and hard copies to be described in the following section) for critique and improvements before commencing distribution for data collection. This was done to ensure that the questions and items were clear for the respondents to follow, and that no ambiguity could skew the data collected. No changes were made to the survey based on the pilot study feedback, but the responses received were excluded from the study results. The pilot study also provided a platform to test the data collation of the online format to confirm that there would be no errors during sample data gathering.

4.7 Data Gathering Process

Comprehensive disclosure of the data-gathering decisions made by the researcher was critical to ensure that the integrity of the interpreted results was not compromised (Meyer et al., 2017). Taking this into account, the researcher has outlined as much relevant information as possible regarding the data-gathering process.

Data was gathered through a combination of online and hardcopy survey responses. The online surveys were self-administered and internet-based using the Google Forms platform. Access to respondents for the online survey was gained through the researcher's contacts and colleagues working with or within mining companies operating within South Africa (the researcher worked within the mining equipment supply industry at the time of this study). Respondents were sent either an email, a message via LinkedIn, or a WhatsApp message with a link to the survey, with a request to voluntarily distribute the link amongst colleagues within the South African mining sector. A snowball sampling technique was used as the primary distribution method once the initial sample members were contacted (Saunders & Lewis, 2018).

In addition to the online survey, hard copies were made available by certain respondents who volunteered to distribute to individuals with limited access to emails, Whatsapp, or data. These surveys were emailed when required to be printed and completed by respondents and were self-administered. The researcher did not physically distribute any hard copies. The researcher collected all hard copies; thereafter, each survey was checked for completeness before manually collating and digitising for analysis.

Each survey contained a cover letter that included an informed consent brief, an overview of the study, the intent of the survey, and the researcher's and research supervisor's contact details (see Appendix A). All surveys, both online and hardcopies, were completed anonymously and with the prior consent of the respondents. No personal information relating to the unique identification of the individuals was collected. This ensured that the respondent's anonymity was maintained for the study.

Regarding timelines related to data gathering, ethical clearance was granted by the GIBS ethics committee in mid-July 2022 (ethical clearance approval can be found in Appendix C), thereafter the survey was refined and distributed for the pilot study with formal data collection taking place over four weeks in August 2022. Collation of the hard copies, data cleaning and coding, and processing of the study results were done thereafter. All the collected data was stored on Google Drive. This cloud-based storage platform provided a secure means to store the data as it was password-protected and offered robust data encryption (both in-transit and in storage). In addition, the researcher made provision to retain this data for a minimum period of ten years.

4.8 Data Preparation and Coding

Data was cleaned after the closed collection window and all responses were collected. The online surveys were designed to require respondents to complete all sections of the survey before it was accepted as complete and registered, which limited the likelihood of collecting incomplete responses. However, the researcher verified all online entries to ensure no errors were generated by the Google Forms platform (no errors were detected). In addition, all collected hardcopies were scrutinized for completeness, with incomplete forms discarded and excluded from the final dataset.

All results were imported into Microsoft Excel for coding in preparation for analysis. Identification labels were allocated to each of the survey questions. Numeric codes were assigned to all nominal data (role within the organisation and demographics), and responses to the TRI and TAM construct questions were aligned to the Likert scale. A code sheet was created in the Excel spreadsheet with numeric allocations done using the VLOOKUP function in Excel to reduce the likelihood of error when assigning the numeric values. The numeric codes and identification labels have been placed in Appendix D for reference.

4.9 Analysis Approach

The prepared and coded data within Microsoft Excel formed the basis for analysis. First, descriptive statistics based on the individual's role and demographic responses were calculated and plotted in Microsoft Excel. The data was then exported into IBM's

Statistical Package for Social Sciences (SPSS) software for statistical inferential analysis of the hypotheses.

However, before performing the hypothesis testing, the quality of the constructs and measurements was assessed. Köhler et al. (2017) argued that the quality of measurement is critical and related to how well the chosen measurement approach allows for uncovering the correct information about the topic of interest. To this end and to demonstrate the measurement quality for the study, the validity and reliability of the data in relation to the constructs were assessed. Once these quality criteria were confirmed, an exploratory factor analysis (EFA) was done to reduce the number of variables considered for the statistical analysis by identifying the underlying makeup of the construct items (Hair et al., 2019). Statistical testing of the hypotheses was done thereafter.

The sections to follow describe the steps that were followed for unpacking the descriptive statistics, validity, reliability, factor analysis, and statistical tests for the hypothesis. All results from these tests have been placed in Chapter 5.

4.10 Descriptive Statistics

The control variables in terms of organisational roles and demographic information (chronological age and level of education) were analysed to evaluate the percentage of respondents falling in each category within the dataset. These indicators gave the researcher a sense of the sample composition of the respondents and associated data (Zikmund et al., 2009). All descriptive statistics were presented in bar chart format based on the nominal data collected instead of frequency tables. The charts provided a more straightforward interpretation of the role and demographic information. Missing data and associated patterns are typically described when presenting descriptive statistics (Hair et al., 2019), however, given the format of the online responses and the review of the respondent hard copies before digitising, there was no missing data to report. In addition to descriptive statistics of the control variables, descriptive statistics for the construct items were presented where when presenting the statistical tests related to the defined hypotheses.

4.11 Pre-Testing of Constructs and Measurement Instrument

Pre-testing of the sample data was done to ensure that the validity and reliability of the measurement instrument were achieved prior to performing hypothesis testing. This was done to assess whether the instrument was effective in measuring the constructs considered for this study. In addition, an EFA was done to assess whether the composition of the construct items could be simplified in preparation for the statistical tests used for hypothesis testing. The following sections describe the approach used for the reliability and validity tests, as well as for the EFA.

4.11.1 Validity

Verifying construct validity is an essential step during the evaluation of measures within a test, and researchers employ several methods to assess evidence of validity (Zikmund et al., 2009). Bivariate correlation is a method typically used to determine validity based on the strength of the relationship between each measurement question and the associated construct (Swank & Mullen, 2017). This method was selected based on the insights gained for each question from this process and its relative simplicity. The correlation between each construct item and the total item score was evaluated using SPSS to determine if the associated relationship was statistically significant ($p < 0.05$). The validity of each question was confirmed if this relationship was found to be statistically significant. A Pearson's correlation test was used in SPSS to test these relationships for each of the TRI and TAM constructs based on the interval data collected through the Likert-scale responses.

1.1.1 Reliability

Reliability testing was done using the internal consistency method, which was used to assess the strength of the correlation relationship between all the items making up each construct. The Cronbach's alpha reliability coefficient is the most broadly used measure to assess internal consistency (Hair et al., 2019) and was selected as the method used for this study. The Cronbach's alpha is used to assess the consistency of variance within a survey's item responses and therefore provided an indication of the correlation between the construct item responses (Vaske et al., 2017). When performing this test, the alpha value ranges between 0 and 1, with 0.70 considered as the acceptable lower limit for reliability (Hair et al., 2019). To confirm the internal consistency of this study, a Cronbach's alpha reliability test was done for the TRI and TAM constructs using the scale reliability analysis function within SPSS and an acceptability threshold of 0.7

4.11.2 Exploratory Factor Analysis

Exploratory factor analysis (EFA) is an approach used to reduce the number of measured items into latent variables (Goretzko et al., 2021). An EFA was used to assess the correlation of items within each construct to determine which items could be grouped together into factors so that average item responses could be used to represent each construct. However, the appropriateness of an EFA needed to be tested prior to performing the factor analysis. This was done by performing a Kaiser-Meyer-Olkin (KMO) test and a Bartlett's test for sphericity for each construct using SPSS. The KMO test was used to measure the suitability of the data by assessing whether the sample size is adequate, while the Bartlett's test for sphericity determined if there is a sufficient correlation within the construct items for a factor analysis to be performed (Shrestha, 2021). For the EFA to be suitable, the Bartlett's test for sphericity needed to produce a significant result ($p < 0.05$) (Shrestha, 2021) and the KMO value needed to be greater than 0.5 ($KMO \geq 0.5$) (Chan et al., 2018).

Using the dimension reduction function, an EFA was performed using SPSS once the KMO and Bartlett's acceptance criteria were met. The analysis was run using the Eigenvalue 1 rule to determine the factor grouping for each construct and the percentage variance represented by the factors. The rotated component matrix (Varimax with Kaiser normalisation) was inspected to determine which construct items were grouped within which factor based on the highest component loading.

4.12 Hypothesis Testing

The hypotheses outlined in Section 3.3 were based on the research question and reviewed literature. Testing whether the claimed hypotheses were valid was achieved using an inferential statistical testing procedure based on the sample data gathered (Wegner, 2016). The tests were done using multivariate statistical analysis based on the conceptual model and dataset comprised of three distinct constructs (Zikmund et al., 2009). Table 2 outlines the various hypotheses and accompanying types, whether relational or difference between groups. The type of hypotheses determined which multivariate statistical tests were used. However, certain underlying assumptions about the data needed to be tested to determine what type of statistical tests were appropriate.

Table 2: Hypotheses and related types

No	Hypothesis Description	Hypothesis Type
H_1	TRIM has a positive relationship with PU	Relational
H_2	TRIM has a positive relationship with UI	Relational
H_3	TRII has a negative relationship with PU	Relational
H_4	TRII have a negative relationship with UI	Relational
H_5	PU has a positive relationship with UI	Relational
H_6	There is a significant difference within distinct chronological age groups in terms of UI	Difference between groups
H_7	There is no significant difference within distinct groups of educational levels in terms of UI	Difference between groups
H_8	There is a significant difference within distinct groups of organisational roles in terms of UI	Difference between groups

Source: Generated by the researcher

4.12.1 Testing of Assumptions

Hypotheses and related tests are based on statistical models that are grounded on a set of assumptions, where the extent to which these models match reality is based on the degree to which the assumptions are valid (Amrhein et al., 2019). Two fundamental assumptions influence most multivariate statistical tests: normality (whether the data is normally distributed) and homoscedasticity (Hair et al., 2019). Given that these assumptions directly impacted whether parametric or non-parametric statistical tests were used, the validity of these assumptions was assessed before defining the statistical tests used and performing the hypothesis testing.

4.12.1.1 Test for Normality

Normality is one of the most important and broadly studied topics within statistical probability modelling, however, the reality is that most collected data typically demonstrates some level of asymmetry (González-Estrada et al., 2022). Researchers use a combination of statistical tests and graphical analyses to evaluate whether a dataset is normally distributed, however both these methods should be used concurrently when assessing normality (Hair et al., 2019). Based on this, both statistical testing and graphical analysis were used for this study for normality evaluation with the methods described below.

Skewness and kurtosis are two statistical measures that help researchers identify the shape of the distribution, where skewness is an indicator of the imbalance (biased to the left or right) and kurtosis indicates the nature of the span and weight of the distribution tails (Bono et al., 2019). Therefore, the below expressions were used to calculate the z-values for both skewness and kurtosis with the critical z-value of ±1.96 (0.05 significance level) used as the assessment criteria (Hair et al., 2019):

$$z_{kurtosis} = \frac{kurtosis\ statistic}{standard\ error}$$

$$z_{skewness} = \frac{skewness\ statistic}{standard\ error}$$

Source: Hair et al. (2019)

Secondary statistical tests for normality include the Kolmogorov-Smirnov and Shapiro-Wilk tests. These tests evaluate the differences from normality based on a calculated level of significance, but these tests have limitations related to sample size (Hair et al., 2019). The Shapiro-Wilk test, the most recognized statistical normality test, is typically limited to samples smaller than 50 (Yap & Sim, 2011), while the Kolmogorov-Smirnov and Shapiro-Wilk tests are sensitive to samples exceeding 1000. Therefore, based on the sample size to be discussed in Section 5.2, the Kolmogorov-Smirnov level of significance was used for the study as one of the indicators for normality combined with graphical analysis. The criteria used for normality was a level of significance greater than 0.05 ($p \geq 0.05$) (Corder & Foreman, 2009).

The normal probability plot is the simplest and most reliable graphical method used to assess normality, which compares the cumulative distribution of sample data to that of the expected normal distribution (Hair et al., 2019). The expected normal is a straight line that runs diagonally on a positive and straight slope and the sample data is plotted for comparison against the expected normal line. For the condition of normality, the plotted sample data typically tracks closely to the expected normal (Hair et al., 2019). The quantile-quantile (Q-Q) plot is typically used by analysts to assess normality (Yap & Sim, 2011) and was therefore used for this study.

4.12.1.2 Test for Homoscedasticity

The assumption of homoscedasticity implies that the dependent variable demonstrates variances that are equal across the continuum of the independent variables (Hair et al., 2019). More simply, homoscedasticity implies that the variances between the variables are approximately equivalent and therefore the statistical prediction is equally applicable for the entire data spectrum (Zikmund et al., 2009). As with normality testing, homoscedasticity can be assessed through both graphical and statistical methods. However, Hair et al. (2019) proposed that quantitative variables' homoscedasticity is best examined through a graphical assessment. Based on this, a scatter plot comparing the standardized residuals against predicted values was generated within SPSS to test homoscedasticity. The plot was assessed in terms of the degree of randomness of scatter which was used as an indicator for homoscedasticity.

4.12.2 Statistical Tests for Hypothesis Testing

After completing the tests for assumptions following the above procedures, it was found that the sample violated the tests for normality and homoscedasticity. Several data transformations proposed by Hair et al. (2019) to achieve normality and homoscedasticity were attempted, which included inversion, square roots, logarithmic transformations, and exponential transformations. However, the sample data continued to fail the tests for normality and homoscedasticity.

As a result, non-parametric statistical analyses were used as the hypotheses testing approach since these tests are used for samples that do not follow a normal distribution (Zikmund et al., 2009). Non-parametric methods are referred to as being “distribution-free” as the tests do not make any assumptions about the nature of the sample distribution (Zikmund et al., 2009). In addition, non-parametric tests reduce the effect of outliers within the sample data (Hair et al., 2019). The Kendell's tau correlation, Mann-Whitney, and Kruskal-Wallis tests were chosen as non-parametric alternatives to multiple linear regression, independent samples t-test, and one-way ANOVA respectively. The Kendell's tau correlation method was chosen for the study due to limitations within SPSS to process non-parametric regression analyses. Statistical conclusions were based on a 5% level of significance based on the p-value within SPSS (equivalent to the Sig value presented in SPSS). A brief overview of each of these methods and their application to the study is discussed in the following sections.

4.12.2.1 Kendell's Tau Correlation Test

The Kendell's tau (τ) is like other correlation tests (such as Pearson's) where the tau value (the correlation coefficient) provides an indication of agreement between two variables and is constrained between +1 and -1 (Brossart et al., 2018). If the correlation coefficient equals 1, then the variables under consideration are ordered in precisely the same way (positive relationship), while a value of -1 implies that the variables are ordered in precisely the opposite way (negative relationship). If the τ value is equal to 0, then it indicates that there is no relationship concerning the variables (indicates independence between the variables). Table 3 was used to assess the strength of the positive or negative relationship based on the calculated τ value. A correlation was deemed significant if the associated p-value was less than 0.05 ($p < 0.05$).

Table 3: Interpretation of the correlation coefficient values

Correlation Coefficient Value	Strength of the Relationship
$\lvert\tau\rvert = 0$	None
$0.00 < \lvert\tau\rvert < 0.09$	Trivial
$0.10 < \lvert\tau\rvert < 0.30$	Weak
$0.31 < \lvert\tau\rvert < 0.50$	Moderate
$0.51 < \lvert\tau\rvert < 0.99$	Strong
$\lvert\tau\rvert = 1$	Perfect

Source: Adapted from Corder and Foreman (2009)

4.12.2.2 Mann-Whitney and Kruskal-Wallis Tests

The Mann-Whitney test is used to assess whether the difference between the means of two groups are statistically significant and is a non-parametric alternative to the independent samples t-test (Emura & Hsu, 2020). The Kruskal-Wallis test is an extended version of the Mann-Whitney test that is used for comparing the differences between group sets larger than two and is a non-parametric alternative to the one-way ANOVA (Dancey & Reidy, 2017). Both these tests do not make any assumptions about the characteristics of the sample data distribution, and they do not require equal sample sizes for the groups under consideration (Dancey & Reidy, 2017). These tests were run in SPSS for the hypothesis testing with the criteria used for determining significance being a p-value less than 0.05 ($p < 0.05$), which translated to there being a significant difference between the groups for the variables under consideration (Corder & Foreman, 2009).

4.13 Research Methodology Limitations

Research studies have certain limitations associated with them due to the nature of the research process (Saunders & Lewis, 2018). The below limitations were identified for this study:

1. The results from the hypothesis and associated statistical tests were limited by the cross-sectional time horizon of the study.
2. Establishing any form of causality was limited based on the study's cross-sectional nature. A longitudinal approach would allow for any variations within the data and associated patterns to be investigated more effectively to assess any potential forms of causality.
3. As will be discussed further in Section 5, the study did not receive an equal number of respondents for each of the three categories of control variables. The results relating to the descriptive statistics could therefore be biased toward the category with a higher number of respondents.
4. The snowballing sampling method could have produced sample data concentrated within groups of individuals with common characteristics. This could have led to a certain amount of similarity within the results.

5. The results from the tests for differences (chronological age, education levels, and organisational role) were limited to the categories of the individuals and therefore are not applicable outside of those categories.
6. Measures were taken to ensure that each respondent completed one questionnaire, however, this could not be guaranteed, and any instances may have skewed the results.

4.14 Conclusion

This chapter outlines the choice of research design, methodological approach, and analysis techniques adopted by the researcher for this study. The philosophy and approach adopted by the researcher were positivist and deductive respectively, with the methodological choice being mono-method quantitative. Primary data was collected from individuals who work within the operational environment of South African mining companies through a survey as the measurement instrument over a cross-sectional time horizon. The researcher distributed the surveys using a non-probability snowballing sampling method, from which data was cleaned and coded in Microsoft Excel. Validity and reliability verification methods were described to assess the efficacy of the measurement instrument, with the EFA used as the dimension reduction technique. An overview of the normality and homoscedasticity tests were presented, followed by a description of the non-parametric statistical methods used for hypothesis testing. This chapter concludes with a description of the limitations associated with the research methodology adopted. The results based on the analyses performed are presented in the following chapter.

5 Chapter 5: Research Results

5.1 Introduction

This chapter summarises the results associated with the sample data collected and the data analysis processes. An outline of the number of valid responses is presented first, followed by the descriptive statistics of the demographic data associated with the valid responses. The results of the validity, reliability, and EFA are then presented, followed by the results for the tests for normality and homoscedasticity. This chapter concludes with the results from the hypothesis tests conducted based on those defined in Chapter 3. The main results are summarised within the main body of this chapter, with supporting outputs placed in the Appendices for reference.

5.2 Research Sample Data

A total of 181 questionnaires were collected during the data collection phase comprising of 146 completed online through Google Forms and 35 hard copies. A total of 14 online entries and five hard copies made up those as part of the pilot study. Seven entries were further discarded based on respondents not meeting the population criteria of working with or for the operational section of a mining company. Five hard copies were discarded as they were found to be partially completed. Therefore, a total of 150 valid questionnaire responses made up the analysed sample size and were imported into Microsoft Excel for coding and preparation for export to SPSS as summarised in Table 4 below.

Table 4: Summary of sample data collected

Description	Value
Total number of questionnaires collected	181
Google Forms entries discarded by pilot study respondents	-14
Hard copies discarded by pilot study respondents	-5
Google Forms entries discarded based on the population criteria	-7
Hard copies discarded as being incomplete	-5
Total number of completed and valid questionnaires	**150**

Source: Generated by the researcher

5.3 Descriptive Statistics of Role and Demographics

There were three demographic-related questions within the questionnaire aimed at segmenting the respondents according to the control variables of the conceptual model. These questions related to the respondent's organisational role relating to technology adoption (user, manager, or decision maker), chronological age, and the highest level of education achieved.

Figure 12 below summarises responses relating to the individual's organisational role. From the 150 respondents, 42.7% indicated they are currently in a position where they expect to use new technologies, 40.7% responded that they would manage people using new technology, and 16.7% reflected that they were in a decision-making position regarding new technology implementation.

