Gordon Institute of Business Science
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Trust as a Moderator in the Influence of AI Technology Readiness on AI Technology Adoption.

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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

Artificial intelligence adoption is accelerating and transforming industries worldwide through a wide range of applications with the potential to generate significant value. Thus, understanding what effectively drives adoption would give organisations a competitive advantage. The study determines whether trust moderates the relationship from AI technology readiness to AI technology adoption by individuals working for organisations. The frameworks used for the study are the technology readiness index and the unified theory of acceptance and use of technology. The data comprising 213 usable responses was collected using an online survey. The correlation and moderation were separately tested using the Spearmans Correlation Coefficient and stepwise hierarchical multiple regression. Although there is support from broader context literature for trust's moderation on the relationship between AI technology readiness and AI technology adoption, the study only found that trust has a significant positive moderating effect on the relationship between Readiness Motivators and the use of AI in specialised tasks. The research delivered a model that managers can use to facilitate the effective adoption of AI technology by individuals in their organisations. Finally, a need was identified to do more research, especially on the adoption of AI technology by individuals in an organisation.

Keywords

AI, Artificial intelligence, Trust, Technology Adoption, Technology Readiness.

Plagiarism 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.

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List of Abbreviations

ADBI – Behavioural intention.

ADU – Use.

ADUD – Use defined tasks.

ADUG – Use general tasks.

ADUS – Use specialised tasks.

AGE – Age of the respondent.

AI – Artificial intelligence.

AIXP – Respondent AI experience.

CD – Developing or developed country.

DV – Dependent Variable.

EFA – Exploratory factor analysis.

GEN – Gender of the respondent.

IQR – Interquartile range.

IV – Independent Vairable.

KMO – Kaiser-Meyer-Olkin measure of sampling adequacy.

TAM – Technology acceptance model.

TCB – Trust cognitive benevolence.

TCC – Trust cognitive competence.

TCI – Trust cognitive integrity.

TE – Trust emotional.

TRA – Theory of reasoned action.

TRD – Technology readiness discomfort.

TRI – Technology readiness index.

TRIS – Technology readiness insecurity.

TRIV – Technology readiness innovativeness.

TRO – Technology readiness optimism.

UA – Unit of analysis.

UTAUT – Unified theory of acceptance and use of technology.

UTEE – Effort expectancy.

UTFC – Facilitating conditions.

UTPE – Performance expectancy.

UTSI – Social influence.

VIF – Variance inflation factor.

1. Definition of Problem and Purpose

1.1. Background

Artificial intelligence (AI) adoption is accelerating and transforming industries worldwide due to the wide range of applications (Yang et al., 2022). AI technology has a broad range of applications, and its potential to generate profits is attracting further interest (Yang et al., 2022). AI technologies are currently widely used in more straightforward applications, e.g., addressing staff information technology problems, verifying accounts to detect fraud, interpreting big data, making restaurant recommendations (Davenport & Ronanki, 2018), driving vehicles, recognising faces, and conducting online searches (Shi et al., 2021). Cutting-edge AI technologies tackle complex problems, e.g., enhancing cancer treatment and interacting with humans using human language and behaviour (Davenport & Ronanki, 2018). Adopting AI technologies is reshaping the world (Shi et al., 2021).

Some AI tools have advanced so much in autonomy and intelligence that the users and their designers sometimes do not understand the precise mechanisms of the AI technology (Navarro et al., 2022). This speaks to the user's AI readiness regarding optimism, innovativeness, discomfort and insecurity, which influences the adoption of AI technology (Parasuraman & Colby, 2015). Adopting or using AI tools increases the employees' productivity, which drives the organisation's productivity (Lu, 2021).

Managers should pay attention to both AI technology and the influence of employee aspects on AI technology adoption; e.g., if the manager does not account for employees' trust and readiness in AI tools, the AI investment is less likely to realise the expected returns (Shamim et al., 2023).