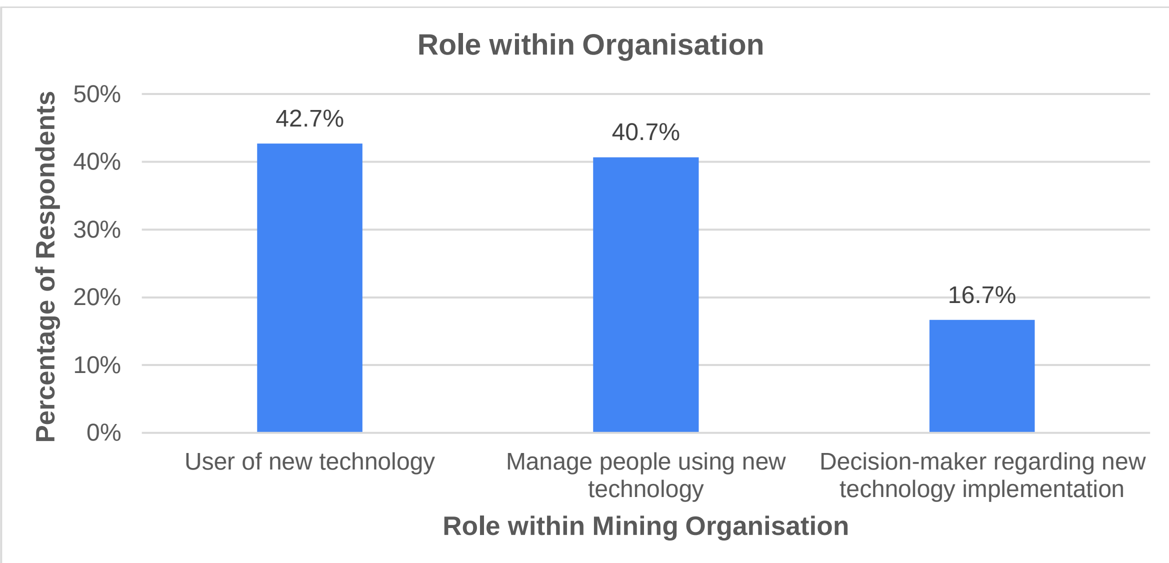

Figure 12: Distribution of organisational role within the sample data

Source: Generated by the researcher

In terms of chronological age, as summarised in Figure 13, none of the respondents were younger than 20 years with most of the respondents falling in the 30-39 years old bracket. Of the respondents above 20 years old, 12% fell within 20-29 years, 51% within 30-39 years, 28% within 40-49 years, 8% within 50-59 years, and 1% over the age of 60 years.

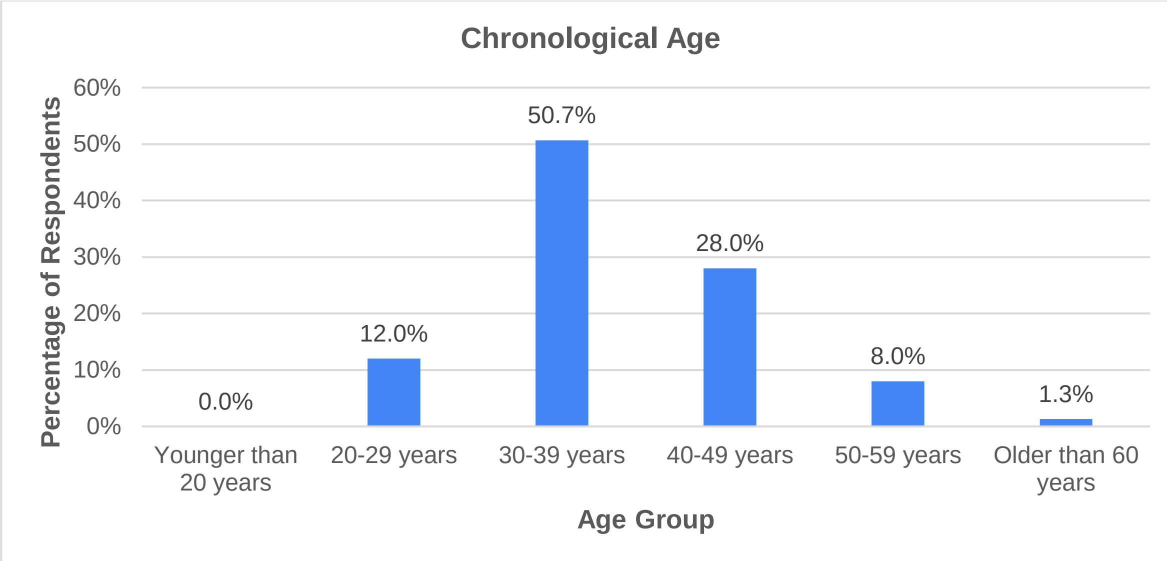

Figure 13: Distribution of chronological age within the sample data

Source: Generated by the researcher

Figure 14 provides a summary of the highest level of education of the individuals within the sample data. Of the three categories (primary schooling, high schooling, and university), no responses indicated primary schooling as the highest education level, with 32% achieving a high school qualification and 68% achieving a university or tertiary education.

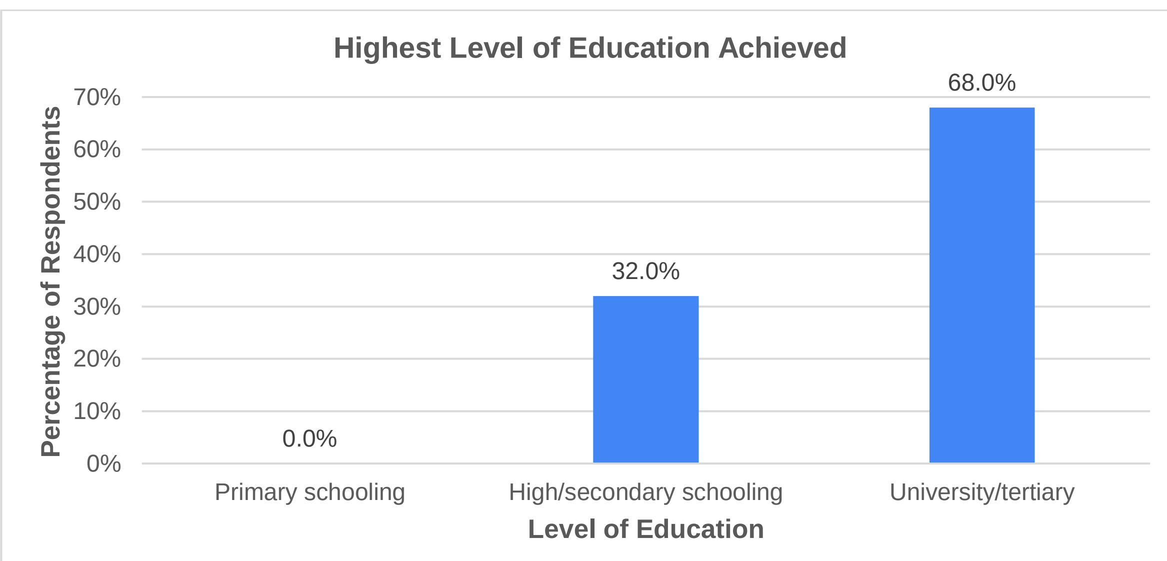

Figure 14: Distribution of highest education level within the sample data

Source: Generated by the researcher

5.4 Validity, Reliability, and Factor Analysis

After producing the descriptive statistics for the 150 valid responses as presented above, an analysis of the reliability, validity, and an EFA was done on the constructs within the conceptual model before performing the inferential statistical analysis related to the hypotheses. This was done to ensure that the construct items used to process the inferential statistics produced meaningful results. These tests were done on a total of 25 items encompassed within the four constructs.

5.4.1 Validity Test Results

The validity of the survey items and associated constructs was assessed by means of analysing the bivariate correlation (Pearson's correlation) between each construct's question and the item's item-total score. All items for each construct were found to have a significant correlation ($p < 0.05$) as shown within the results in Table 5 with the complete SPSS outputs placed within Appendix E. It should be noted that the TRI motivator and inhibitor constructs comprised eight items, while the PU and UI constructs comprised five and four items respectively. Therefore, the blank entries in the below table indicate no corresponding items for the TAM constructs. It was determined that all constructs were valid based on the significant correlations in Table 5 between each construct item and the total item score. Therefore, all construct items were found to meet the requirements for validity and were retained for reliability testing.

Table 5: Correlation results for construct question validity

Correlations					
		TRIM Total	TRII Total	PU Total	UI Total
Construct Item 1	Pearson Correlation	0.515**	0.448**	0.870**	0.927**
	p-value (2-tailed)	<0.001	<0.001	<0.001	<0.001
	N	150	150	150	150
Construct Item 2	Pearson Correlation	0.741**	0.697**	0.905**	0.951**
	p-value (2-tailed)	<0.001	<0.001	<0.001	<0.001
	N	150	150	150	150
Construct Item 3	Pearson Correlation	0.676**	0.606**	0.898**	0.933**
	p-value (2-tailed)	<0.001	<0.001	<0.001	<0.001
	N	150	150	150	150
	Pearson Correlation	0.733**	0.598**	0.902**	0.908**

Correlations		TRIM Total	TRII Total	PU Total	UI Total
Construct Item 4	p-value (2-tailed)	<0.001	<0.001	<0.001	<0.001
	N	150	150	150	150
Construct Item 5	Pearson Correlation	0.672**	0.553**	0.918**	-
	p-value (2-tailed)	<0.001	<0.001	<0.001	-
	N	150	150	150	-
Construct Item 6	Pearson Correlation	0.591**	0.666**	-	-
	p-value (2-tailed)	<0.001	<0.001	-	-
	N	150	150	-	-
Construct Item 7	Pearson Correlation	0.499**	0.594**	-	-
	p-value (2-tailed)	<0.001	<0.001	-	-
	N	150	150	-	-
Construct Item 8	Pearson Correlation	0.753**	0.589**	-	-
	p-value (2-tailed)	<0.001	<0.001	-	-
	N	150	150	-	-

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Source: Generated by the researcher based on an SPSS output

5.4.2 Reliability Test Results

An analysis of each construct's internal consistency was done by calculating their respective Cronbach's Alpha value to evaluate the scale reliability of the construct questions. The results presented in Table 6 show that the Cronbach's Alpha results for all the constructs are greater than the 0.7 acceptability threshold. Therefore, all scale items were considered for subsequent analyses. A complete set of reliability statistics outputs from SPSS can be found in Appendix F for reference.

Table 6: Cronbach's Alpha results indicating internal consistency reliability

Reliability Statistics	No of Items Prior to Cronbach's Alpha Test	Cronbach's Alpha	No of Items After Cronbach's Alpha Test
TRIM	8	0.79	8
TRII	8	0.74	8
PU	5	0.94	5
UI	4	0.95	4

Source: Generated by the researcher based on an SPSS output

5.4.3 Exploratory Factor Analysis Results

An EFA was done on each construct and associated questions to reduce the total number of variables to a smaller set for the inferential statistical analyses. The EFA results showed that construct questions produced at least one correlation coefficient above 0.3 (correlation results have been placed in Appendix G). Kaiser-Meyer-Olkin (KMO) values were then considered to determine if a factor analysis would be appropriate, followed by the Bartlett's test of sphericity to confirm if the variable reduction was meaningful. Kaiser-Meyer-Olkin (KMO) values were above 0.5 and there was a significant result for Bartlett's test of sphericity ($p < 0.05$) for all constructs as shown in Table 7 below. These results confirmed that factor analysis was suitable for the TRI and TAM constructs and their related items.

Table 7: Results for KMO and Bartlett's test for sphericity

Factor Analysis		
	KMO	Bartlett's Test of Sphericity p-value
TRIM	0.82	<0.001
TRII	0.79	<0.001
PU	0.81	<0.001
UI	0.87	<0.001

Source: Generated by the researcher based on an SPSS output

Once the appropriateness of the EFA was confirmed, the total variance and rotated matrix outputs from SPSS were considered to determine if the construct data could be reduced to related components. Based on the Eigenvalue one rule, it was found that the TRIM and TRII constructs could be reduced to two components, while the TAM constructs of PU and UI were both grouped within one component. For the TRIM and TRII constructs, the two components represented 60.1% and of the variance and 50.5% of the Eigenvalue variance respectively. The loading of the questions for each component of the TRI questions are presented in Table 8.

Table 8: Rotated component matrices for TRI motivators and inhibitors

Rotated Component Matrix[a]					
	Component			Component	
	1	2		1	2
TRIM1	**0.65**	-0.05	TRII3	**0.57**	0.25
TRIM2	**0.83**	0.24	TRII5	**0.53**	0.21
TRIM3	**0.77**	0.19	TRII6	**0.76**	0.12
TRIM4	**0.75**	0.30	TRII7	**0.79**	-0.08
TRIM5	0.33	**0.65**	TRII8	**0.54**	0.24
TRIM6	0.11	**0.73**	TRII1	-0.07	**0.80**
TRIM7	-0.05	**0.76**	TRII2	0.39	**0.70**
TRIM8	0.34	**0.76**	TRII4	0.27	**0.65**

Extraction Method: Principal Component Analysis
Rotation Method: Varimax with Kaizer Normalization. [a]
a. Rotation converged in 3 iterations

Source: Generated by the researcher based on an SPSS output

Based on the above results for the EFA, the TRI meta-constructs were subdivided into the components of optimism (component 1) and innovation (component 2) for TRI motivators, while the TRI inhibitors were subdivided into discomfort (component 1) and insecurity (component 2). The item labels for the TRI items were updated to assign new labels per component (OPT for optimism, INO for innovation, INS for insecurity, and DIS for discomfort). The post-EFA construct item labels can be found in Table 9.

Table 9: Revised labels and construct items based on EFA

Construct	New Label	Items
TRIM	OPT	TRIM1 - TRIM4
	INO	TRIM5 – TRIM8
TRII	DIS	TRII1 - TRII2, TRII4
	INS	TRII3, TRII5 – TRII8
PU	PU	PU1 – PU5
UI	UI	UI1 – UI4

Source: Generated by the researcher

It should be noted that the naming convention of these components were aligned to those proposed for the original TRI model by Parasuraman and Colby (2015); however, the items within each component differed from the original model and were allocated based on the EFA. The revised and expanded conceptual model based on the results of the EFA is presented in Figure 15. As can be seen in the figure, the hypotheses relating to the TRI motivators and inhibitors were deconstructed based on the EFA results so that hypothesis testing could be done at the component or sub-construct level (sub-hypotheses were integrated as denoted by an “a” or “b” in subscript). The item scores for each of the constructs were calculated by taking the item average score per respondent and were subsequently used for normality, homoscedasticity, and hypothesis testing.

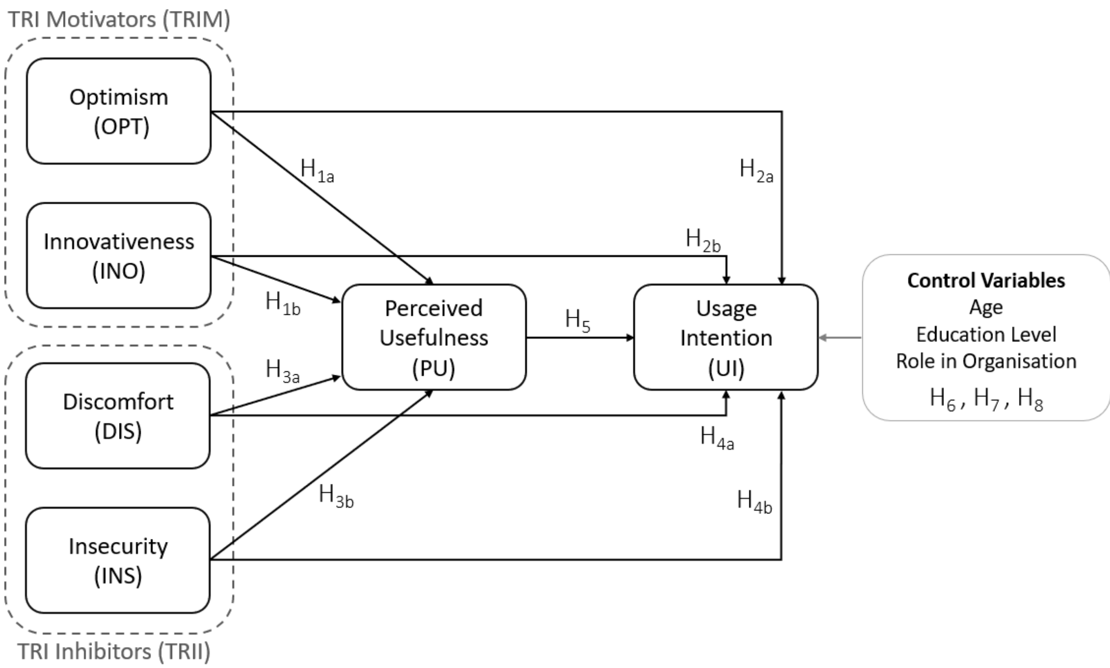

Figure 15: Revised conceptual model with sub-constructs based on the EFA

Source: Generated by the researcher

5.5 Statistical Assumptions Test Results

The statistical tests used for the hypothesis testing were tested for normality and homoscedasticity prior to performing the statistical tests. The results for these pre-tests are presented followed by the results for hypothesis tests.

5.5.1 Results for Normality Test

The normality of the sample distribution was assessed through SPSS by calculating the z-values for skewness and kurtosis, the Kolmogorov-Smirnov test for normality, and by analysing the Q-Q plots.

Table 10 presents the results for the skewness and kurtosis z-values, where the cells highlighted in green represent those constructs where the z-values met the normality criteria. The results showed that only PU satisfied both the skewness and kurtosis condition for normality (z-value within ±1.96), with UI satisfying the kurtosis condition. These results indicate that most of the constructs were not normally distributed. The Kolmogorov-Smirnov test was used as a secondary statistic to verify these results (based on the 150 valid responses).

Table 10: Results for skewness and kurtosis z-values

Descriptive Statistics									
Construct	N	Mean	Std. Deviation	Skewness			Kurtosis		
				Statistic	Std. Error	z-skewness	Statistic	Std. Error	z-kurtosis
OPT	150	4.11	0.84	-1.19	0.20	-5.99	1.55	0.39	3.93
INO	150	3.64	0.78	-1.82	0.20	-9.17	4.09	0.39	10.39
DIS	150	2.72	0.87	-1.41	0.20	-7.13	2.33	0.39	5.93
INS	150	3.21	0.79	-0.77	0.20	-3.86	0.86	0.39	2.18
PU	150	4.21	0.84	0.02	0.20	0.12	-0.63	0.39	-1.59
UI	150	4.39	0.82	-0.39	0.20	-1.99	-0.40	0.39	-1.02

Source: Generated by the researcher based on SPSS output

The results for the Kolmogorov-Smirnov and Shapiro-Wilk normality tests are presented in Table 10, with the Shapiro-Wilk test results included as a comparative check. As can be seen in the table, all the constructs produced p-values of less than 0.05 ($p \leq 0.05$), which indicated that none portrayed the characteristics of normality according to these statistical tests.

The final method of assessing normality was by inspecting Q-Q plots generated for the constructs. As discussed in Section 4.12.1.1, these plots represent the expected normal on the Y-axis (solid diagonal line) and the actual observed values on the X-axis (scattered points). As can be seen in Figure 16 and Figure 18, the scatter points for PU, UI, OPT, and INO displayed significant deviations from the expected normal line toward the lower end of the spectrum (regions highlighted in red). However, the plots for INS and DIS (Figure 17) displayed a scatter that was within close proximity of the normal line and, therefore, were approximated as being normal based on the Q-Q plots.