1.2. Research Problem

1.2.1. What is Known

In organisations, technology use is often preceded by a behavioural intention forming adoption (Venkatesh et al., 2003). Adoption is determined by various factors, including technology readiness, social influence, facilitating conditions, performance expectancy, and effort expectancy (Parasuraman & Colby, 2015; Venkatesh et al., 2003).

Venkatesh et al. (2012) highlighted trust as crucial in driving technology adoption. Thus, this influence of trust on the relationships determining adoption mentioned above is the foundation of the research problem and the need for further exploration.

1.2.2. What is Unknown

Although AI technology is widespread and readily available, its adoption must be better understood (Venkatesh, 2022). It was recommended to investigate further how trust influences the adoption of AI technology (Dwivedi et al., 2019; Navarro et al., 2018; Navarro et al., 2022; Shamim et al., 2023). While it was shown that trust drives technology adoption (Venkatesh et al., 2012), research (Blut & Wang, 2020; Chin et al., 2024) suggest that trust moderates the relationships from technology readiness, social influence, performance expectancy, and effort expectancy to adoption.

1.2.3. The Importance of Understanding What is Unknown

With AI technology becoming more powerful and more widely used (Yang et al., 2022), there is a need to improve the understanding of the moderation of user trust in the influence of AI technology readiness on AI technology adoption to enable organisations to extract value from increased adoption through the added performance which AI technology offers (Navarro et al., 2022).

1.3. Research Purpose

This study aims to determine if user trust moderates the influence of AI technology readiness on AI technology adoption in organisations. Specifically, the aim is to determine how user trust in organisations enhances or impedes the relationship from readiness motivators (innovativeness and optimism), readiness inhibitors (insecurity and discomfort), social influence, performance expectancy, and effort expectancy on adoption in the AI technology context.

1.4. Business Significance

AI adoption in companies is poised to drive competitive advantage (Flavián et al., 2022). Using AI tools increases the employees' productivity, which drives the organisation's productivity (Lu, 2021). AI technology is essential for future economic growth because AI tools can increase productivity and replace human labour, effectively expanding the labour market (Berg et al., 2018; Lu, 2021). AI tools drive down the cost of operation in organisations (Berg et al., 2018). The share of organisations that can successfully adopt AI for value is increasing, forcing other organisations to drive AI adoption (Vohra et al., 2022).

Examples of AI tools used include a leading solar panel installer that analysed satellite photos to optimise their process, yielding a 25% decrease in sales costs. The metro of Madrid analysed data from their substations using AI, which enabled them to reduce energy consumption by 25%, and a beverage bottling company consolidated data sources using AI, which helped them to boost sales by 3% (Vohra et al., 2022).

Surveys have shown that less than 40% of organisations investing in AI can show business gains, and many AI technology projects experience setbacks or fail (Davenport & Ronanki, 2018; Ransbotham et al., 2019). Research (Blut & Wang, 2020) indicated that trust is essential in driving technology adoption. Even though AI technology is being introduced into firms, investing in AI technology alone is not sufficient, as organisations need to understand the human aspect of the adoption process better, especially since many individuals lack trust in it (Shamim et al., 2023).

1.5. Academic Significance

While it was shown that trust drives technology adoption (Venkatesh et al., 2012), research (Blut & Wang, 2020; Chin et al., 2024) suggest that trust moderates the relationships from technology readiness, social influence, performance expectancy, and effort expectancy to adoption. Further research into the user trust's influence on adopting AI technology was suggested (Dwivedi et al., 2019; Navarro et al., 2018; Navarro et al., 2022; Shamim et al., 2023). The research quantitively measured the moderating influence of trust in relationships from readiness motivators (innovativeness and optimism), readiness inhibitors (insecurity and discomfort), performance expectancy, effort expectancy, and social influence on adoption in the context of AI technology.

1.6. Distinctiveness of the Research Setting

The quantitative research drew from two theories, namely the technology readiness index 2.0 (TRI 2.0) (Parasuraman & Colby, 2015) and the extended unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). It combined these two frameworks in an adapted form. Blut and Wang (2020) have suggested that usage intention and usage behaviour can be grouped as a single construct of technology usage. Thus, the concept model was adopted from UTAUT grouping behavioural intention and used as a single construct named adoption since the mediating effect of usage intention is not the focus of this study. Blut and Wang

(2020) have also shown that by grouping the four dimensions specified by TRI into two dimensions of readiness motivators (innovativeness and optimism) and readiness inhibitors (insecurity and discomfort), the construct of technology readiness is best conceptualised. This research adopted TRI 2.0 with the two dimensions of motivators (innovativeness and optimism) and inhibitors (insecurity and discomfort). Lastly, the merging of the frameworks by pointing the independent variables of both frameworks to the same construct of adoption defined in both frameworks as the intent to utilise and use.

The combined framework enables analysis of the moderating influence of trust on the relationship from technology readiness to adoption because, according to the literature (Blut & Wang, 2020; Chin et al., 2024), trust influences the relationship to adoption from readiness motivators (innovativeness and optimism), readiness inhibitors (insecurity and discomfort), social influence, performance expectancy, and effort expectancy. To the researcher's best knowledge, research has not been done using TRI 2.0 and UTAUT with trust as a moderator in the relationship between readiness motivators (innovativeness and optimism) and technology adoption and readiness inhibitors (insecurity and discomfort) and technology adoption.

1.7. Research Scope

The boundaries of this research were the context of AI technology adoption by the individual in an organisational setting. The scope was limited to technology readiness, trust, and adoption constructs. Parasuraman and Colby, 2015 describe technology readiness as consisting of readiness motivators (innovativeness and optimism) and readiness inhibitors (insecurity and discomfort). Venkatesh et al. (2003) describe adoption as consisting of behavioural intention preceding use, driven by social influence, facilitating conditions, performance expectancy, and effort expectancy.

1.8. Brief Outline of Document

In Chapter Two, the relevant literature is reviewed to provide theory and background information. In Chapter Three, the research question is stated, and the hypotheses are hypothesised. In Chapter Four, the research methodology and design were documented. In Chapter Five, the demographic results and the results after testing the hypotheses were given. In Chapter Six, the results are contextualised and compared to the previously published literature. Finally, in Chapter Seven, the conclusions, recommendations and limitations of the research are documented. Multiple appendixes were attached, which are referred to from the chapter text to allow the reader to access further details on specific topics.

2. Literature Review

2.1. Introduction

Huang and Rust (2018) have defined AI as “machines that exhibit aspects of human intelligence” (p. 155). Li et al. (2019) have defined AI as “the simulation of human intelligence processes that allows computer systems to automatically learn from experience and perform humanlike tasks to improve the efficiency of daily tasks” (p. 173). Thus, AI is an intelligent machine that can perform humanlike tasks and learn from experience.

AI technology has a broad range of applications, and its potential to generate profits is attracting further interest (Yang et al., 2022). AI technologies are currently widely used in more straightforward applications, e.g., addressing staff information, technology problems, verifying accounts to detect fraud, interpreting big data, making restaurant recommendations (Davenport & Ronanki, 2018), driving vehicles, recognising faces, and conducting online searches (Shi et al., 2021). The new generation of AI technologies is tackling complex problems, e.g., enhancing cancer treatment and interacting with humans using human language and behaviour (Davenport & Ronanki, 2018). Although AI technology and AI tools are widespread and readily available, their adoption is not well understood (Venkatesh, 2022). The following sections explore the key constructs influencing AI technology adoption: technology readiness, trust, and adoption.

2.2. Technology Readiness

Technological advances have proliferated widely among consumers, but despite this, the use of technology is not guaranteed (Blut & Wang, 2020). Individual reactions to new technology vary broadly (Flavián et al., 2022). Emotions can explain the favourable and unfavourable reactions that technology elicits from users (Flavián et al., 2022). In line with this, Parasuraman (2000) defined technology readiness as “people’s propensity to embrace and use new technologies for accomplishing goals in home life and at work” (p. 308). Technology readiness refers to a person’s inclination to embrace and utilise technology, including their attitude toward adopting new technologies (Blut & Wang, 2020). A person’s psychological preparedness toward technology usage forms part of technology readiness (Flavián et al., 2022).