Table 11: Kolmogorov-Smirnov and Shapiro-Wilk normality test results

Tests of Normality						
Construct	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	p-value	Statistic	df	p-value
OPT	0.17	150.00	0.00	0.86	150.00	0.00
INO	0.12	150.00	0.00	0.95	150.00	0.00
DIS	0.13	150.00	0.00	0.97	150.00	0.00
INS	0.12	150.00	0.00	0.97	150.00	0.01
PU	0.18	150.00	0.00	0.85	150.00	0.00
UI	0.24	150.00	0.00	0.75	150.00	0.00

Source: Generated by the researcher based on SPSS output

Normal Q-Q Plot of OPT

Normal Q-Q Plot of INO

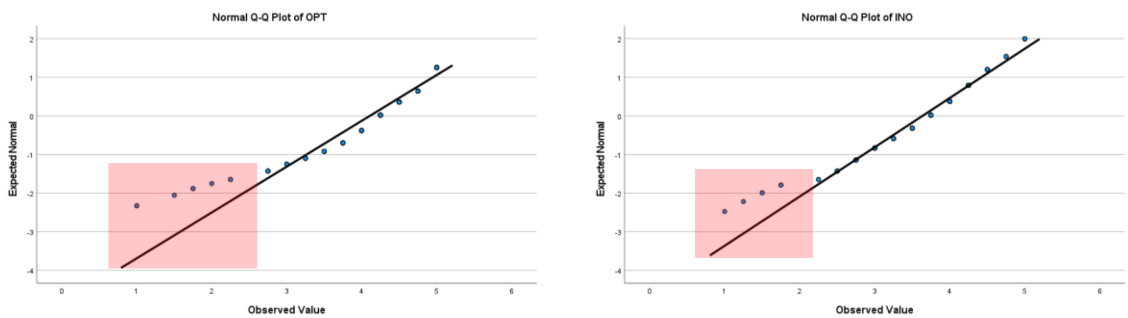

Figure 16: Normal Q-Q plots for OPT and INO

Source: SPSS output

Normal Q-Q Plot of INS

Normal Q-Q Plot of DIS

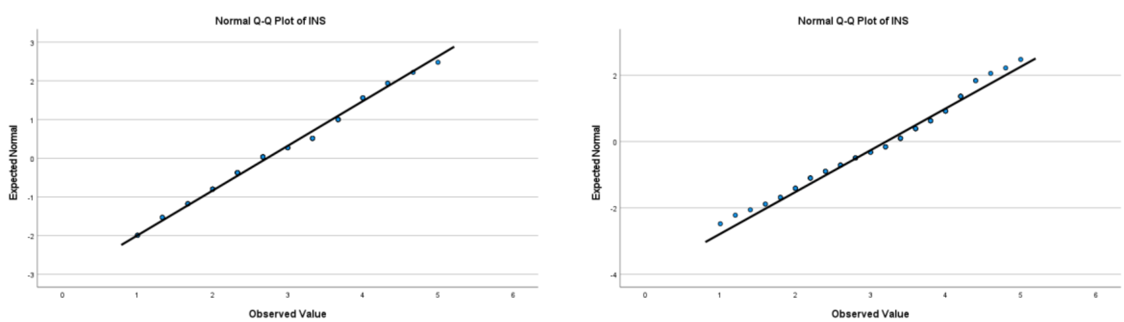

Figure 17: Normal Q-Q plots for INS and DIS

Source: SPSS output

Normal Q-Q Plot of PU Normal Q-Q Plot of UI

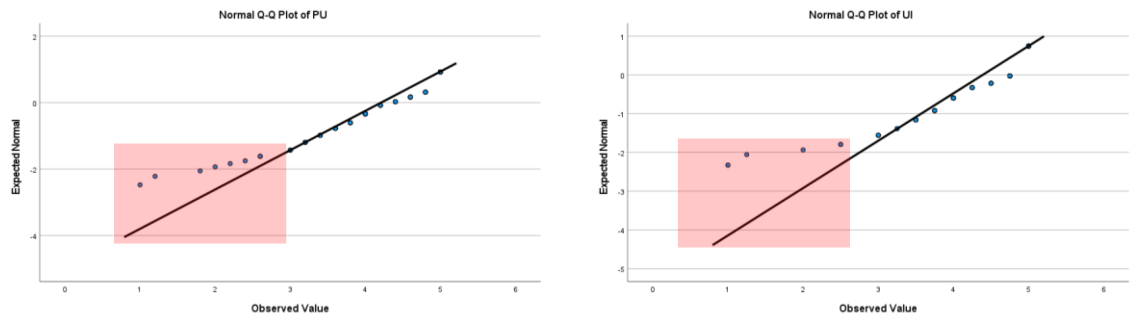

Figure 18: Normal Q-Q plots for PU and UI

Source: SPSS output

The tests for normality produced mixed results. The skewness and kurtosis criteria demonstrated that PU was normally distributed, but this was contradicted by the Kolmogorov-Smirnov and Q-Q plot results. The Q-Q plots for the TRI inhibitor constructs of INS and DIS showed that these constructs could be approximated as being normally distributed, however the skewness, kurtosis, and Kolmogorov-Smirnov results demonstrated non-normality. Based on these constructs only producing one out of three test results that demonstrated normality, and that UI, OPT, and INO not producing any results indicating normality, this assumption was deemed to be violated, and the constructs were treated as having non-normal distributions.

5.5.2 Result for Homoscedasticity Test

As discussed in Section 4.12.1.2, homoscedasticity was assessed by creating a plot of standardized residuals against predicted values using SPSS. This plot is presented in Figure 19 and shows that there were distinct patterns of non-randomness between -2 and +2 and -1 and +1 on the standardised residual and predicted value spectrum respectively (the red highlighted region on the plot). Based on these patterns, it was concluded that the sample data was not homoscedastic in nature, and the condition of homoscedasticity was therefore violated.

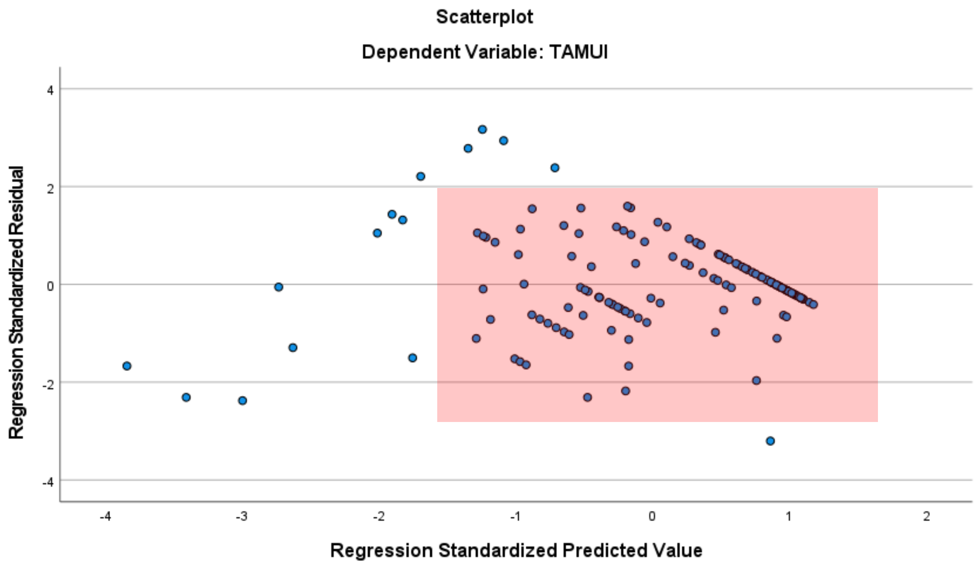

Figure 19: Standardised residual versus predicted values for homoscedasticity test

Source: SPSS output

5.6 Hypotheses Test Results

Non-parametric statistical analyses were used for hypothesis testing, given that the conditions of normality and homoscedasticity were violated. A summary of the hypotheses, the associated type, and the statistical test used is summarised in Table 12, which has been updated to include the components and associated sub-hypotheses based on Figure 15. Therefore, the statistical tests used for hypothesis testing comprised the Kendell's tau correlation test for H1 to H5 (including sub-hypotheses) and the Kruskal-Wallis test for H_6 and H_8. In addition, the Mann-Whitney test was used for H_7 as there were no responses within the sample data that attended primary school as their highest level of education. The results in the following sections encompass a summary of the descriptive statistics related to the construct items followed by the hypothesis testing results.

Table 12: Hypotheses, related types, and statistical tests applied

No	Hypothesis Description	Hypothesis Type	Statistical Test
H_{1a}	The TRIM dimension of OPT has a positive relationship with PU	Relational	Kendall's tau
H_{1b}	The TRIM dimension of INO has a positive relationship with PU	Relational	Kendall's tau
H_{2a}	The TRIM dimension of OPT has a positive relationship with UI	Relational	Kendall's tau

No	Hypothesis Description	Hypothesis Type	Statistical Test
H_{2b}	The TRIM dimension of INO has a positive relationship with UI	Relational	Kendall's tau
H_{3b}	The TRII dimension of DIS has a negative relationship with PU	Relational	Kendall's tau
H_{3a}	The TRII dimension of INS has a negative relationship with PU	Relational	Kendall's tau
H_{4a}	The TRII dimension of DIS has a negative relationship with UI	Relational	Kendall's tau
H_{4b}	The TRII dimension of INS has a negative relationship with UI	Relational	Kendall's tau
H_5	PU has a positive relationship with UI	Relational	Kendall's tau
H_6	There is a significant difference within distinct chronological age groups in terms of UI	Difference between groups	Kruskal-Wallis
H_7	There is no significant difference within distinct groups of educational levels in terms of UI	Difference between groups	Mann-Whitney
H_8	There is a significant difference within distinct groups of organisational roles in terms of UI	Difference between groups	Kruskal-Wallis

Source: Generated by the researcher

5.6.1 Kendell's Tau Correlation Test Results (H_{1a} to H_5)

Table 13 summarises the descriptive statistics for the construct items, with the scatter plots placed in Appendix H for reference. Table 14 provides the descriptive statistics for the scale items for all constructs. Histograms indicating the frequency of scale responses are presented in Figure 20 to Figure 25 for each construct. It was observed that the mean values for the TRI motivators (OPT and INO), PU, and UI were generally higher than that of the TRI inhibitors (DIS and INS). In addition, the standard deviations for all constructs were all within the same range (0.79 – 0.87), indicating a similar degree of variation within the responses.

Table 13: Descriptive statistics for construct items

Descriptive Statistics			
Construct	N	Mean	Std. Deviation
OPT	150	4.11	0.84
INO	150	3.64	0.78
DIS	150	2.72	0.87
INS	150	3.21	0.79
PU	150	4.21	0.84
UI	150	4.39	0.82

Source: Generated by the researcher based on SPSS output

Table 14: Descriptive statistics for scale items for all constructs

Item Label	Item Statement	Mean	Std. Deviation
	Descriptive Statistics		
OPT1	New technologies contribute to a better quality of life	4.14	1.29
OPT2	Technology gives me more freedom of mobility	4.23	0.98
OPT3	Technology gives people more control over their daily lives	4.04	1.07
OPT4	Technology makes me more productive in my personal life	4.03	1.05
INO1	Other people come to me for advice on new technologies	3.63	1.00
INO2	In general, I am among the first in my circle of friends to acquire new technology when it appears	3.23	1.14
INO3	I can usually figure out new high-tech products and services without help from others	3.54	1.07
INO4	I keep up with the latest technological developments in my areas of interest	4.15	0.97
DIS1	When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do	2.51	1.14
DIS2	Technical support lines are not helpful because they do not explain things in terms that I understand	2.76	1.11
DIS3	There is no such thing as a manual for a high-tech product or service that is written in plain language	2.90	1.19
INS1	Sometimes, I think that technology systems are not designed for use by ordinary people	2.98	1.18
INS2	People are too dependent on technology to do things for them	3.46	1.16
INS3	Too much technology distracts people to a point that is harmful	3.10	1.20
INS4	Technology lowers the quality of relationships by reducing personal interaction	3.49	1.20
INS5	I do not feel confident doing business with a service that can only be reached online	3.01	1.25
PU1	I believe using new technology would help me be more productive	4.24	0.95
PU2	I believe using new technology would help me be more effective	4.25	0.96
PU3	Using new technology would be useful in my life	4.30	0.87
PU4	Using new technology would improve my life	4.15	0.95
PU5	Using new technology would enhance my effectiveness in life	4.12	0.96
UI1	There is a high likelihood that I will use new technology within the foreseeable future	4.46	0.83
UI2	I intend to use new technology within the foreseeable future	4.41	0.88
UI3	I will use new technology in the foreseeable future	4.42	0.85
UI4	Using new technology in the foreseeable future is important to me	4.27	0.96