Technology acceptance model (TAM) literature generally indicates that individuals with higher technology readiness often view technology as more beneficial and more straightforward to utilise, making them more likely to adopt it (Blut & Wang, 2020). Technology readiness consists of less stable, lower-order situational traits that typically vary since it is field specific and shaped by the current environment and past experiences (Blut & Wang, 2020). The more readiness an individual has for technology, the greater the likelihood of the use of the specific technology (Blut & Wang, 2020). Parasuraman and Colby (2015) measured and showed the validity of four dimensions describing technology readiness: two motivators, innovativeness and optimism, and two inhibitors, insecurity and discomfort. Blut and Wang (2020) have shown that technology readiness is best conceptualised by grouping the four dimensions into two dimensions of readiness motivators (optimism and innovativeness) and readiness inhibitors (discomfort and insecurity). Flavián et al. (2022) proposed an additional dimension to technology readiness: awareness.

Optimism toward technology is “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). Optimistic users have a higher inclination to use novel technologies than pessimistic users since they view novel technology as functional, reliable, and beneficial while paying less attention to possible adverse outcomes (Blut & Wang, 2020; Flavián et al., 2022). This relationship between optimism and use is held even when individuals receive good and bad information about the service in a study (Hwang & Good, 2014). Therefore, optimistic users tend to have a positive predisposition toward new technologies (Flavián et al., 2022).

Innovativeness is “a tendency to be a technology pioneer and thought leader” (Parasuraman & Colby, 2015, p. 60). Innovative people are open to experimenting with novel technology; when they are very creative, they are typically open-minded and more inclined to utilise technology (Blut & Wang, 2020; Flavián et al., 2022). Innovative people generally view technology’s functionality positively, even if uncertainty exists regarding its releasable value (Flavián et al., 2022).

Discomfort toward technology is “a perceived lack of control over technology and a feeling of being overwhelmed by it” (Parasuraman & Colby, 2015, p. 60). Individuals feel discomfort from technology use because they perceive it as complex, overwhelming and incapable of fulfilling their requirements (Blut & Wang, 2020; Flavián et al., 2022). People who experience elevated levels of discomfort from a particular technology can have an aversion to using products based on new technologies (Flavián et al., 2022). The perceived lack of control or ability to manage technology can lead to the rejection of said technology (Blut & Wang, 2020; Flavián et al., 2022). The perceived lack of control in persons who are discomforted by ceding power to automated products may avoid their use (Blut & Wang, 2020; Flavián et al., 2022). In contrast, it was also discovered that individuals who suffer from elevated discomfort towards technology may prefer the use of technology, which automates the process to a high degree because it reduces the burden of learning and understanding the technology itself (Flavián et al., 2022).

Insecurity toward technology is defined as "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 combines concerns about overall safety, worries about adverse outcomes and a desire to have certainty of abilities (Blut & Wang, 2020). People who usually do not trust technology, who are sceptical of technology, and who anticipate more risks than benefits of technology likely avoid using it (Blut & Wang, 2020). People with elevated insecurity towards technology may prevent its use (Flavián et al., 2022). A user requires, at minimum, a fundamental understanding of the functionality of systems using AI to feel confident during use (Flavián et al., 2022).

Awareness of a service offered by technology means knowing about its existence, being knowledgeable about it, or having information about it (Flavián et al., 2022). People who are more knowledgeable about a service and its options use it more than those who have just heard about it (Flavián et al., 2022). The individual's awareness is determined by the information received, information research, and their exposure to the service (Flavián et al., 2022).

Multiple AI (Belanche et al., 2020; Mende et al., 2019) domain experts have suggested that TRI is a suitable framework for AI technology (Flavián et al., 2022). Thus, TRI should be a good framework for understanding the user's willingness to use AI tools.

2.3. Trust

Trust in the information technology context is defined as “a user’s expectation that information technology artefacts such as websites, virtual peers, recommendation agents, automated online assistants, robots, and the like will fulfil the expected responsibilities” (Tussyadiah et al., 2020, p. 5). When it is referred to as the individual’s trust in AI technology, it is the willingness to embrace the technological risk and use it to get the best results (Gillath et al., 2021). To build trust, the trustors' beliefs should align with the expected actions of the trustee (Shamim et al., 2023). Trust and persuasive social interactions are related strongly, where the statements' quality and promises' reliability must satisfy anticipated outcomes (Kim et al., 2023). Trust is crucial to persuade people in uncertain situations with potential risks (Kim et al., 2023; Shi et al., 2021). During decision-making, trust formation relates closely to the level of risk (Shi et al., 2021). The travelling individual’s reliance on the recommendation of an AI-based system is determined mainly by trust (Shi et al., 2021).

While technology adoption is primarily motivated by cognitive factors, e.g., performance expectancy and effort expectancy, AI technology adoption is driven by cognitive and emotional factors (Shi et al., 2021). It was proposed to conceptualise trust as a construct consisting of two dimensions: emotional trust and cognitive trust (Kim et al., 2023; Shi et al., 2021). Cognitive trust is rooted primarily in knowledge and reliability, where the relationship is built on rational judgment and evidence of competence and dependability (Lewis & Weigert, 1985). Emotional trust is based primarily on emotional connection and feelings based on empathy, affection and personal bonding (Lewis & Weigert, 1985).

The theory of bounded rationality articulates that people have a limited ability to make cognitive decisions; thus, the individual with cognitive trust using AI technology needs to use significant cognitive effort if they want to evaluate the outcome proposed by the AI technology. In contrast, when the individual has emotional trust, the decision is more irrational and driven by emotions, which usually results in adopting the technology (Shi et al., 2021).

Shi et al. (2021) used AI as a planning agent and found that emotional trust substantially influences adoption more than cognitive trust. Thus, emotional trust from the person's positive feelings has more substantial predictive power to rely entirely on AI technology than cognitive trust, which requires rational evaluations emphasising the need to include both cognitive and emotional trust (Shi et al., 2021).

McKnight et al. (2011) argued that trust characteristics should be distinguished between technology and interpersonal interaction. The three dimensions proposed for technology are reliability, helpfulness, and functionality (Kim et al., 2023; McKnight et al., 2011).

People fear AI because of its complexity, nondeterministic AI systems, and that predicted future AI technology will replace many current jobs (Shamim et al., 2023). The uncanny valley theory suggests that the human-like attributes of AI technology might create anxiety and fear in people (Shi et al., 2021). This fear harms trust in AI technologies (Shamim et al., 2023).

AI is usually best suited for very complex environments, which makes its nature indeterministic (Shamim et al., 2023). This complexity and the non-deterministic nature of AI technology make its decision-making process incomprehensible to the user, negatively affecting trust (Shamim et al., 2023).

While AI technology excels in specific domains, it could be better and is prone to commit errors (Kim et al., 2023). These errors lead to changes in consumer perspectives on AI technology (Kim et al., 2023). In the case of ChatGPT, the large user base has been perceived by individuals as social proof, increasing their trust even though it occasionally generates incorrect information (Kim et al., 2023). It was concluded that providing accurate information is essential for establishing trust, which could facilitate embracing AI technology (Kim et al., 2023). Security regarding AI technology is vital to building trust in a system (Chin et al., 2024). The system's security should ensure a low probability of data breaches, vulnerabilities, technological failures, system failures, and situations that could compromise the user's well-being (Chin et al., 2024).

Employees need to trust the technology to extract value from implementing AI technologies (Shamim et al., 2023). Furthermore, with trust in the technology, organisations can transform when implementing their digital strategy (Shamim et al., 2023). AI trust is pivotal in enabling value creation and essential to maximise the value an organisation can realise from AI technology adoption (Shamim et al., 2023). A lack of trust may be a driver of the slow adoption of technology (Chin et al., 2024).