Source: Generated by the researcher based on SPSS output

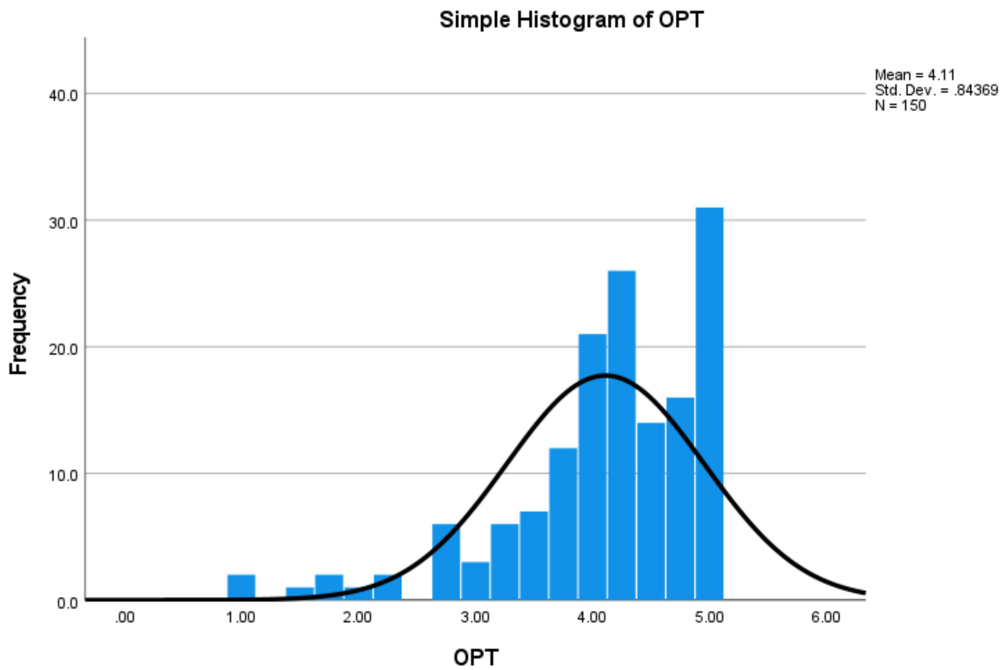

Figure 20: Histogram for OPT showing scale frequencies

Source: SPSS output

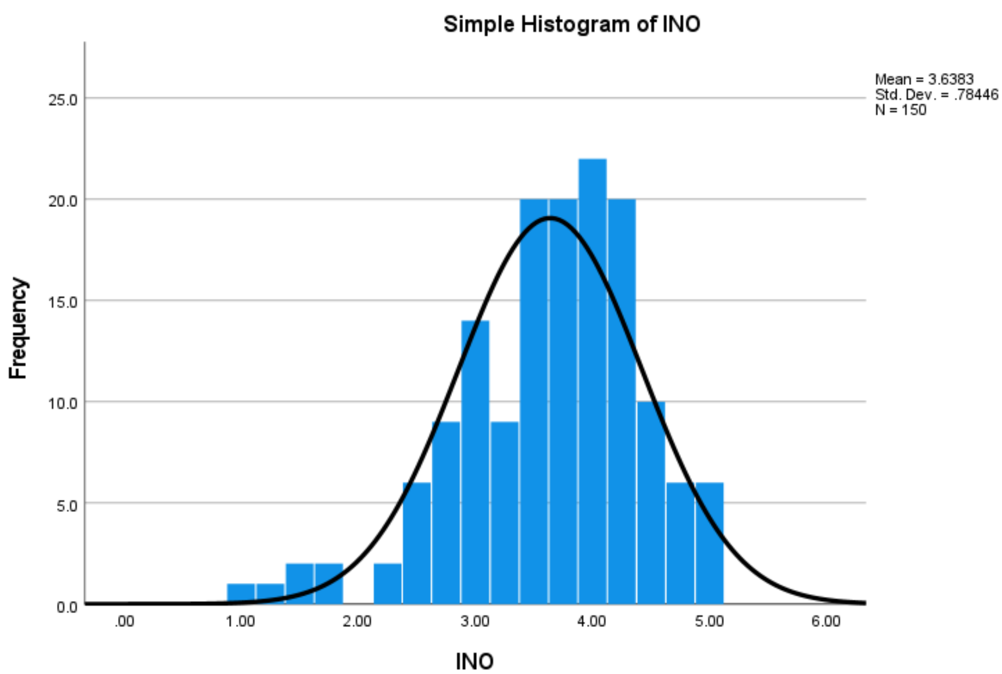

Figure 21: Histogram for INO showing scale frequencies

Source: SPSS output

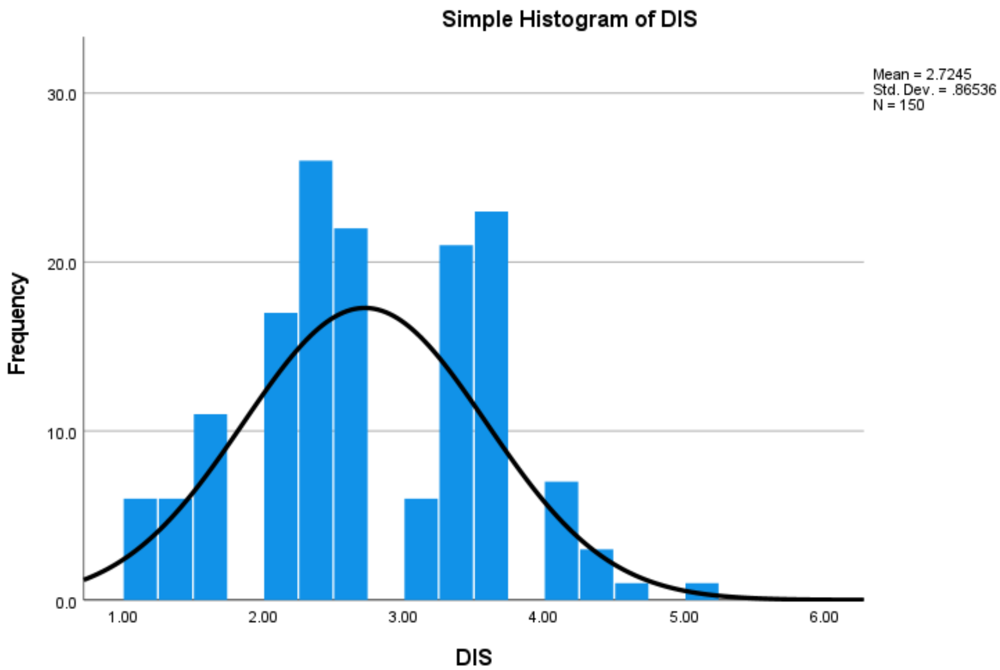

Figure 22: Histogram for DIS showing scale frequencies

Source: SPSS output

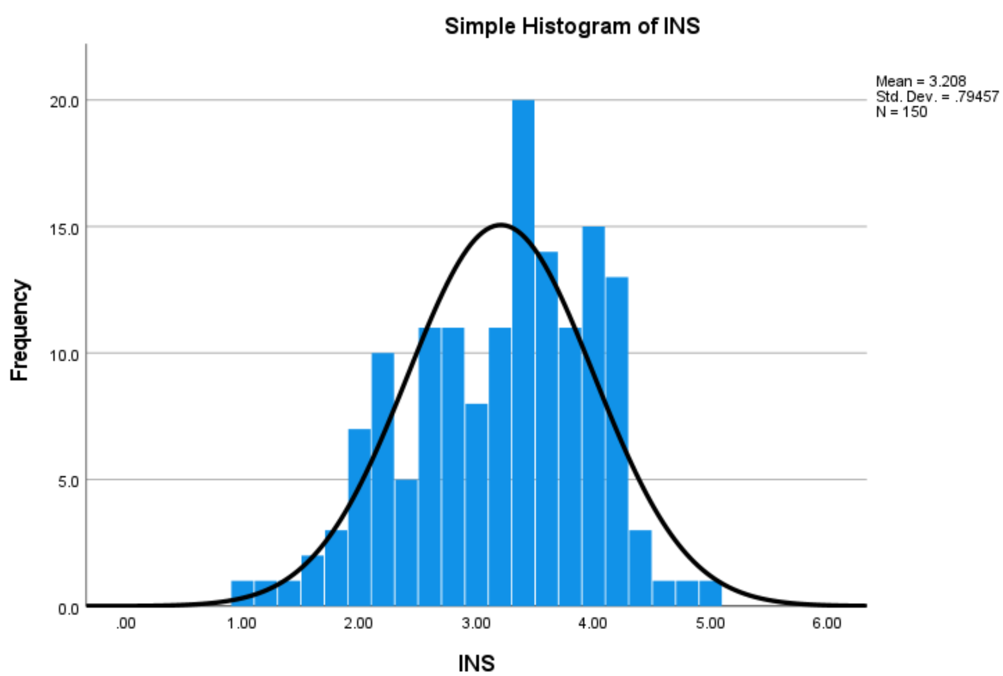

Figure 23: Histogram for INS showing scale frequencies

Source: SPSS output

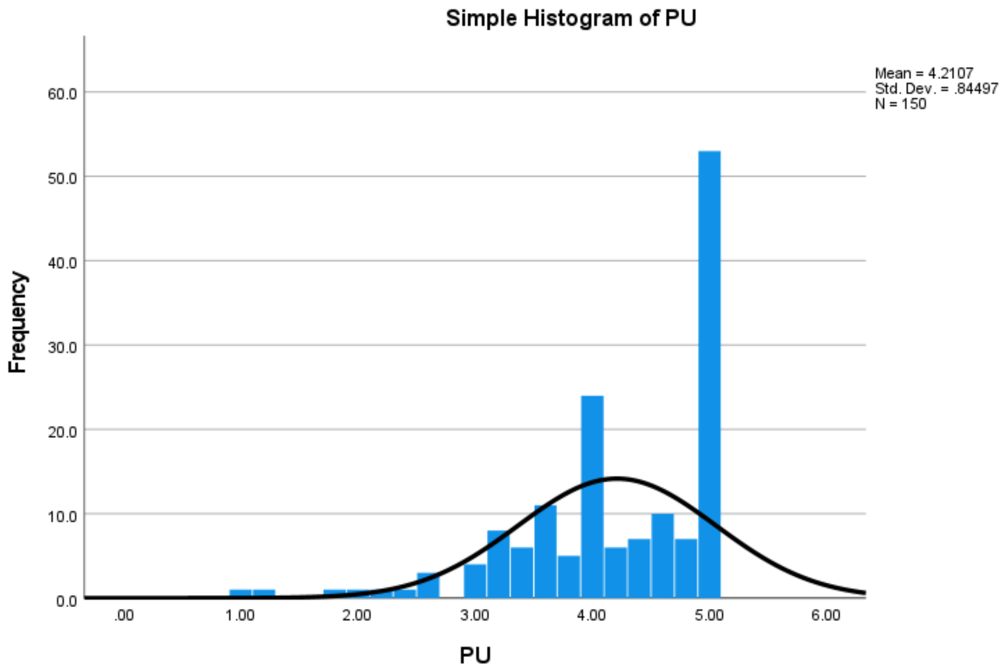

Figure 24: Histogram for PU showing scale frequencies

Source: SPSS output

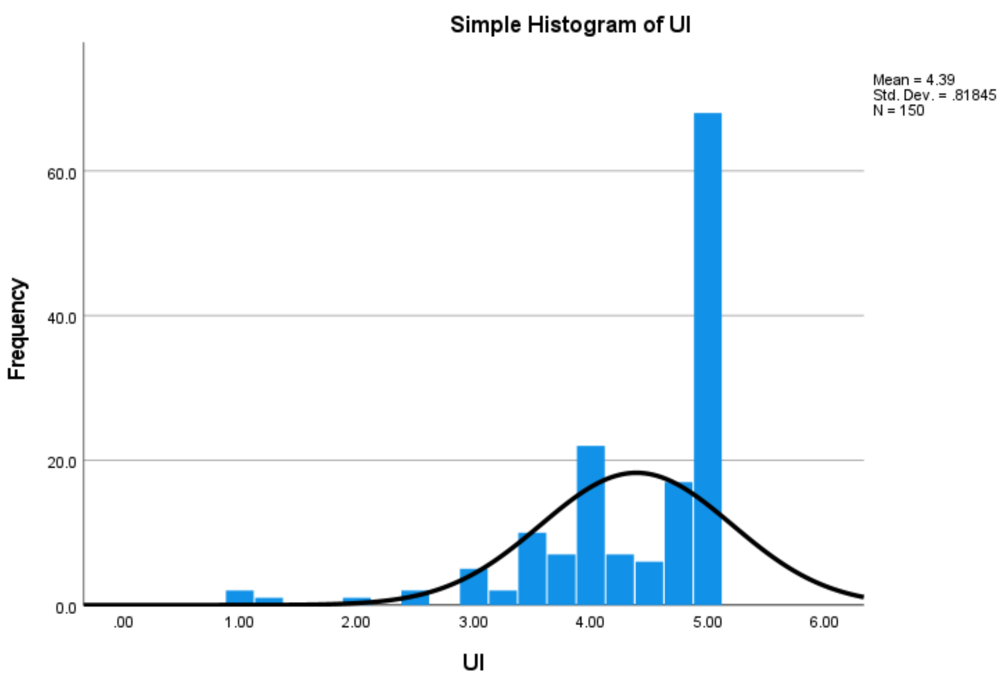

Figure 25: Histogram for UI showing scale frequencies

Source: SPSS output

As discussed within Section 4.12.2, the Kendell's tau was selected as the method for hypothesis testing for H_{1a} to H_5 based on limitations within SPSS concerning non-parametric regression. The Kendell's tau correlation matrix is presented in Table 15 which summarises the correlation coefficients between each of the constructs relating to hypotheses H_{1a} to H_5 with the complete SPSS output placed in Appendix I. Values labelled with a double asterisk indicate those relationships that are significant at the 0.01 confidence level ($p < 0.01$), which implies that the relationships are significant at the 0.05 level ($p < 0.05$). It was found that there are significant relationships between the constructs under consideration for hypotheses H_1 to H_5 (including the sub-hypotheses H_{1a}, H_{1b}, H_{2a}, H_{2b} H_{3a}, H_{3b}, H_{4a}, and H_{4b}). The nature and strength of these significant relationships are presented in Table 16. Relationships were defined as being either positive or negative depending on the sign associated with the correlation coefficient and the strength of the relationship was assigned based on the criteria presented in Table 3 within Section 4.12.2.1.

Table 15: Kendell's tau correlation matrix from SPSS

Non-Parametric Correlation Correlations							
Construct	Measure	OPT	INO	DIS	INS	PU	UI
OPT	**Correlation Coefficient**	1.00	0.22**	-0.07	-0.06	**0.48****	**0.38****
	p-value	-	0.00	0.22	0.30	0.00	0.00
INO	**Correlation Coefficient**	0.22**	1.00	-0.03	-0.07	**0.37****	**0.38****
	p-value	0.00	-	0.65	0.27	0.00	0.00
DIS	**Correlation Coefficient**	-0.07	-0.03	1.00	0.31**	**-0.17****	**-0.20****
	p-value	0.22	0.65	-	0.00	0.01	0.00
INS	**Correlation Coefficient**	-0.06	-0.07	0.31**	1.00	**-0.20****	**-0.18****
	p-value	0.30	0.27	0.00	-	0.00	0.00
PU	**Correlation Coefficient**	**0.48****	**0.37****	**-0.17****	**-0.20****	1.00	**0.68****
	p-value	0.00	0.00	0.01	0.00	-	0.00
UI	**Correlation Coefficient**	**0.37****	**0.38****	**-0.20****	**-0.18****	**0.68****	1.00
	p-value	0.00	0.00	0.00	0.00	0.00	-
**. Correlation is significant at the 0.01 level (2-tailed).							

Source: Generated by the researcher based on SPSS output

Table 16: Correlation strength and relationships for H_{1a} – H_5

No	Hypothesis Description	Correlation Coefficient	Nature and Strength of Relationship
H_{1a}	The TRIM dimension of OPT has a positive relationship with PU	0.48**	Moderate positive
H_{1b}	The TRIM dimension of INO has a positive relationship with PU	0.37**	Moderate positive
H_{2a}	The TRIM dimension of OPT has a positive relationship with UI	0.38**	Moderate positive
H_{2b}	The TRIM dimension of INO has a positive relationship with UI	0.38**	Moderate positive
H_{3a}	The TRII dimension of DIS has a negative relationship with PU	-0.17**	Weak negative
H_{3b}	The TRII dimension of INS has a negative relationship with PU	-0.20**	Weak negative
H_{4a}	The TRII dimension of DIS has a negative relationship with UI	-0.20**	Weak negative
H_{4b}	The TRII dimension of INS has a negative relationship with UI	-0.18**	Weak negative
H_5	PU has a positive relationship with UI	0.68**	Strong positive
** Correlation is significant at the 0.01 level (2-tailed).			

Source: Generated by the researcher

5.6.2 Kruskal-Wallis Test Results (H_6 and H_8)

The Kruskal-Wallis test was used for hypotheses H_6 and H_8 to determine whether there was a significant difference between the groups of chronological age and organisational role in relation to the UI construct. Descriptive statistics and hypothesis test results for chronological age and organisational role are presented in the following sections. It was observed from the analysis that the sample sizes for chronological age and organisational role were different amongst the groups, which was acceptable for the Kruskal-Wallis test as discussed in Section 4.12.2.2.

5.6.2.1 Results for Differences Between Chronological Age (H_6)

The descriptive statistics for chronological age relating to UI are presented in Table 17. The minimum and maximum mean values for UI ranged between 3.94 and 4.63 for the 50-59 year and 20-29 year age groups respectively. The largest variation in UI (standard deviation of 1.01) was observed for the 40-49 year age group, with the lowest variation (standard deviation of 0.64) seen within the 50-59 year group.

Table 17: Descriptive statistics for chronological age in relation to UI

Descriptive Statistics				
Construct	Group	N	Mean	Std. Deviation
UI	20-29 years	18	3.94	0.89
	30-39 years	76	4.45	0.68
	40-49 years	42	4.39	1.01
	50-59 years	12	4.63	0.64
	Older than 60 years	2	4.50	0.71
	Total	150	4.39	0.82

Source: Generated by the researcher based on SPSS output

The test results for differences (H6) are presented in Table 18 with the SPSS output in Appendix J. For the hypothesis test, the null hypotheses were automatically assigned by SPSS, which assumed no significant difference between the groups for each construct. A significance value (p-value) greater than 0.05 ($p \geq 0.05$) confirmed that the null hypothesis was retained. In contrast, a p-value value less than 0.05 ($p < 0.05$) indicated a significant difference resulting in the null hypothesis being rejected. It was observed that there was no significant difference ($p \geq 0.05$) between the chronological age groups in terms of UI. Based on this result, the null hypothesis was retained and pairwise comparisons did not need to be performed to draw comparative differences.

Table 18: Kruskal-Wallis test results for differences in chronological age (H_6)

Independent-Samples Kruskal-Wallis Test Summary: Chronological Age			
No	Null Hypothesis	p-value	Decision
1	The distribution of UI is the same across categories of Age.	0.13	Retain the null hypothesis.
a. The significance level is 0.05 b. Asymptotic significance is displayed.			

Source: Generated by the researcher based on SPSS output

5.6.2.2 Results for Differences Between Organisational Roles (H_8)

Table 19 summarises the descriptive statistics for UI related to the different groups of organisational roles. The mean scores between the different groups were comparable, with the minimum and maximum values for users and managers found to be 4.30 and 4.48 respectively. The variation in scores between users and managers were highly comparable, with decision-makers exhibiting the highest degree of variation based on the standard deviation values.

Table 19: Descriptive statistics for organisational role in relation to UI

Descriptive Statistics				
Construct	Group	N	Mean	Std. Deviation
UI	User	64	4.30	0.75
	Manager	61	4.48	0.77
	Decision-Maker	25	4.42	1.09
	Total	150	4.39	0.82

Source: Generated by the researcher based on SPSS output

Table 20 summarises results for H_8 based on the test for differences between organisational roles in relation to UI with the complete SPSS output placed in Appendix J. The results were presented in the same manner as for chronological age ($p \geq 0.05$ and confirmed that the null hypothesis was retained, while a $p < 0.05$ indicated that there was a significant difference resulting in the null hypothesis being rejected). From the results in Table 20, it was observed that there was no significant difference ($p \geq 0.05$) between the organisational role groups in terms of UI. Based on these results, pairwise comparisons did not need to be performed to draw comparative differences.

Table 20: Kruskal-Wallis test results from SPSS for differences in organisational roles (H_8)

Independent-Samples Kruskal-Wallis Test Summary: Organisational Roles			
No	Null Hypothesis	p-value	Decision
1	The distribution of UI is the same across categories of Role.	0.16	Retain the null hypothesis.
a. The significance level is 0.05 b. Asymptotic significance is displayed.			

Source: Generated by the researcher based on SPSS output

5.6.3 Mann-Whitney Test Results (H_7)

The Mann-Whitney test was used to determine if there was a significant difference between the respondent’s highest level of education achieved in relation to the constructs. This test was selected over the Kruskal-Wallis test as there were no respondents who completed primary schooling as their highest education level, resulting in a comparison between high schooling and university/tertiary (two-group comparison).

The descriptive statistics have been placed in Table 21. As with the Kruskal-Willis tests, the sample sizes for the high school and tertiary/university groups were not equivalent which was acceptable for the Mann-Whitney test as discussed in 4.12.2.2. The mean UI for the university education level group (4.50) was observed to be higher than the high schooling group (4.16), with the high school group presenting a larger variation in results based on a standard deviation of 0.92 compared to the 0.75 for the university group.

Table 21: Descriptive statistics for education levels in relation to UI

Descriptive Statistics				
Construct	Group	N	Mean	Std. Deviation
UI	High/Secondary Schooling	48	4.16	0.92
	University/Tertiary	102	4.50	0.75

Source: Generated by the researcher based on SPSS output

The test results for the construct comparison for the different education level groups is presented in Table 22 below with the results in the same format as the Kruskal-Willis tables ($p \geq 0.05$ confirmed that the null hypothesis was retained, while a $p < 0.05$ indicating that there was a significant difference resulting in the null hypothesis being rejected). It was found that there was a significant difference ($p < 0.05$) between the groups for the UI construct. The SPSS output for this Mann-Whitney test can be found in Appendix J.

Table 22: Mann-Whitney test results from SPSS for education level (H_7)

Independent-Samples Mann-Whitney Test Summary: Education Level			
No	Null Hypothesis	p-value	Decision
1	The distribution of UI is the same across categories of Edu.	0.01	Reject the null hypothesis.
a. The significance level is 0.05			
b. Asymptotic significance is displayed.			

Source: Generated by the researcher based on SPSS output

A comparison between the UI score frequencies and medians are presented in the figures below to provide context to the result presented in Table 22 based on the means and standard deviations in Table 21 being relatively dissimilar.

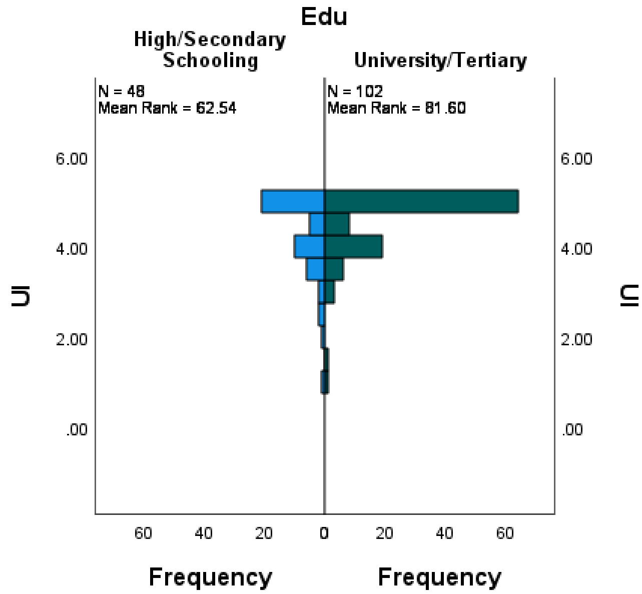

Figure 26: Comparison of the UI score frequencies for the level of education groups.

Source: SPSS output

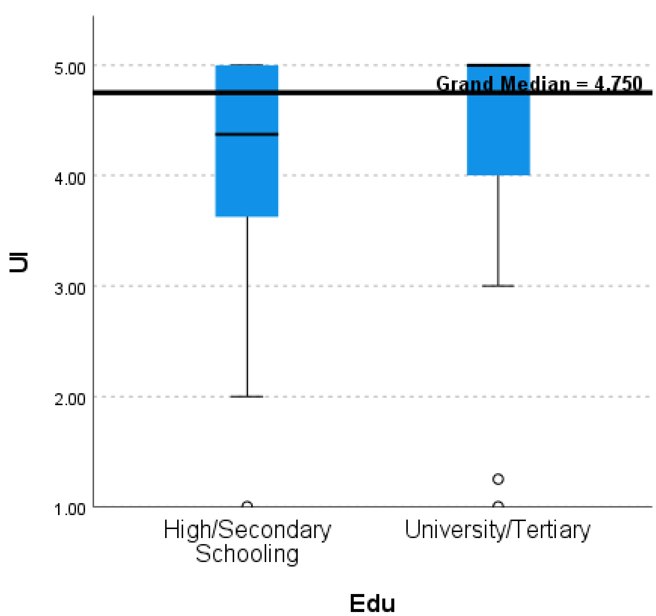

Figure 27: Box and whisker plot of UI relating to different education levels

Source: SPSS output

5.7 Conclusion

This chapter presented a summary of the results of this study. A total of 150 valid responses were collected as part of the data-gathering process. Descriptive statistics associated with the demographic information was presented in graphical format, followed by the results for validity, reliability, and EFA. It was found that the items within the measurement instrument were valid and reliable based on the methods and criteria defined in Chapter 4. The TRIM and TRII constructs were divided into sub-constructs; however, the meta-constructs of PU and UI were retained based on the EFA. It was deduced that the sample data was not normally distributed and violated the criteria for homoscedasticity, resulting in non-parametric statistical methods being used for hypothesis testing. The Kendell’s tau, Kruskal-Wallis, and Mann-Whitney techniques were used for hypothesis testing and the related results were presented. All results were consolidated for presentation and discussion within the following chapter.

6 Chapter Six: Discussion of Results

6.1 Introduction

The results from this study are discussed in this chapter. This chapter begins with a summary of all the results within Chapter 5. Then, a discussion of the validity, reliability, EFA, normality, and homoscedasticity findings are presented. Finally, this chapter concludes with a discussion on the hypothesis tests conducted, where the result of each hypothesis test is presented, compared to existing literature, discussed in terms of implications, and specific conclusions are drawn.

6.2 Summary of Research Results

A summary of the results leading up to the hypothesis testing are presented in Table 23, with a summary of the hypothesis tests presented in Table 24. These tables serve as a reference to the discussion of results covered in the sections to follow.

Table 23: Summary of all data collected and demographics

Section Number	Section and Result Description	Result
5.2	Research Sample Data	A total of 181 respondents comprised of all data collected. The total number of valid responses equated to 150 once the responses relating to the pilot studies, online forms that did not meet the population criteria, and incomplete hard copies were discarded from the sample set.
5.3	Overview of Demographics	**Chronological age: percentage of responses (number of responses)** • 20-29 years:12% (18) • 30-39 years: 50.7% (76) • 40-49 years: 28% (42) • 50-59 years: 8% (12) • Over the age of 60: 1.3% (2) **Level of education: percentage of responses (number of responses)** • Primary schooling: 0% (0) • High schooling: 32% (48) • University/tertiary: 68% (102) **Role within the organisation: percentage of responses (number of responses)**

Section Number	Section and Result Description	Result
		• Users of technology: 42.7% (64) • Managers: 40.7% (61) • Decision makers: 16.7% (25)
5.4.1	Validity	The validity of all survey items and the associated constructs was confirmed through a bivariate correlation test.
5.4.2	Reliability	The internal consistency of the constructs was confirmed through their respective Cronbach's alpha value, which were all above the 0.7 acceptability criteria
5.4.3	Exploratory Factor Analysis (EFA)	The EFA was found to be valid through the KMO value and Bartlett's test of sphericity. The TRIM and TRII constructs were subdivided into two components each, while the PU and UI items were grouped within a single component.
5.5.1	Normality	The normality assessments in terms of skewness, kurtosis, Kolmogorov-Smirnov, and Q-Q plots produced conflicting results. However, based on the assessments, the sample data violated the normality criteria and was therefore deemed to be non-normally distributed. Non-parametric statistical methods were therefore used for hypothesis testing.
5.5.2	Homoscedasticity	The standardised residual versus predicted value plot found that the sample data was non-homoscedastic. Non-parametric statistical methods were therefore used for hypothesis testing.