Trust is related to technology readiness insecurity in terms of the ability of the technology to execute its purpose successfully, which then fosters distrust of technology and scepticism of its performance (Lin & Hsieh, 2007). A study was conducted to determine how technology readiness influences behavioural intention, after which it was noted that the link of trust to the relationship should be further explored (Lin & Hsieh, 2007). It was found that the relationship between technology readiness and customer engagement behaviour, which is similar to use and adoption in the commercial AI environment, was both moderated and mediated by trust (Yin et al., 2023).

In terms of readiness inhibitors (insecurity and discomfort), trust plays an essential role in decision-making when there are risks involved (Kaur & Arora, 2021). It is expected that when individuals have higher levels of trust in the technology, their behavioural intention increases, which is a precursor to use (Kaur & Arora, 2021). When risk is involved, trust alleviates the anxiety due to uncertainty and acts as a catalyst for behavioural intention (Kaur & Arora, 2021). The negative relationship between insecurity induced by risk and behavioural intention, the precursor of adoption, is moderated by trust (Kaur & Arora, 2021). Thus, when the individual has trust in the technology, the negative influence of insecurity has a lesser effect on the adoption of the technology (Kaur & Arora, 2021).

Trust influences the adoption of emerging technologies (Shamim et al., 2023). Trust is crucial in determining technology adoption behaviour (Blut & Wang, 2020). Trust in the technology helps users to accept AI technologies (Yang et al., 2022).

Kim et al. (2023) note that trust is essential in an individual’s decision to adopt technology. A study of AI-powered devices showed that an increased perception of usefulness drives an increase in trust (Shin, 2021). A technology adoption study of devices used at home powered by AI suggested that perceived usefulness, perceived ease of use, perceived technology security, perceived social presence, and social identity moderated the relationships to adoption, where the sample of the study tested that trust significantly moderated the relationships to adoption from social identity, perceived ease of use, and perceived social presence (Chin et al., 2024).

In contrast, Shi et al. (2021) showed that cognitive trust mediates the relationship between performance efficacy, which is related to performance expectancy, and intention to adopt. Shi et al. (2021) have also shown that emotional trust mediates the relationship between social influence and intention to adopt.

2.4. Technology Adoption

Scholars have recently shown high interest in AI technology and the adoption thereof (Balakrishnan et al., 2022; Budhathoki et al., 2024; Chin et al., 2024; Damerji & Salimi, 2021; Dwivedi et al., 2019; Khan et al., 2023; Shi et al., 2021; Venkatesh, 2022; Vimalkumar et al., 2021). These scholars have drawn upon conventional technology adoption theories, namely the theory of reasoned action (TRA), TAM, and UTAUT, to explain the adoption of technology by the individual (Shi et al., 2021). The TAM is a variation of the TRA and describes how individuals accept and use technology within the Information Systems discipline (Chin et al., 2024). The TAM is based on two core dimensions, perceived usefulness and ease of use, which shape the individual's perception of technology and influence the adoption of novel technology (Chin et al., 2024). TAM's perceived usefulness and ease of use are the core dimensions driving AI technology use and, thus, adoption (Chin et al., 2024). Technology usage or adoption is proposed as a single construct consisting of two dimensions use intention and usage behaviour (Blut & Wang, 2020).

Davis (1985) defines perceived usefulness as "the degree to which an individual believes that using a particular system would enhance his or her job performance" (p. 26). Davis (1989) gives an updated definition as "the prospective user's subjective probability that using a specific application system will increase users' performance" (p. 320). Both definitions were recently referenced by Chin et al. (2024). Venkatesh et al. (2012) updated the dimension name to performance expectancy with the revised definition of "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (p. 447). The most influential factor for planning to use and the actual utilisation of AI technology in the context of household devices powered by AI was how useful the product was perceived (Chin et al., 2024), which also aligns with other technology adoption research (Davis, 1989; Venkatesh et al., 2003).