Source: Generated by the researcher

Table 24: Summary of hypothesis test results and outcomes

No	Hypothesis Description	Test Result	Outcome
H_{1a}	The TRIM dimension of OPT has a positive relationship with PU	Significant, moderate positive relationship	Supported
H_{1b}	The TRIM dimension of INO has a positive relationship with PU	Significant, moderate positive relationship	Supported
H_{2a}	The TRIM dimension of OPT has a positive relationship with UI	Significant, moderate positive relationship	Supported
H_{2b}	The TRIM dimension of INO has a positive relationship with UI	Significant, moderate positive relationship	Supported
H_{3a}	The TRII dimension of DIS has a negative relationship with PU	Significant, weak negative relationship	Supported
H_{3b}	The TRII dimension of INS has a negative relationship with PU	Significant, weak negative relationship	Supported
H_{4a}	The TRII dimension of DIS has a negative relationship with UI	Significant, weak negative relationship	Supported

No	Hypothesis Description	Test Result	Outcome
H_{4b}	The TRII dimension of INS has a negative relationship with UI	Significant, weak negative relationship	Supported
H_5	PU has a positive relationship with UI	Significant, strong positive relationship	Supported
H_6	There is a significant difference within distinct chronological age groups in terms of UI	No significant difference was observed	Not Supported
H_7	There is no significant difference within distinct groups of educational levels in terms of UI	A significant difference was observed	Not Supported
H_8	There is a significant difference within distinct groups of organisational roles in terms of UI	No significant difference was observed	Not Supported

Source: Generated by the researcher

6.3 Data Collected and Demographics

Of the 150 valid responses, only 9.3% were accounted for by respondents over the age of 50 years. Therefore, over 90% of the respondents fell within the chronological age group of 20-49 years, with more than 50% within 30-39 years. The data collected was therefore seen to be skewed towards younger employees. The high number of responses within the 30-39 year segment was attributed to the researcher and associated personal networks in the mining industry falling within the same age range. All respondents either completed high schooling or tertiary education as their high level of education completed, with a 32% and 68% response rate respectively. These results inferred that the sample population primarily consisted of respondents within the 30-39 year age group and had a tertiary-level qualification.

The sample data contained an insightful mix of respondents in terms of organisational roles. Of the 150 valid responses, most of the respondents fell within the user of technology category, with managers and decision-makers followed in order of the number of responses. This indicated the effectiveness of the snowball sampling method as all the respondents initially contacted via Whatsapp, email, and LinkedIn fell within either the manager or decision-maker categories. The high response by users was a noteworthy statistic given that several of the respondents initially contacted (managers and decision makers) requested a copy of the results from this study. This was interpreted as an indicator of a high degree of curiosity among decision-makers and managers relating to the levels of technology readiness and acceptance among users.

6.4 Statistical Analysis of Constructs and Items

The below sections summarise the results and related outcomes for each of the pre-tests associated with the study's measurement instrument and constructs. The sections also contain the results and outcomes linked to the tests for assumptions for the statistical tests used for hypothesis testing.

6.4.1 Construct Validity

The validity of all construct items was tested using a bivariate correlation method. It was found that all construct items (TRIM, TRII, PU, and UI) had significant and positive correlations with their respective item total scores ($p < 0.05$ as summarised in Table 5). It was concluded that all constructs demonstrated validity, and therefore the construct items were deemed appropriate in terms of measuring the dimensions that they were intended to measure within the study.

6.4.2 Reliability

The reliability of the TRI and TAM constructs were assessed through the Cronbach's alpha test for internal consistency. Per the results in Table 6, it was found that all constructs produced a Cronbach's alpha reliability coefficient value greater than the threshold of 0.7. The correlation between each construct and their respective constituent items was therefore deemed acceptable and each construct's reliability was confirmed.

6.4.3 Exploratory Factor Analysis

All KMO values coupled to the EFA were found to be above the 0.5 threshold as shown in Table 7 for the TRI and TAM constructs. Additionally, the p-values for the Bartlett's test for sphericity were less than 0.05 ($p < 0.05$), producing significant results. The KMO values and significant results for Bartlett's test for sphericity demonstrated that an EFA was suitable. The EFA indicated that the TAM construct items for PU and UI were loaded onto a single component, while the TRI motivators and inhibitors items were both loaded onto two components. Based on this, the TRIM and TRII meta-constructs were divided into sub-constructs comprising of optimism (OPT) and innovativeness (INO) for the TRIM meta-construct, while the TRII was divided into insecurity (INS) and discomfort (DIS).

6.4.4 Normality

The construct's sample distribution was tested by assessing the z-values for skewness and kurtosis, the Kolmogorov-Smirnov normality test, and Q-Q plots. The skewness and kurtosis z-values produced results indicating non-normality for all constructs apart from UI for kurtosis, and PU for skewness and kurtosis. None of the constructs produced Kolmogorov-Smirnov p-values greater than 0.05 ($p < 0.05$), indicating that the sample distribution displayed non-normal characteristics. The results for the Q-Q plots were mixed, with the TRII dimensions of DIS and INS displaying normality characteristics. Based on certain constructs only demonstrating normality within one of the three tests, the sample distribution was treated as being non-normal.

6.4.5 Homoscedasticity

Homoscedasticity was assessed by searching for any indications of trends within the plot of standardized residuals against predicted values based on UI set as the dependent variable. It was found that distinct trends were present within the plot, so the assumption of homoscedasticity was deemed violated.

6.5 Discussion of Hypothesis Test Results

The sections to follow discusses the results associated with the hypotheses tested. Results from each hypothesis test were discussed first, followed by a comparison between the results and

6.5.1 Hypothesis 1: TRI Motivators and PU

H_1 stated that TRIM has a positive relationship with PU. This hypothesis was tested at the sub-construct level on the TRIM dimensions of OPT and INO based on the results of the EFA. The resulting hypotheses at the sub-construct level were:

> **H_{1a}**: The TRIM dimension of OPT has a positive relationship with PU

H_{1b}: The TRIM dimension of INO has a positive relationship with PU

It was found through the Kendell's tau non-parametric correlation that there was a significant, moderate, and positive relationship for both OPT and INO with PU (as indicated within Table 16). The correlation coefficients for OPT and INO concerning UI were comparable with results of 0.48 and 0.37 respectively as shown in Table 15 and Table 16 within Section 5.6.1.

Therefore, the results supported the hypothesis and indicated that TRIM had a positive relationship with PU.

The above results confirmed those of S. A. Rahman et al. (2017), Chiu and Cho (2020), Rejikumar et al. (2020), and Lee et al. (2020) who found that higher scores concerning TRI motivators are robust predictors of PU (although in their study, it was found that there was a strong positive relationship). The result was somewhat dissimilar from that of Chen and Lin (2018) who found that optimism has a positive influence on both PU and PEOU, while innovativeness only influenced PEOU in their study on fitness applications. The results within this study indicated that individuals with a higher inclination towards the TRI motivator dimension are more inclined towards perceiving usefulness in technology. In contrast, those on the lower end of the TRI motivators scale do not see personal advantages resulting in a lower PU.

In addition to the above, the descriptive statistics associated with the correlation test showed that the mean scores for OPT and INO were 4.11 and 3.64, with standard deviations of 0.84 and 0.78 respectively as shown in Table 13. This indicated that the respondents demonstrated a higher inclination towards both OPT and INO with a relatively low variation. This is further illustrated within the histograms in Figure 20 and Figure 21 which illustrates the skewness of data towards the higher scale items for OPT and INO. These results implied that the respondents primarily demonstrated a higher degree of technology readiness in terms of the TRI motivators. Therefore, it was inferred that there was a higher inclination towards PU based on the correlation test result. This inference was supported by the mean for PU (mean of 4.21 as shown in Table 13) and the histogram plot for PU (Figure 24) that shows that the scale frequencies are skewed towards the higher end of the scale.

The result implied that individuals who voluntarily familiarise themselves with the latest technology trends, perceive technology as promoting an enhanced quality of life, and provides a better degree of control, have an associated higher level of technology readiness, and therefore perceive that technology will improve his/her work performance (Parasuraman, 2000). A higher level of technology readiness, therefore, not only signified that they will actively seek out technologies that provide personal benefit (Goebert & Greenhalgh, 2020), but also signified that individuals view technology as having benefits toward achieving competitive advantage for their organisations (Sun et al., 2020).

Within the context of this study, the result was in contradictory to the views of Gruenhagen and Parker (2020) who argued that individuals within the mining industry have a traditionalist culture and are therefore typically resistant to change. While the results of this study may not confirm this conjuncture for the entire mining industry within South Africa, it does provide credibility to the notion. There were pockets of individuals that have a low degree of technology readiness leading to low PU. However, based on the positive correlation and the skewed positive results for the TRI motivators and PU, it was deduced that individuals within the South African mining sector primarily held an optimistic and innovative view of technology resulting in a high degree of PU.

6.5.2 Hypothesis 2: TRI Motivators and UI

H_2 stated that TRIM has a positive relationship with UI. As with $H_{1,}$ this hypothesis was tested at the sub-construct level on the TRIM dimensions of OPT and INO based on the results of the EFA. The resulting hypotheses at the sub-construct level were:

H_{2a}: The TRIM dimension of OPT has a positive relationship with UI

H_{2b}: The TRIM dimension of INO has a positive relationship with UI

It was found through the Kendell's tau non-parametric correlation that there was a significant, moderate, and positive relationship for both OPT and INO with PU as summarised in Table 16. Table 16 also shows that both OPT and INO had a correlation coefficient equivalent to 0.38 concerning UI.

Therefore, the results supported the hypothesis and indicated that TRIM had a positive relationship with UI.

This result confirmed the findings of Lee et al. (2020), Tavera-Mesías et al. (2022), and Chang and Chen (2021), but were partially dissimilar to Flavián et al. (2021) who found that the OPT construct had a positive influence on UI with INO having no effect. The relationship between the TRI motivators and UI was expected given that the TRI motivators demonstrated a significant and positive correlation with PU. As with the results for PU, the mean UI result of 4.39 and standard deviation of 0.82 as summarised in Table 13 demonstrated that the data was skewed towards the higher end of the scale which is clearly evident in the histogram plot in Figure 25. It was inferred that the positive relationship between the TRI motivators and PU (H_1) translated into a positive relationship with UI.

Based on the above, a higher result for the positive dimensions of TRI was linked to individuals' assured propensity toward intention to use technology in the near future, demonstrating that the use of technology was personally important. Therefore, the result from this hypothesis and hypothesis H_1 indicated that individuals who have a positive stance towards technology in terms of optimism and innovativeness showed positivity towards their technological beliefs and therefore UI (Tavera-Mesías et al., 2022). Thus, it was confirmed that those who score high on the TRI motivators scale have a greater inclination toward technology usage. In addition, and per the argument by Blut and Wang (2020), individuals who rank highly in terms of the TRI motivators are expected to have technology usage intentions both personally and within their organisation. Consequently, it was inferred based on the results, that individuals within the South African mining industry who hold a positive view on technology in their personal lives also have this stance concerning their organisational environment.

The supported result for H_2 and the mean values for OPT, INO, and UI were important within the context of this study. While this study considers technology in mining in a generalised sense (i.e., not focusing on a specific type or application of technology), the addition of the TRI dimensions to the TAM provided the advantage of unpacking individuals' personal predispositions and beliefs (Tavera-Mesías et al., 2022). As discussed in Section 2.4.3, Razmak and Bélanger (2018) argued that UI is a significant indicator of actual use and therefore technology adoption. Therefore, it was inferred that individuals primarily held a positive view of the TRI motivators, resulting in a higher inclination towards UI and, consequentially, a higher likelihood of technology adoption and actual use. As with the results from H_1, there were segments of individuals with a lower degree of technology readiness leading to lower UI based on the relationship between the TRI motivators and UI.

6.5.3 Hypothesis 3: TRI Inhibitors and PU

H_3 stated that TRII has a negative relationship with PU. This hypothesis was tested at the sub-construct level on the TRII dimensions of DIS and INS based on the results of the EFA. The resulting hypotheses at the sub-construct level were:

> **H_{3a}**: The TRII dimension of DIS has a negative relationship with PU
> **H_{3b}**: The TRII dimension of INS has a negative relationship with PU

It was found through the Kendell's tau non-parametric correlation that there was a significant, weak, and negative relationship for both DIS and INS with PU as summarised in Table 16. Table 16 also shows that the correlation coefficients for DIS and INS concerning PU were comparable with results of -0.17 and -0.20 respectively.

Therefore, the results supported the hypothesis and indicated that TRII had a negative relationship with PU.

It was found that the individual's feelings of technological fear and doubt were inversely related with PU. This result was expected given the outcomes for H_1 and H_2. While the correlation relationship found was weak, the result of H_3 confirmed the findings of Kim and Chiu (2019), Chang and Chen (2021), and Acheampong et al. (2017). The result conflicted with that of Kamble et al. (2019) (who found no significant relationship between the TRI inhibitors and PU) and partially supported S. A. Rahman et al. (2017) who observed that there was a significant negative relationship for insecurity only. However, the mean scores and standard deviations of 2.72 and 0.87 for DIS and 3.21 and 0.79 for INS respectively (extracted from Table 13) indicated a degree of TR inhibition among the respondents, prompting further investigation.

Further analysis of the scale items of the TRI inhibitors within Table 14 showed that the constructs of INS2, INS3, and INS4 exhibited higher mean values (the TRI inhibitor construct items and mean scores have been placed in Table 25 for easy reference). These specific construct items were deemed outward-looking as they refer to the individual's perspective on technology from a social perspective and not necessarily from an individual's position regarding technology inhibition. Given that the TRI has been used broadly within existing studies, this observation was not positioned to dispute the results regarding the TRI inhibitor dimension of INS within this study, but the researcher deemed this noteworthy given the outcomes of H_1 and H_2.

Table 25: Descriptive statistics for the TRI inhibitor construct items

Descriptive Statistics			
Item Label	Item Statement	Mean	Std. Deviation
DIS1	When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do	2.51	1.14
DIS2	Technical support lines are not helpful because they do not explain things in terms that I understand	2.76	1.11
DIS3	There is no such thing as a manual for a high-tech product or service that is written in plain language	2.90	1.19
INS1	Sometimes, I think that technology systems are not designed for use by ordinary people	2.98	1.18
INS2	**People are too dependent on technology to do things for them**	**3.46**	**1.16**
INS3	**Too much technology distracts people to a point that is harmful**	**3.10**	**1.20**

Descriptive Statistics			
Item Label	Item Statement	Mean	Std. Deviation
INS4	**Technology lowers the quality of relationships by reducing personal interaction**	**3.49**	**1.20**
INS5	I do not feel confident doing business with a service that can only be reached online	3.01	1.25

Source: Generated by the researcher based on SPSS output

The weak negative correlation of the TRI inhibitors with PU, the high PU mean value (4.21 per Table 13), and the higher-than-expected mean values for the TRI inhibitors could be attributed to the fact that the study considered technology in a generalised manner and did not focus on a specific type of technology or use context. As argued by Acheampong et al. (2017), individuals may overcome their insecurity and discomfort if the benefits associated with the technology are deemed to be worth the potential uneasiness or risk. Therefore, the lack of technology specificity may have resulted in respondents finding it challenging to perceive tangible and utilitarian benefits. It could then be argued that, with a specific type of technology and the resulting conceptualisation of its application, respondents may have had a higher level of trust and lower perceived risks resulting in lower TRI inhibitor scores.

Nevertheless, the results of this study demonstrated that, while there was a significant negative correlation between the TRI inhibitors and PU, the mean scores and weak relationship indicated that there was a certain degree of discomfort and insecurity concerning individuals' PU. It was believed that the generalised perspective on technology as adopted within this study had an influence on the results.

6.5.4 Hypothesis 4: TRI Inhibitors and UI

H_4 stated that TRII has a negative relationship with UI. This hypothesis was tested at the sub-construct level on the TRII dimensions of DIS and INS based on the results of the EFA. The resulting hypotheses at the sub-construct level were:

H_{4a}: The TRII dimension of DIS has a negative relationship with UI

H_{4b}: The TRII dimension of INS has a negative relationship with UI

Using the Kendell’s tau non-parametric correlation, it was found that there was a significant, weak, and negative relationship for both DIS and INS with UI per Table 16. The correlation coefficients in Table 16 for DIS and INS concerning UI were comparable with results of -0.20 and -0.18 respectively.

Therefore, these results supported the hypothesis and indicated that TRII had a negative relationship with UI.

While the mean UI score was deemed to be high (4.39 per Table 13), the mean scores for DIS and INS were found to be moderate within this study (2.72 and 3.21 for DIS and INS respectively per Table 13). Therefore, the relatively restrained relationship between the TRI inhibitors on PU also translated to the UI construct. Even so, the significant negative relationship confirmed the findings of Phung et al. (2022), Lee et al. (2020), and Blut and Wang (2020), with the latter also concluding that the TRI motivators had stronger relationships compared to the TRI inhibitors.

The results between the TRI inhibitors and UI were found to be aligned with that of PU, and therefore the propositions put forward for H_3 were also applicable to the relationship between INS, DIS, and UI. In addition, and as discussed in Section 2.4.2, trust plays a key role in the UI relating to technology adoption. Schaefer et al. (2016) argued that trust is influenced by the cognitive factors relating to one’s ability to understand the technology and self-perceptions on usage abilities. Therefore, in the case of this study and as discussed in the previous section, the non-specificity of the type of technology could have influenced the respondent's trust and position concerning DIS and INS.

The above deductions were deemed relevant within the South African mining industry context. Given that operations within mining is a highly technical field comprising primarily of technically focused individuals, the respondents may have felt the need to have a more comprehensive understanding of the nature of technology considered to alleviate the sense of discomfort and insecurity. Having tangibility regarding the utilitarian benefits of the technology, whether the individual can understand its workings, and whether they are able to use the technology plays a key role towards increasing their perceived control (relating to discomfort) and technological trust (relating to insecurity) concerning UI.

Aligned with the findings related to H_4, it was inferred based on the results of H_5 that there was a significant but weak correlation between the TRI inhibitors and UI. Therefore, those individuals who had a lower perception of comfort and security relating to technology had a lower likelihood of considering technology for use, with converse perceptions of comfort and security resulting in a higher likelihood of technology use.

6.5.5 Hypothesis 5: Perceived Usefulness and Usage Intention

H_5 stated that PU has a positive relationship with UI. Per Table 16, it was found through non-parametric correlation that there was a significant, strong, and positive relationship between PU and UI. The correlation coefficient for PU concerning UI was found to be 0.68 as shown in Table 16. Therefore, the result supported the hypothesis and indicated that PU had a positive relationship with UI.

The strong positive correlation result confirmed the findings of several previous studies encompassing the TAM, including those by Marakarkandy et al. (2017), Schmidthuber et al. (2020), Singh et al. (2020), and Verma et al. (2018). The high mean results for PU and UI of 4.21 and 4.39 respectively per Table 13 combined with the histogram in Figure 24 and Figure 25 demonstrated that the results for these constructs were positively skewed. These results indicated that the respondents were positively inclined towards the perceived usefulness of new and innovative technologies and were fervent regarding usage.

The results confirm that individuals within the mining sector who have high convictions in the ability of technology to be useful also have a high inclination towards usage intentions, while those who do not believe in the technologies usefulness will have a low UI. The strong positive correlation between PU and UI confirmed the findings of Singh et al. (2020) who argued that PU is the most robust indicator of UI. Based on this, mining organisations considering innovative technologies to address operational and business challenges should emphasize the benefits before implementation. In addition, the communicated benefits should ideally be tailored to speak to the ways in which the new technology makes day-to-day tasks easier and more efficient at the individual level for the stakeholders involved. The communicated benefits are expected to increase the likelihood of individuals recognising the value of the technology, leading to an increased PU and ultimately UI.

Y. Wang et al. (2020) also argued that outward considerations such as environmental awareness could play a role in individuals' PU and UI. While they found that the impact of environmental awareness on UI was moderate in their study focused on China, individuals within the local South African context may have increased PU and UI if technologies are able to reduce the environmental impact of mining activities, especially given that local communities are often within close proximity to mine sites. Innovative technologies could also have a positive social impact, leading to increased PU if implementation leads to training and development that improves human capital. Therefore, these benefits should be communicated if applicable as well.

To conclude, the results from this hypothesis implied that those individuals with a higher appreciation of technology's usefulness had a higher intention towards its use. However, the inverse of this deduction holds true, based on the strong and significant positive correlation between PU and UI. These results were consistent with several previous studies and reaffirmed the strong dependency of UI on PU.

6.5.6 Hypothesis 6: Usage Intention and Chronological Age

H_6 looked at whether there was a difference in UI between chronological age groups:

> **H_6:** There is a significant difference within distinct chronological age groups in terms of UI

It was found using the Kruskal-Wallis non-parametric test for differences that there was no significant difference between the chronological age groups in relation to UI ($p \geq 0.05$) as shown in Table 18. This result indicated that H_6 was not supported.

Even though there was no significant difference found between the groups, an interesting result was that the 50-59 year old age group exhibited the highest mean value and lowest standard deviation of 4.63 and 0.64 respectively as shown in Table 17, even though this group only made up 8% of the total sample (12 respondents out of a total of 150). In contrast, the youngest segment comprising the 20-29 year old group presented with the lowest mean of 3.94. Therefore, not only was the hypothesis not supported in that there was no significant difference between the age groups, but the results of this study also contradicted the findings Hauk et al. (2018), who concluded that UI was negatively related to chronological age. Additionally, the results oppose the arguments of Sundstrup et al. (2022) who stated that older employees may find it more difficult to navigate innovative technologies based on mistrust, fear of job loss, and a sense of being controlled.

The outcome corroborated with views of Santini et al. (2020) who argued that the nature of the results between technology and age varies depending on the context, nature of the technology, and sample type considered. All age groups were found to have a statistically equal degree of UI regarding technology which, based on the mean values presented within Table 17, were found to be positively skewed. Therefore, and based on the results of H_5 (positive correlation between PU and UI), it is argued that individuals of different age groups within the South African mining industry primarily perceive innovative technologies as being useful and have a high inclination towards usage intentions and technology adoption regardless of age.

It should be noted, however, that the non-specificity of the technology considered for this study may have impacted the results (as discussed for H3 within Section 6.5.3). The results were expected to be similar if specific considerations were made towards technologies such as process or equipment automation. These are typically designed to make tasks more efficient and safer and can facilitate removal of individuals from dangerous working conditions. These technology forms would appeal to older individuals, resulting in a higher PU and UI. However, if technologies such as artificial intelligence or data analytics were put forward, these more complex forms of technology could have had greater appeal to younger individuals, with older persons having an increased degree of insecurity and/or discomfort, leading to lower PU and UI. These deductions confirmed the findings of Hauk et al. (2018) who concluded that PEOU was the strongest determining factor between chronological age and technology acceptance, where PEOU was dependent on the type of technology considered.

This study considered technology in a generalised sense, and it was found within this context that there was no significant difference between age and UI. It was concluded that individuals within the mining industry held a positive view of UI across the various bands of chronological age based on the mean values for UI ranging between 3.94 and 4.63. However, if considerations were made toward a specific type of technology, the outcomes of the results could have been different.

6.5.7 Hypothesis 7: Usage Intention and Levels of Education

H_7 considered whether there was a difference in UI between individuals with distinct levels of education:

> **H_7:** There is no significant difference within distinct groups of educational levels in terms of UI

It was found using the Mann-Whitney non-parametric test for differences that there was a significant difference between the groups of education levels in relation to UI as shown in Table 22 ($p < 0.05$). This result indicated that H_7 was not supported.

This result was unexpected given that the mean for the different groups concerning UI were 4.16 and 4.50 with standard deviations of 0.82 and 0.75 respectively for high schooling and tertiary education per Table 21. However, further investigation of the frequency and box plots represented in Figure 26 and Figure 27 indicated that the score distribution for high schooling was discernibly more extensive for high schooling compared to the tertiary group. In addition, the tertiary group was observed to have greater positive skew concerning UI. It was therefore concluded that these two factors contributed to the significant difference observed between the two education level groups. Consequentially, while the mean results were comparable between the two groups, a significant difference was present.

These results confirmed those of Rojas-Méndez et al. (2017) and Santini et al. (2020) who found that individuals with higher levels of education have a greater sense of self-efficacy resulting in reduced anxiety when making considerations toward the intention to use innovative technologies. However, one of the shortcomings of this study was that there were no respondents who had primary schooling as their highest level of education and that the inclusion of such respondents would have crystallised the relationship between education levels and UI.

Based on the results of H_7, mining organisations need to be cognisant of project stakeholders with differing levels of education involved in the implementation of new technologies. As argued by Sundstrup et al. (2022), upskilling individuals to develop the required competencies can compensate for the lack of formal education amongst individuals and also provides a means of increasing individuals' sense of self-efficacy leading to higher UI. Additionally, Cruz-Cárdenas et al. (2019) contended that the segments of individuals with lower levels of education are typically those who fall within the lower income brackets, and these individuals in particular require skills support to augment technological UI. Income inequalities are a particular characteristic of developing nations and that lower-income segments' perceptions of technology usage are impacted given that they often do not have the means to entertain it within their personal space (Rojas-Méndez et al., 2017).

It was recognised that the above generalisations do not always hold true. As discussed in Section 2.2.2, individuals with limited income and therefore educational opportunities could view technology implementation within their organisations as an avenue to facilitate upskilling that can lead to personal growth and career advancement. While this may not have been apparent within this study's results, it was deemed a notable point for consideration by organisational managers looking for innovative technologies to solve operational challenges. The availability of data from respondents that had primary schooling as their highest level of education may have provided more insights to this notion. Within the context of this study, however, it was concluded that there was a significant difference between education levels and UI.

6.5.8 Hypothesis 8: Usage Intention and Organisational Role

H_8 considered whether there was a difference in UI for individuals with distinct roles within their organisation:

> **H_7:** There is a significant difference within distinct groups of organisational roles in terms of UI

It was found through the Kruskal-Wallis non-parametric test for differences that there was no significant difference between the groups of different organisational roles in relation to UI ($p \geq 0.05$) as shown in Table 20. This result indicates that H_8 was not supported.

There was no discernible difference between the mean values for the distinct role groups relating to UI, which were found to be 4.30, 4.48, and 4.42 for users, managers, and decision-makers respectively per Table 15. While the standard deviations for users and managers were comparable, 0.75 and 0.77 respectively, the decision-maker group was noticeably higher at 1.09.

As discussed in Section 2.2.3, there is limited research on the impact on PU and UI for individuals within different organisational roles. However, individuals' influence on technology adoption was a significant consideration based on those who decide whether a certain technology will be used to address organisational challenges, how it is facilitated through the application of appropriate skills and resources, and if it is ultimately used at ground-level (Hameed et al., 2012; Roberts et al., 2021). Therefore, considerations needed to be made towards potential decision-makers, managers, and users and their perceptions toward UI.

It was determined that the individuals within the groups all exhibited a high degree of UI based on the positively skewed results for UI as illustrated in Figure 25, the high mean values for the three groups of organisational roles (as outlined above), and the finding that there was no significant difference concerning UI between the groups. This finding was deemed an important contributor toward the adoption of innovative technologies within the South African mining industry as it indicated a high likelihood of new technologies being considered to solve operational challenges by decision-makers, being effectively overseen and implemented by applicable managers, and expected to be adopted by end-users.

Within the context of this study, decision-makers are expected to make pro-technology choices regarding organisational strategies driven toward innovative means to address operational challenges, and are expected to promote an organisational culture that embraces these innovations (Damanpour & Schneider, 2006). This pre-adoption setting is likely to assist managers in creating an environment where resources and human capital development can be adequately allocated to technology-related projects, thereby allowing managers to facilitate implementation driven towards a high probability of adoption at the user level. Furthermore, with appropriate facilitating conditions by managers, users of technology are less likely to experience anxiety and uncertainty and, therefore, focus on the value that technology can bring to their daily work, which will result in an increased probability of adoption. These aspects are expected to increase mining organisations' competitiveness through technology implementation and improve their agility regarding innovation.

Based on the results and the arguments put forward above, it was concluded that there was no significant difference between the various groups of individuals concerning organisational roles and UI. It was inferred that there is a high probability of technology being considered within an organisational setting, with subsequent support through its life cycle, and effectively used at ground level based on the high observed mean values for UI.

6.6 Summary of the Hypothesis Test Results

The figures below present a graphical summary of the hypothesis test results. Figure 28 presents the results at the sub-construct level, while Figure 29 presents those at the meta-construct level. The hypothesis test results indicated that there was a significant positive relationship between TRIM with PU and UI (H_1 and H_2), a significant negative relationship between TRII with PU and UI (H_5 and H_4), and a significant positive relationship between PU and UI (H_5). No significant difference was found between chronological age and organisational role with UI (H_6 and H_8), with a significant difference between difference levels of education (H_7).

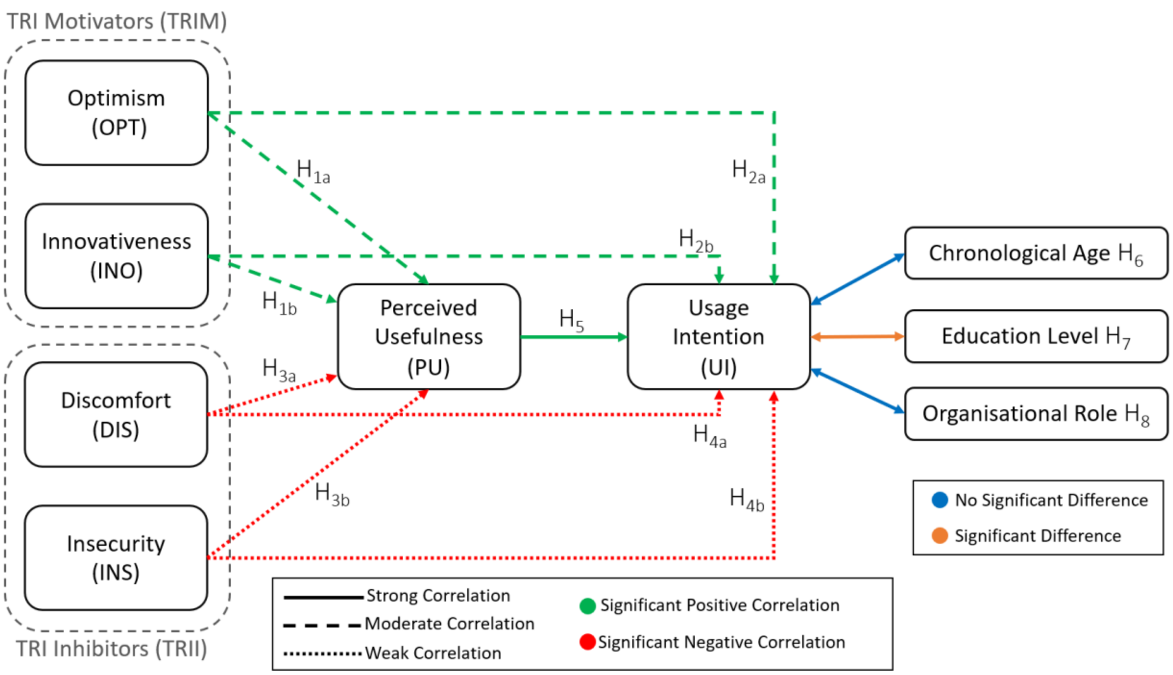

Figure 28: Summary of hypothesis test results at the sub-construct level

Source: Generated by the researcher

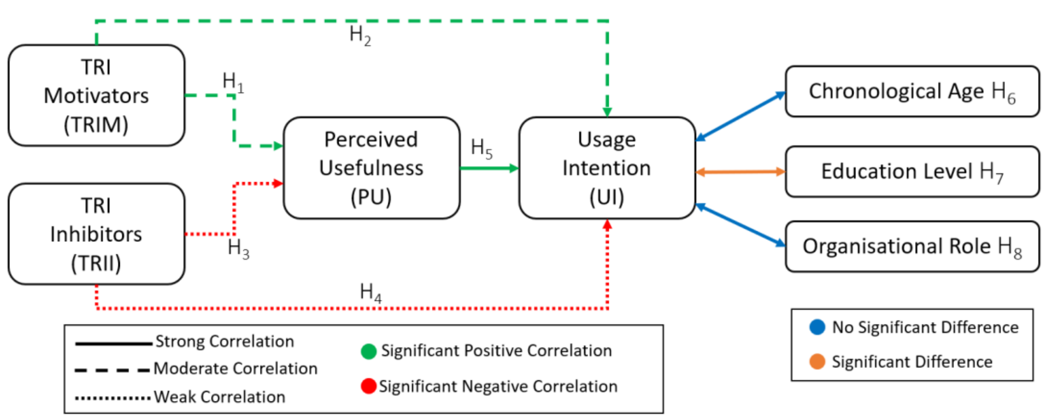

Figure 29: Summary of hypothesis test results at the meta-construct level

Source: Generated by the researcher

6.7 Conclusion

This chapter presented a discussion of the results presented within Chapter 5. A discussion of the results of the statistical analysis of the constructs and related items were presented in terms of validity, reliability, EFA, normality, and homoscedasticity. The hypothesis tests were then discussed in terms of the results, whether the hypotheses were supported, compared against existing literature, and conclusions drawn. Further conclusions relating to this study are presented in the next chapter.

7 Chapter Seven: Conclusions and Recommendations

7.1 Introduction

This research study aimed to determine the current perceptions and predispositions toward technology adoption amongst individuals in the South African mining industry as defined based on the problem statement and primary research question in Chapter 1. A review of existing literature was discussed within Chapter 2, where it was gathered that the extension of the TAM to include the TRI constructs provided a framework that was able to provide the insights required to answer the research question. Chapter 3 presented the hypotheses involving the constructs and demographic factors that were formulated based on existing literature and the resulting conceptual model. This study was executed based on the research methodology described in Chapter 4 with the results and associated discussions presented in Chapters 5 and 6 respectively. This chapter discusses the principal conclusions based on the discussions within Chapter 6, followed by theoretical contributions and implications for management and stakeholders, before concluding with the research limitations of this study and suggestions for future research.

7.2 Principal Conclusions

The importance of the South African mining sector concerning economic and social contributions are significant. With other nations implementing innovative technologies to address operational challenges and improve efficiencies, the South African mining industry needs to follow suit in order to remain competitive and globally relevant. Ediriweera and Wiewiora (2021) reported that the adoption of new and innovative technologies are typically adopted gradually or pushed back against entirely within the mining industry, with Gruenhagen and Parker (2020) arguing that this is due to the industry's traditionalist and resistive culture. Referring to Section 1.2.4, Singh et al. (2020) argued that the successful adoption of innovative technologies is highly dependent on individual perceptions. Therefore, these considerations became the core facet of the research question.

The extension of the TAM to include the TRI motivators and TRI inhibitors provided valuable insights into individuals' perceptions toward technology and their PU and UI compared to if these models were used in isolation (Tavera-Mesías et al., 2022). The reliability and validity of the measurement instrument based on the TRI and TAM constructs were confirmed, indicating that the construct items were appropriate for measurement and consistent. Additionally, assumptions associated with multivariate statistical methods were tested to ensure that the correct statistical tests were applied to draw accurate deductions based on the hypothesis testing. These factors support the robustness of the research methodology adopted and the results presented.

The results from hypotheses one and two found that there was a significant positive correlation concerning the TRI motivators with PU and UI. In addition to the positive correlation, it was concluded that individuals primarily had positive perceptions regarding technology, technology's usefulness, and intentions towards use based on the high mean scores for the TRI motivators (OPT and INO), PU, and UI. However, the overall positive relationship between the TRI motivators with PU and UI implied that individuals with a higher degree of technological optimism and innovativeness were more inclined to perceive usefulness and have a higher intention to use technology.

While there have been mixed views within existing literature regarding the relationship between the TRI motivators and PU, the results within this study confirmed the intuitive nature of the relationship, as well as existing studies encompassing TRI motivators and PU by S. A. Rahman et al. (2017), Chiu and Cho (2020), Rejikumar et al. (2020), and Lee et al. (2020). It was concluded that the positive relationship between the TRI motivators and PU directly affected individuals' inclination toward UI, and the relationship between the positive TRI dimensions and UI was aligned with that of Tavera-Mesías et al. (2022) and Chen and Lin (2018).

In addition to the above findings supporting existing literature, it was concluded that individuals' positive views concerning the usefulness of technology extended beyond their personal context into recognised usefulness for their organisations, leading to increased work efficacy and organisational competitive advantage (Sun et al., 2020). Not only did individuals perceive that technology will be useful, but they have also demonstrated that the perceptions translated into an intention to actual use (UI) the technology. This link between individual perceptions and UI was concluded as an important aspect of this study based on the argument by Razmak and Bélanger (2018), who states that UI is a significant indicator of actual use and associated technology adoption.

The above conclusions contradicted the notion that the mining industry has a conventionalist and traditionalist culture that is typically unwilling to change and, therefore, would not be inclined towards new and innovative technologies (Gruenhagen & Parker, 2020). While Ediriweera and Wiewiora (2021) argued that new technologies are gradually adopted or resisted entirely within the industry, the findings within this study indicated that this could be due to factors outside of individuals' perceptions (such as readiness for technology or slow governance processes regarding implementation).

The results of hypotheses three and four indicated that there was a significant negative relationship between the TRI inhibitors (INS and DIS) with PU and UI. These results aligned with Kim and Chiu (2019) regarding the TRI inhibitors' relationship with PU and the findings by Blut and Wang (2020) between the TRI inhibitors with UI. These results were unsurprising given the relationship between PU, UI, and the TRI motivators. Therefore, increased technological discomfort and insecurity are expected to reduce individuals' PU and UI.

Despite the negative relationship and high mean scores for PU and UI, the moderate mean scores for DIS and INS indicated that there was a degree of technological discomfort and insecurity for the respondents within the sample data. It was inferred that the higher mean for the inhibitor dimension of INS (compared to DIS) was attributed to certain items within the sub-construct being outward-looking about their views on how technology affects other people and social interactions. While this inference was not deemed a concluding statement based on the TRI used in several individual-focused studies previously, it was deemed noteworthy.

As a supplement to the above, it was concluded that the moderate mean scores for DIS and INS were attributed to this study not encompassing a specific type of technology.

Given that respondents could not grasp the utilitarian benefits associated with the concept of generalised technology, this introduced a sense of uneasiness and potential risk which affected PU. This conclusion was based on the argument by Acheampong et al. (2017) that individuals have a lower degree of technological inhibition if they believe that the benefits associated with the technology outweigh the perceived risks. Additionally, based on mining operations comprising technical individuals, respondents would have had a higher level of trust leading to a lower sense of apprehension towards UI. Therefore, it was concluded that ambiguity relating to nature and use of technology increased the likelihood that individuals felt a sense of discomfort and insecurity.

The results from hypothesis five found that there was a strong, significant, and positive correlation between the TAM dimensions of PU and UI. This result was aligned with several previous studies encompassing the TAM including the meta-analysis by Marangunić and Granić (2015), and reaffirmed the views of Marakarkandy et al. (2017) Singh et al. (2020) that PU is a reliable indicator of UI. In support of this, the results from the correlation test indicated that PU had the strongest correlation coefficient with UI when compared to the TRI dimensions of motivators and inhibitors.

Hypotheses six, seven, and eight made considerations toward the impact of the individual-related factors on technology UI. It was concluded that there were no significant differences between groups of different chronological ages and organisational roles, while there was a significant difference between different groups in terms of the highest education level achieved. Within all of these groups, the mean score of UI was above 4.00, apart from the age group of 20-29 years of age with a mean score of 3.94. These scores, as discussed previously, indicated that individuals were primarily inclined toward technology use. This was an important finding given the scale of the mining industry and that the industry comprises a broad range of individuals with varying demographics.

The result relating to chronological age (no significant difference) contradict those by Hauk et al. (2018) and Sundstrup et al. (2022) who found that technology propensity was negatively related to age. However, per Santini et al. (2020), studies relating to age and technology have produced mixed results depending on the context and nature of the technology. In this study, an interesting result was that individuals over 50 years of age had a higher UI than those younger than 29. Based on this, it was concluded that older individuals perceive that the benefits compensate for any perceived risks and that they have a more positive view of technology. However, it was also concluded that different types of technology might have impacted the views of individuals across the various segments of the age spectrum.

The significant difference between education levels and UI confirmed the findings of existing studies by Rojas-Méndez et al. (2017) and Santini et al. (2020), even though the mean scores of UI across the groups of high schooling and tertiary education were comparable. One of the weaknesses of this study was that there were no respondents with primary schooling as their highest level of education, and the inclusion of such respondents would have provided further insights in terms of the differences between the groups.

Lastly, hypothesis eight found no significant difference between individuals comprising different organisational roles and UI. While there was limited research considering the organisational role and the TRI and TAM constructs, this outcome was deemed to be important given the stages and multiple stakeholders involved in technology implementation. Based on the results from hypothesis eight, and the positively skewed mean values for UI, it was concluded that the positive views on technology will increase the likelihood of cross-functional stakeholders collaborating to create a positive outcome for innovation projects and foster a pro-technology organisational culture (Damanpour & Schneider, 2006).

7.3 Theoretical Contributions

Technology adoption and acceptance has been a widely studied field within the existing literature. This study not only adds to the body of existing technology acceptance research, but also adds to the relatively small number of studies within the mining industry based on the findings of Gruenhagen and Parker (2020). The extension of the TAM with the TRI constructs in this study extends the current body of knowledge in technology adoption and innovation in the mining context. Additionally, most explanatory studies encompassing the TRI and TAM constructs have been focused on consumer product acceptance based on the literature reviewed. In contrast, this study is applied to an industrial organisational context.

Theoretical insights were gained on the influence of chronological age, levels of education, and organisational roles relating to the TAM and TRI constructs used within this study. There have been mixed results concerning age and education within the existing literature and, to the best of the researcher’s knowledge, this study is among the first to explore the technology perceptions and usage intentions for different organisational roles. Therefore, the results presented within this study contribute to the theoretical understanding of the influence of individual-related differences on technological perceptions and adoption intentions.

7.4 Implications for Management and Other Relevant Stakeholders

The primary implication of this study for management was that individuals' perceptions of technology bode well for innovative technology implementation within the South African mining industry. Furthermore, the intuitive results associated with the relationships between the TRI motivators and inhibitors with PU and UI imply predictability relating to individuals' perceptions of technology adoption. Essentially, those more optimistic and innovative individuals are more likely to perceive the value and benefits associated with technology, with a contrary stance for those who are insecure and uncomfortable.

Mining organisations (specifically those accountable for technology decisions) need to highlight the benefits of new technologies before implementation to increase individuals' PU and their UI for successful and effective adoption. It is recommended that the benefits communicated should be focused on those at the organisational level, but more specifically, conveying sufficient information on how the technology can enhance an individual’s work efficacy. There is a higher probability of insecurity and discomfort being introduced if there is ambiguity in the benefits communicated. Additionally, if technologies serve to address environmental impact, increase human capital, or benefit adjacent communities, then it is probable that individuals will have a higher PU leading to higher UI regarding that specific technology. These supplementary aspects must be highlighted in conjunction with the personal utilitarian benefits.

Based on the study's findings, and contrary to certain societal notions, it should be noted by managers that older individuals favour innovations that enhance their work performance. However, the type of technology introduced could influence perceptions across different age groups, with sophisticated computer-based technologies such as data analytics favouring younger individuals and machine/process automation having a more positive impact on older individuals. Therefore, decision-makers and managers need to be cognisant of these aspects and explore the potential of developing competencies linked to specific technology implementation strategies. Overall, developing the competencies of individuals through formal training can increase individuals sense of self-efficacy (Sundstrup et al., 2022).

Individuals within lower income brackets are typically not afforded educational opportunities, and the findings within this study indicated a significant difference between education level and technology UI. Individuals within lower income brackets do not have the luxury of experimenting with technology in their personal capacity, which can influence their UI within an organisational context. Decision-makers and managers would find it beneficial to facilitate individuals having exposure to technology projects within their organisation before implementing projects that affect the individual's work. Exposure to technology, especially exposure that does not necessarily impact the individual’s work efforts in the short term, decreases their sense of discomfort and insecurity in the longer term.

7.5 Research Limitations

Despite the theoretical contributions and implications for management and other stakeholders, this study had certain limitations that needed to be stated. The limitations below were separate from those stated in Chapter 4, which expressly referred to the adopted research methodology.

This study was isolated to individuals within the South African mining industry and cannot be generalised beyond this context. Additionally, this study did not measure the individuals' views on their company in terms of organisational culture concerning technological innovation. Therefore, each company's culture in terms of innovation may have influenced the respondent's feelings toward technology adoption. It is also expected that different mining organisations are in different phases regarding innovation adoption, with some organisations providing exposure and upskilling to their employees, which is expected to improve individuals' technological perceptions and inclinations toward adoption. Conversely, some mining organisations have a traditionalist approach to their operations. As such, employees within these organisations have less exposure to technological innovations and, therefore, have a lower propensity and likelihood of adoption.

Within the data collected, it was observed that there was a low number of respondents below 29 years of age (12%) and above 50 years of age (9.3%). The distribution of respondents, therefore, primarily fell between the ages of 30 and 49. While the statistical methods used in this study ignored the differences in sample sizes, the low number of responses was deemed to be an underrepresentation of younger and older age groups, which could have skewed the results. Additionally, concerning levels of education, there were no responses from individuals who completed high schooling as their highest level of education. In both age and education levels, a more even number of responses across the groups were seen to provide more robust insights and was considered to be a limitation.

7.6 Recommendations for Future Research

There are three recommendations for future research concerning innovative technology adoption within the mining industry. The first recommendation relates to the lack of utilitarian tangibility associated with this study's generalised nature of technology. It is recommended that future studies consider a specific type of new technology so that respondents can appreciate its practical uses and benefits. Secondly, it is recommended that future studies be carried out within a specific organisation to assess the impact of organisational culture on individuals' apprehension or confidence regarding technology and its adoption intentions. Finally, it is proposed that the conceptual model used within this study be expanded further to include supplementary external predictors, constructs from other models, and contextual elements. The extension of the conceptual model will build on this study and expand the academic understanding of individuals' propensity toward technology adoption in the mining industry.

7.7 Conclusion

This research study sought to investigate the current perceptions and predispositions toward technology adoption amongst individuals in the South African mining industry. Based on the literature reviewed, the hypotheses generated, the methodology adopted, the data gathered, and the analysis of results, it was found within the sample data that individuals primarily held a positive perception and had a strong inclination toward technology adoption. It was also concluded that there is a high degree of predictability regarding technology adoption based on their perceptions. This concluding chapter presented principal conclusions, the study’s theoretical contributions, and implications for management and stakeholders. Finally, the chapter concluded with identified limitations and recommendations for future research.

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Appendix A: Questionnaire for Research Study

Dear Respondent,

I am currently a student at the University of Pretoria's Gordon Institute of Business Science and completing my research in partial fulfilment of an MBA.

I am conducting research on the propensity of people towards new technology adoption.

My focus is around new emerging technologies within the mining sector which include, but not limited to, equipment automation, integrated process automation, digitalization, artificial intelligence, drone and scanning technology, machine learning, big data processing and analytics, emerging energy technology, advanced materials, and communications technology (e.g., industrial internet of things).

To this end, I would greatly appreciate it if you could participate in the survey by completing this questionnaire, which should take no more than 10 minutes of your time.

Your participation is voluntary, and you can withdraw at any time without penalty. Your participation is anonymous and only aggregated data will be reported. By completing this survey, you indicate that you voluntarily participate in this research.

If you have any questions or concerns, please contact my supervisor or me. Our details are provided below.

Thank you in advance for your time.

Researcher name: Vikesh Chiba

Email: 11383438@mygibs.co.za

Phone: 079 838 0858

Research supervisor: Hugh Myers

Email: myresh@gibs.co.za

Phone: 011 771 4000

	Yes	No
Do you agree to participate?	○	○

	Yes	No
Do you currently work with or for the operations section of a mining company in South Africa?	○	○

Section 1: Role within the Organisation

Please select an option that is most appropriate given your role and responsibilities regarding new technology implementation in your organisation (select one only):

Decision-maker whether a new technology will be implemented	○
Manage people that will be using new technology	○
User of new technology	○

Section 2: Demographics

How old are you?

Younger than 20 years	○
20-29 years	○
30-39 years	○
40-49 years	○
50-59 years	○
Older than 60 years	○

What is your highest level of education?

Primary schooling	○
High/secondary schooling	○
University/tertiary	○

How many years of work experience do you have?

Less than 5 years	○

5-10 years	○
11-15 years	○
16-20 years	○
21-25 years	○
26-30 years	○
31-35 years	○
36-40 years	○
41-45 years	○

Section 3: Describe your views on technology

Please select one option only for each statement below:

	Strongly disagree	Somewhat disagree	Neutral	Somewhat agree	Strongly agree
New technologies contribute to a better quality of life	○	○	○	○	○
When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do	○	○	○	○	○
Technology gives me more freedom of mobility	○	○	○	○	○
Technology gives people more control over their daily lives	○	○	○	○	○
People are too dependent on technology to do things for them	○	○	○	○	○
Technology makes me more productive in my personal life	○	○	○	○	○
I do not feel confident doing business with a service that can only be reached online	○	○	○	○	○
Technology lowers the quality of relationships by reducing personal interaction	○	○	○	○	○
Other people come to me for advice on new technologies	○	○	○	○	○

	Strongly disagree	Somewhat disagree	Neutral	Somewhat agree	Strongly agree
Sometimes, I think that technology systems are not designed for use by ordinary people	○	○	○	○	○
I keep up with the latest technological developments in my areas of interest	○	○	○	○	○
Technical support lines are not helpful because they do not explain things in terms that I understand	○	○	○	○	○
In general, I am among the first in my circle of friends to acquire new technology when it appears	○	○	○	○	○
There is no such thing as a manual for a high-tech product or service that is written in plain language	○	○	○	○	○
I can usually figure out new high-tech products and services without help from others	○	○	○	○	○
Too much technology distracts people to a point that is harmful	○	○	○	○	○

Note:

Section 4: Describe your stance on technology

	Strongly disagree	Somewhat disagree	Neutral	Somewhat agree	Strongly agree
I believe using new technology would be easy for me	○	○	○	○	○
I believe it would be easy to get new technology to do what I want it to do	○	○	○	○	○
I believe using new technology would be clear and understandable	○	○	○	○	○

	Strongly disagree	Somewhat disagree	Neutral	Somewhat agree	Strongly agree
I believe using new technology would be easy for me	O	O	O	O	O
I would find new technology flexible to interact with	O	O	O	O	O
It would be easy for me to become skilful at using new technology	O	O	O	O	O
I believe using new technology would help me be more productive	O	O	O	O	O
I believe using new technology would help me be more effective	O	O	O	O	O
Using new technology would be useful in my life	O	O	O	O	O
Using new technology would improve my life	O	O	O	O	O
Using new technology would enhance my effectiveness in life	O	O	O	O	O
There is a high likelihood that I will use new technology within the foreseeable future	O	O	O	O	O
I intend to use new technology within the foreseeable future	O	O	O	O	O
I will use new technology in the foreseeable future	O	O	O	O	O
Using new technology in the foreseeable future is important to me	O	O	O	O	O

Appendix B: Written Permission for use of TRI Scale Items

Subject: RE: Re[2]: Request for Permission - TRI for Quantitative Study in South Africa
From: "Charles Colby" <ccolby@rockresearch.com>
Sent: 06-Jul-22 5:55:34 PM
To: "Vikesh Chiba" <vikesh.chiba@gmail.com>;
CC: "Hugh Myres" <Myresh@gibs.co.za>; "rockinfo" <rockinfo@rockresearch.com>; "parsu@miami.edu" <parsu@miami.edu>;
Attachments: TR Index 2.0 List for Academic Subscribers.docx

July 6, 2022

Vikesh Chiba
Gordon Institute of Business Science
Johannesburg, South Africa

Dear Vikesh:

Thank you for completing the licensing agreement for the TRI 2.0. This letter is to let you know that you officially have a one-time use license (and permission) to use the TRI 2.0 for your academic study. I am attaching a list of scale items and recommendations on using the scale. Please let me know if you have any questions.

Regards,

Charles L. Colby
Principal, Chief Methodologist and Founder
Office: 703 757 5213 ext. 112
10130 G Colvin Run Road, Great Falls, VA 22066
www.rockresearch.com | ccolby@rockresearch.com

Appendix C: Ethical Clearance Approval

GIBS ETHICAL CLEARANCE APPLICATION FORM 2021/22

G. APPROVALS FOR/OF THIS APPLICATION

When the applicant is a student of GIBS, the applicant must please ensure that the supervisor and co-supervisor (where relevant) has signed the form before submission

STUDENT RESEARCHER/APPLICANT:

29. I affirm that all relevant information has been provided in this form and its attachments and that all statements made are correct.

Student Researcher's Name in capital letters:	VIKESH CHIBA
Date:	07 Jul 2022
Supervisor Name in capital letters:	HUGH MYRES
Date:	09 Jul 2022
Co-supervisor Name in capital letters:	
Date:	07 Jul 2022

Note: GIBS shall do everything in its power to protect the personal information supplied herein, in accordance to its company privacy policies as well the Protection of Personal Information Act, 2013. Access to all of the above provided personal information is restricted, only employees who need the information to perform a specific job are granted access to this information.

Decision:

Approved

REC comments:

Well done on a well-compiled ethics application. Good luck with your research.

Date: 11 Jul 2022

Appendix D: Code Books

Table 26: Codes used for numeric allocation for nominal data

Question	Item Label	Possible Answers	Code
Role within the organisation:	Role	User of new technology if implemented	1
		Manage people that will be using new technology	2
		Decision-maker whether a new technology will be implemented	3
What age group do you fall within?	Age	Younger than 20 years	1
		20-29 years	2
		30-39 years	3
		40-49 years	4
		50-59 years	5
		Older than 60 years	6
What is your highest level of education?	Edu	Primary schooling	1
		High/secondary schooling	2
		University/tertiary	3
How many years of work experience do you have?	WE	Less than 5 years	1
		5-15 years	2
		16-25 years	3
		26-35 years	4
		36-45 years	5
		More than 45 years	6

Source: Generated by the researcher

Table 27: Label assignments to construct items

	Construct Item	Label Pre-EFA	Label Post-EFA
TRI Motivators (TRIM)	New technologies contribute to a better quality of life	TRIM1	OPT1
	Technology gives me more freedom of mobility	TRIM2	OPT2
	Technology gives people more control over their daily lives	TRIM3	OPT3
	Technology makes me more productive in my personal life	TRIM4	OPT4
	Other people come to me for advice on new technologies	TRIM5	INO1
	In general, I am among the first in my circle of friends to acquire new technology when it appears	TRIM6	INO2
	I can usually figure out new high-tech products and services without help from others	TRIM7	INO3
	I keep up with the latest technological developments in my areas of interest	TRIM8	INO4

	Construct Item	Label Pre-EFA	Label Post-EFA
TRI Inhibitors (TRII)	When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I am being taken advantage of by someone who knows more than I do	TRII1	INS1
	Technical support lines are not helpful because they do not explain things in terms that I understand	TRII2	INS2
	Sometimes, I think that technology systems are not designed for use by ordinary people	TRII3	DIS1
	There is no such thing as a manual for a high-tech product or service that is written in plain language	TRII4	INS3
	People are too dependent on technology to do things for them	TRII5	DIS2
	Too much technology distracts people to a point that is harmful	TRII6	DIS3
	Technology lowers the quality of relationships by reducing personal interaction	TRII7	DIS4
	I do not feel confident doing business with a service that can only be reached online	TRII8	DIS5
TAM Perceived Usefulness (PU)	I believe using new technology would help me be more productive	PU1	PU1
	I believe using new technology would help me be more effective	PU2	PU2
	Using new technology would be useful in my life	PU3	PU3
	Using new technology would improve my life	PU4	PU4
	Using new technology would enhance my effectiveness in life	PU5	PU5
TAM Usage Intention (UI)	There is a high likelihood that I will use new technology within the foreseeable future	UI1	UI1
	I intend to use new technology within the foreseeable future	UI2	UI2
	I will use new technology in the foreseeable future	UI3	UI3
	Using new technology in the foreseeable future is important to me	UI4	UI4

Source: Construct items adapted from Manis and Choi (2019) and Parasuraman and Colby (2015), with labels generated by the researcher

Table 28: Codes used for Likert-scale responses

Likert-scale Response	Code
Strongly disagree	1
Somewhat disagree	2
Neutral	3
Somewhat agree	4
Strongly agree	5

Source: Generated by the researcher

Appendix E: Construct Validity Results

Table 29: Pearson correlation results for TRI motivators construct

		TRIM1	TRIM2	TRIM3	TRIM4	TRIM5	TRIM6	TRIM7	TRIM8	TRIMTotal
TRIM1	Pearson Correlation	1	.345**	.282**	.343**	.227**	.101	-.021	.226**	.515**
	Sig. (2-tailed)		<.001	<.001	<.001	.005	.221	.798	.005	<.001
	N	150	150	150	150	150	150	150	150	150
TRIM2	Pearson Correlation	.345**	1	.665**	.648**	.385**	.245**	.182*	.403**	.741**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	.003	.026	<.001	<.001
	N	150	150	150	150	150	150	150	150	150
TRIM3	Pearson Correlation	.282**	.665**	1	.516**	.308**	.211**	.156	.383**	.676**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	.010	.057	<.001	<.001
	N	150	150	150	150	150	150	150	150	150
TRIM4	Pearson Correlation	.343**	.648**	.516**	1	.369**	.272**	.204*	.465**	.733**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001	.012	<.001	<.001
	N	150	150	150	150	150	150	150	150	150
TRIM5	Pearson Correlation	.227**	.385**	.308**	.369**	1	.392**	.355**	.494**	.672**
	Sig. (2-tailed)	.005	<.001	<.001	<.001		<.001	<.001	<.001	<.001
	N	150	150	150	150	150	150	150	150	150
TRIM6	Pearson Correlation	.101	.245**	.211**	.272**	.392**	1	.302**	.528**	.591**
	Sig. (2-tailed)	.221	.003	.010	<.001	<.001		<.001	<.001	<.001
	N	150	150	150	150	150	150	150	150	150
TRIM7	Pearson Correlation	-.021	.182*	.156	.204*	.355**	.302**	1	.455**	.499**
	Sig. (2-tailed)	.798	.026	.057	.012	<.001	<.001		<.001	<.001
	N	150	150	150	150	150	150	150	150	150
TRIM8	Pearson Correlation	.226**	.403**	.383**	.465**	.494**	.528**	.455**	1	.753**
	Sig. (2-tailed)	.005	<.001	<.001	<.001	<.001	<.001	<.001		<.001
	N	150	150	150	150	150	150	150	150	150
TRIMTotal	Pearson Correlation	.515**	.741**	.676**	.733**	.672**	.591**	.499**	.753**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
	N	150	150	150	150	150	150	150	150	150

**. Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS Output

Table 30: Pearson correlation results for TRI inhibitor construct

		TRII1	TRII2	TRII3	TRII4	TRII5	TRII6	TRII7	TRII8	TRIITotal
TRII1	Pearson Correlation	1	.353**	.238**	.256**	.079	.119	.017	.113	.448**
	Sig. (2-tailed)		<.001	.003	.002	.337	.147	.834	.170	<.001
	N	150	150	150	150	150	150	150	150	150
TRII2	Pearson Correlation	.353**	1	.289**	.454**	.305**	.360**	.229**	.360**	.697**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001	.005	<.001	<.001
	N	150	150	150	150	150	150	150	150	150
TRII3	Pearson Correlation	.238**	.289**	1	.171*	.242**	.409**	.301**	.232**	.606**
	Sig. (2-tailed)	.003	<.001		.037	.003	<.001	<.001	.004	<.001
	N	150	150	150	150	150	150	150	150	150
TRII4	Pearson Correlation	.256**	.454**	.171*	1	.276**	.232**	.208*	.253**	.598**
	Sig. (2-tailed)	.002	<.001	.037		<.001	.004	.011	.002	<.001
	N	150	150	150	150	150	150	150	150	150
TRII5	Pearson Correlation	.079	.305**	.242**	.276**	1	.289**	.271**	.180*	.553**
	Sig. (2-tailed)	.337	<.001	.003	<.001		<.001	<.001	.027	<.001
	N	150	150	150	150	150	150	150	150	150
TRII6	Pearson Correlation	.119	.360**	.409**	.232**	.289**	1	.444**	.293**	.666**
	Sig. (2-tailed)	.147	<.001	<.001	.004	<.001		<.001	<.001	<.001
	N	150	150	150	150	150	150	150	150	150
TRII7	Pearson Correlation	.017	.229**	.301**	.208*	.271**	.444**	1	.321**	.594**
	Sig. (2-tailed)	.834	.005	<.001	.011	<.001	<.001		<.001	<.001
	N	150	150	150	150	150	150	150	150	150
TRII8	Pearson Correlation	.113	.360**	.232**	.253**	.180*	.293**	.321**	1	.589**
	Sig. (2-tailed)	.170	<.001	.004	.002	.027	<.001	<.001		<.001
	N	150	150	150	150	150	150	150	150	150
TRIITotal	Pearson Correlation	.448**	.697**	.606**	.598**	.553**	.666**	.594**	.589**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	
	N	150	150	150	150	150	150	150	150	150

**. Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS Output

Table 31: Pearson correlation results for TAM perceived usefulness (PU) construct

Correlations

		PU1	PU2	PU3	PU4	PU5	PUTotal
PU1	Pearson Correlation	1	.762**	.687**	.716**	.737**	.870**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001
	N	150	150	150	150	150	150
PU2	Pearson Correlation	.762**	1	.847**	.694**	.766**	.905**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001
	N	150	150	150	150	150	150
PU3	Pearson Correlation	.687**	.847**	1	.771**	.748**	.898**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001
	N	150	150	150	150	150	150
PU4	Pearson Correlation	.716**	.694**	.771**	1	.868**	.902**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001
	N	150	150	150	150	150	150
PU5	Pearson Correlation	.737**	.766**	.748**	.868**	1	.918**
	Sig. (2-tailed)	<.001	<.001	<.001	<.001		<.001
	N	150	150	150	150	150	150
PUTotal	Pearson Correlation	.870**	.905**	.898**	.902**	.918**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	
	N	150	150	150	150	150	150

**. Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS Output

Table 32: Pearson correlation results for TAM usage intention (UI) construct

Correlations

		UI1	UI2	UI3	UI4	UITotal
UI1	Pearson Correlation	1	.867**	.830**	.764**	.927**
	Sig. (2-tailed)		<.001	<.001	<.001	<.001
	N	150	150	150	150	150
UI2	Pearson Correlation	.867**	1	.866**	.809**	.951**
	Sig. (2-tailed)	<.001		<.001	<.001	<.001
	N	150	150	150	150	150
UI3	Pearson Correlation	.830**	.866**	1	.782**	.933**
	Sig. (2-tailed)	<.001	<.001		<.001	<.001
	N	150	150	150	150	150
UI4	Pearson Correlation	.764**	.809**	.782**	1	.908**
	Sig. (2-tailed)	<.001	<.001	<.001		<.001
	N	150	150	150	150	150
UITotal	Pearson Correlation	.927**	.951**	.933**	.908**	1
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	
	N	150	150	150	150	150

**. Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS Output

Appendix F: Reliability Results

Table 33: Cronbach's Alpha result for TRI motivators (TRIM)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.792	.803	8

Source: SPSS Output

Table 34: Cronbach's Alpha result for TRI inhibitors (TRII)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.737	.738	8

Source: SPSS Output

Table 35: Cronbach's Alpha result for PU

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.940	.940	5

Source: SPSS Output

Table 36: Cronbach's Alpha result for UI

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.946	.948	4

Source: SPSS Output

Appendix G: Factor Analysis Results

The tables below present the correlation results as part of the EFA done on the research constructs. The red blocks indicate the first correlation values above 0.3 for each of the construct questions. Each table was extracted from SPSS after the factor reduction analysis was completed.

Table 37: Factor analysis correlation matrix for TRI motivators (TRIM)

Correlation Matrix

		TRIM1	TRIM2	TRIM3	TRIM4	TRIM5	TRIM6	TRIM7	TRIM8
Correlation	TRIM1	1.000	.345	.282	.343	.227	.101	-.021	.226
	TRIM2	.345	1.000	.665	.648	.385	.245	.182	.403
	TRIM3	.282	.665	1.000	.516	.308	.211	.156	.383
	TRIM4	.343	.648	.516	1.000	.369	.272	.204	.465
	TRIM5	.227	.385	.308	.369	1.000	.392	.355	.494
	TRIM6	.101	.245	.211	.272	.392	1.000	.302	.528
	TRIM7	-.021	.182	.156	.204	.355	.302	1.000	.455
	TRIM8	.226	.403	.383	.465	.494	.528	.455	1.000

Source: SPSS Output

Table 38: Factor analysis correlation matrix for TRI inhibitors (TRII)

Correlation Matrix

		TRII1	TRII2	TRII3	TRII4	TRII5	TRII6	TRII7	TRII8
Correlation	TRII1	1.000	.353	.238	.256	.079	.119	.017	.113
	TRII2	.353	1.000	.289	.454	.305	.360	.229	.360
	TRII3	.238	.289	1.000	.171	.242	.409	.301	.232
	TRII4	.256	.454	.171	1.000	.276	.232	.208	.253
	TRII5	.079	.305	.242	.276	1.000	.289	.271	.180
	TRII6	.119	.360	.409	.232	.289	1.000	.444	.293
	TRII7	.017	.229	.301	.208	.271	.444	1.000	.321
	TRII8	.113	.360	.232	.253	.180	.293	.321	1.000

Source: SPSS Output

Table 39: Factor analysis correlation matrix for TAM perceived usefulness (PU)

Correlation Matrix

		PU1	PU2	PU3	PU4	PU5
Correlation	PU1	1.000	.762	.687	.716	.737
	PU2	.762	1.000	.847	.694	.766
	PU3	.687	.847	1.000	.771	.748
	PU4	.716	.694	.771	1.000	.868
	PU5	.737	.766	.748	.868	1.000

Source: SPSS Output

Table 40: Factor analysis correlation matrix for TAM usage intention (UI)

Correlation Matrix

		UI1	UI2	UI3	UI4
Correlation	UI1	1.000	.867	.830	.764
	UI2	.867	1.000	.866	.809
	UI3	.830	.866	1.000	.782
	UI4	.764	.809	.782	1.000

Source: SPSS Output

Appendix H: Scatter Plots for Construct Sample Data

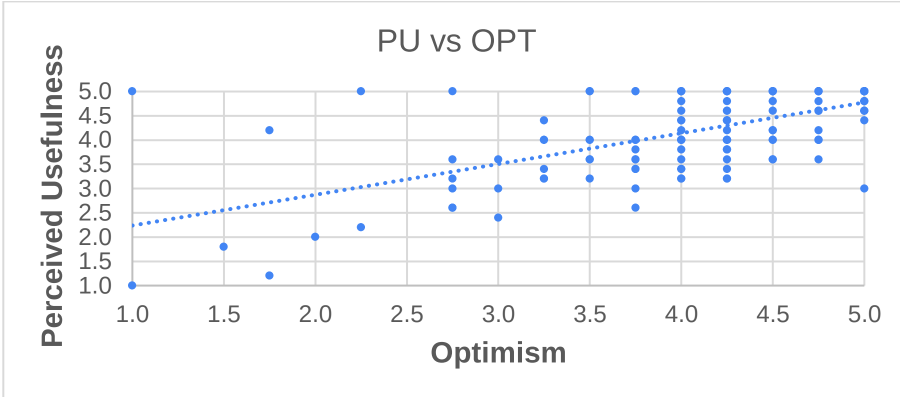

Figure 30: Scatter plot for PU and OPT

Source: Generated by the researcher

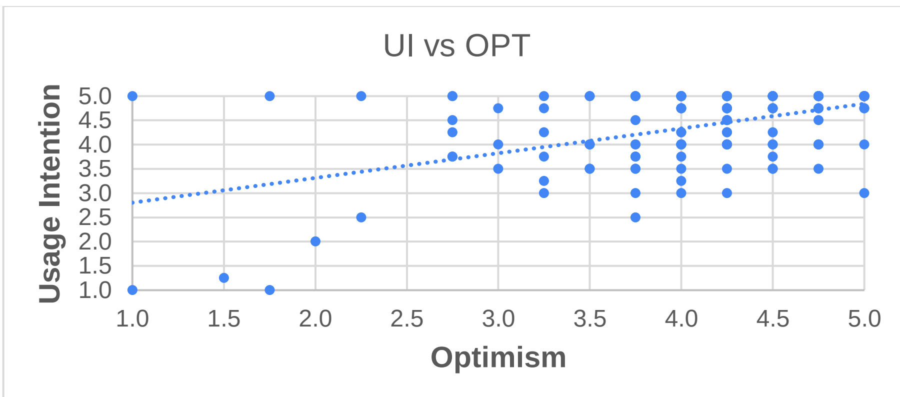

Figure 31: Scatter plot for UI and OPT

Source: Generated by the researcher

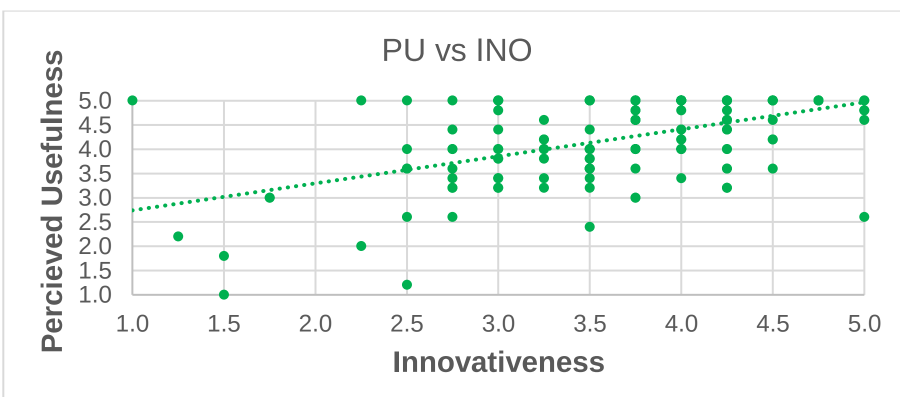

Figure 32: Scatter plot for PU and INO

Source: Generated by the researcher

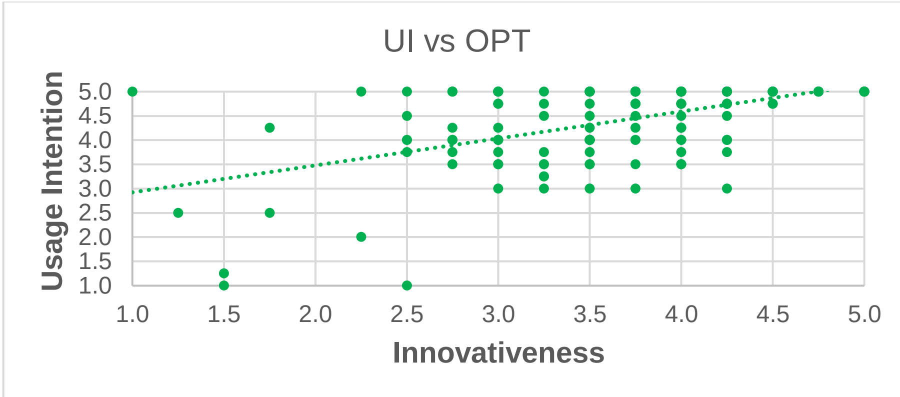

Figure 33: Scatter plot of UI and OPT

Source: Generated by the researcher

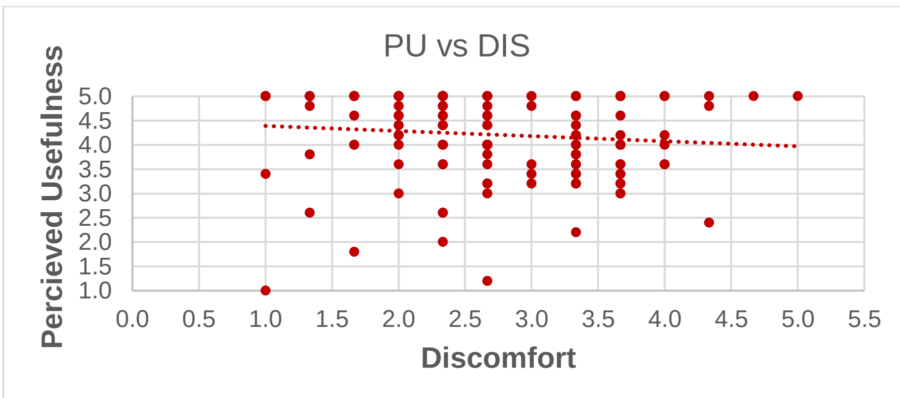

Figure 34: Scatter plot of PU and DIS

Source: Generated by the researcher

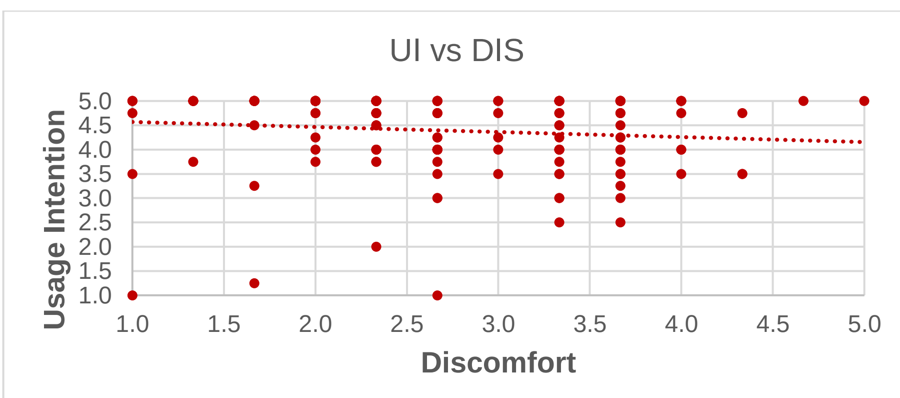

Figure 35: Scatter plot of UI and DIS

Source: Generated by the researcher

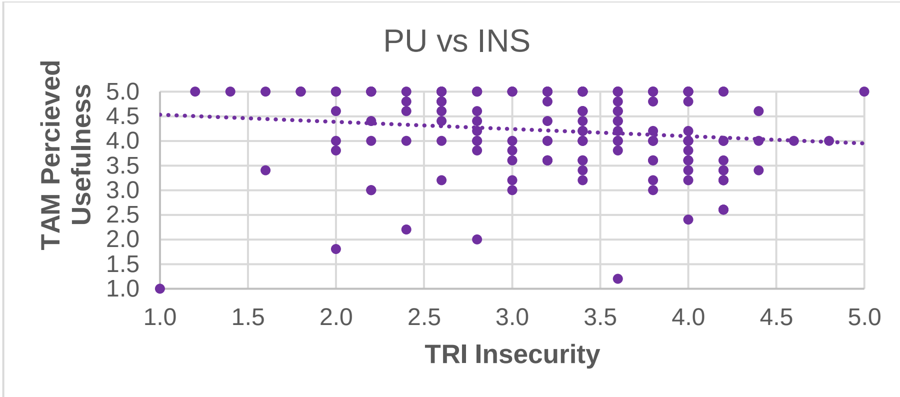

Figure 36: Scatter plot of PU and INS

Source: Generated by the researcher

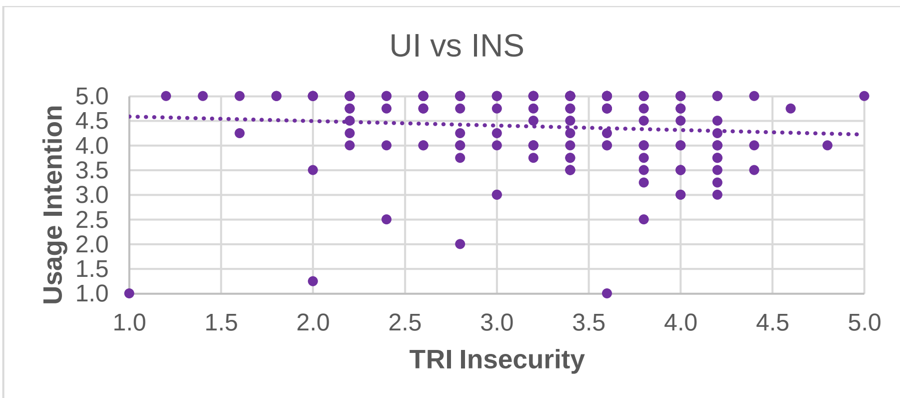

Figure 37: Scatter plot of UI and INS

Source: Generated by the researcher

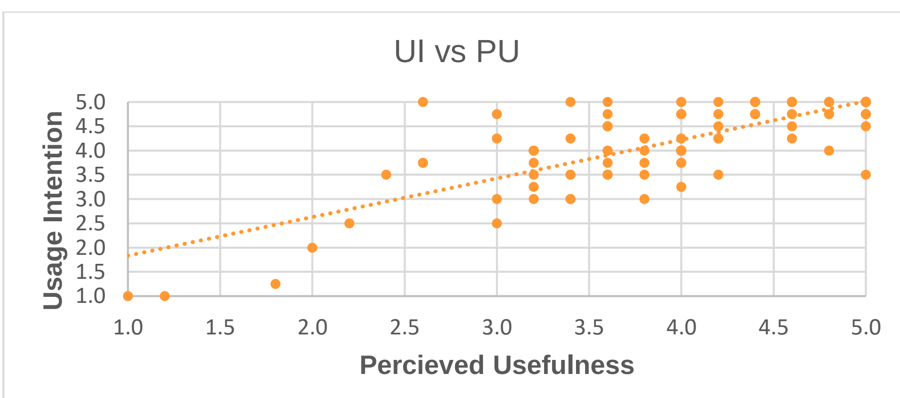

Figure 38: Scatter of UI and PU

Source: Generated by the researcher

Appendix I: Kendell’s Tau Correlation Output from SPSS

Table 41: Kendells’ tau correlation output from SPSS for TAM and TRI constructs

Correlations

			OPT	INO	DIS	INS	PU	UI
Kendall's tau_b	OPT	Correlation Coefficient	1.000	.220**	-.075	-.062	.480**	.375**
		Sig. (2-tailed)	.	<.001	.221	.301	<.001	<.001
		N	150	150	150	150	150	150
	INO	Correlation Coefficient	.220**	1.000	-.028	-.066	.368**	.379**
		Sig. (2-tailed)	<.001	.	.646	.266	<.001	<.001
		N	150	150	150	150	150	150
	DIS	Correlation Coefficient	-.075	-.028	1.000	.306**	-.169**	-.203**
		Sig. (2-tailed)	.221	.646	.	<.001	.006	.001
		N	150	150	150	150	150	150
	INS	Correlation Coefficient	-.062	-.066	.306**	1.000	-.200**	-.183**
		Sig. (2-tailed)	.301	.266	<.001	.	.001	.003
		N	150	150	150	150	150	150
	PU	Correlation Coefficient	.480**	.368**	-.169**	-.200**	1.000	.682**
		Sig. (2-tailed)	<.001	<.001	.006	.001	.	<.001
		N	150	150	150	150	150	150
	UI	Correlation Coefficient	.375**	.379**	-.203**	-.183**	.682**	1.000
		Sig. (2-tailed)	<.001	<.001	.001	.003	<.001	.
		N	150	150	150	150	150	150

**. Correlation is significant at the 0.01 level (2-tailed).

Source: SPSS output

Appendix J: Kruskal-Wallis and Mann-Whitney SPSS Outputs

Table 42: Kruskal-Wallis output from SPSS for age and UI

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of UI is the same across categories of Age.	Independent-Samples Kruskal-Wallis Test	.130	Retain the null hypothesis.

a. The significance level is .050.

b. Asymptotic significance is displayed.

Independent-Samples Kruskal-Wallis Test

UI across Age

Independent-Samples Kruskal-Wallis Test Summary

Total N	150
Test Statistic	7.104[a]
Degree Of Freedom	4
Asymptotic Sig.(2-sided test)	.130

a. The test statistic is adjusted for ties.

Source: SPSS output

Table 43: Mann-Whitney output from SPSS for education level and UI

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of UI is the same across categories of Edu.	Independent-Samples Mann-Whitney U Test	.008	Reject the null hypothesis.

a. The significance level is .050.

b. Asymptotic significance is displayed.

Independent-Samples Mann-Whitney U Test

UI across Edu

Independent-Samples Mann-Whitney U Test Summary

Total N	150
Mann-Whitney U	3070.000
Wilcoxon W	8323.000
Test Statistic	3070.000
Standard Error	235.689
Standardized Test Statistic	2.639
Asymptotic Sig.(2-sided test)	.008

Source: SPSS output

Table 44: Kruskal-Wallis output from SPSS for role and UI

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of UI is the same across categories of Role.	Independent-Samples Kruskal-Wallis Test	.155	Retain the null hypothesis.

a. The significance level is .050.

b. Asymptotic significance is displayed.

Independent-Samples Kruskal-Wallis Test

UI across Role

Independent-Samples Kruskal-Wallis Test Summary

Total N	150
Test Statistic	3.732[a]
Degree Of Freedom	2
Asymptotic Sig.(2-sided test)	.155

a. The test statistic is adjusted for ties.

Source: SPSS output