Davis (1985) defines perceived ease of use as “the degree to which an individual believes that using a particular system would be free of physical and mental effort” (p. 26). Venkatesh et al. (2012) updated the dimension name to effort expectancy with the revised definition of “the degree of ease associated with the use of the system” (p. 450). Perceived ease of use includes various factors: straightforward interface, consistency, attractiveness, and technology complexity (Chin et al., 2024). Perceived ease of use can reliably predict technology adoption (Venkatesh & Zhang, 2010; Venkatesh et al., 2012) and AI technology (Chin et al., 2024). Even if a system is the easiest to use when its functionality does not serve a useful purpose, the ease of use will not help to drive adoption (Davis, 1989). It follows that ease of use is a precursor to usability when the causality of these dimensions is considered (Davis, 1989).

Venkatesh et al. (2003) studied eight preexisting adoption theories and compared them to identify four dimensions that directly influence user acceptance. These four consisted of performance and effort expectancy, which were already discussed above, along with the inclusion of Social influence and facilitating conditions (Venkatesh et al., 2003).

Social influence is “the degree to which an individual perceives that important others believe he or she should use the new system” (Venkatesh et al., 2003, p. 451). Social influence is primarily derived from subjective norms, social factors and perceived image (Venkatesh et al., 2003). Subjective norm is what the individual thinks people vital to him want him to do or not to do (Venkatesh et al., 2003). Social Factors are the association with a reference group and specific agreements with individuals in certain situations (Venkatesh et al., 2003). Image refers to the perception that using the product increases a person’s status or reputation among their social circles (Venkatesh et al., 2003).

Facilitating conditions are “the degree to which an individual believes that an organisational and technical infrastructure exists to support use of the system” (Venkatesh et al., 2003, p. 453). Facilitating conditions include factors such as the perceived ability to manage behaviour and the technological alignment with systems already in place (Venkatesh et al., 2003). Perceived behavioural control is a combination of behavioural constraints, self-efficacy, and conditions that make it easy to use resources and technology (Venkatesh et al., 2003). Compatibility is the perception of alignment between the product and the existing values, as well as the requirements and the experience of users who are potential product users (Venkatesh et al., 2003). Facilitating conditions do not directly influence use intention but actual use because these factors' influence is already covered by effort expectancy (Venkatesh et al., 2003).

Other elements that potentially have an influential effect on the use of AI technology include customer traits (e.g. technology readiness), consumer sociodemographics (Blut & Wang, 2020), the AI technology's anthropomorphic features (Shi et al., 2021), social identity, perceived technology security, perceived social presence (Chin et al., 2024), habit, price value, and hedonic motivation (Venkatesh et al., 2012). Venkatesh et al. (2003) state that the dimensions of performance expectancy, effort expectancy, social influence, and facilitating conditions account for the majority (70%) of the variability in the adoption of technology by individuals in organisations, which might be close to the practical limit (Venkatesh et al., 2003).

The following recent studies used the UTAUT framework. The study by Budhathoki et al. (2024) is similar to this study in that it focuses on AI use and adoption; they, however, focused only on one AI tool, ChatGPT, and in the context of students in higher education, whereas this study considers the adoption of a wide range of AI tools in an organisation by individuals. The study by Dwivedi et al. (2019) is significantly broader in context than this study since they have done a study using data from 162 previous studies on information technology systems. The study done by Khan et al. (2023) focuses on AI adoption in conservative industries.

2.5. Frameworks

The study used existing frameworks to describe and measure the constructs under study. For AI technology readiness, TRI 2.0 (Parasuraman & Colby, 2015) was adopted, and for AI technology adoption, UTAUT (Venkatesh et al., 2003) was adapted.

The TRI 2.0 framework has multiple items to determine the individual's readiness to use technology. The construct is referred to as technology readiness (Parasuraman, 2000). Subsequently, the TRI framework was optimised to TRI 2.0 by reducing the required questions without a utility (Parasuraman & Colby, 2015). The technology-readiness construct describes the tendency of individuals to adopt and utilise new technologies towards meeting goals at work and home (Parasuraman, 2000). The construct can be defined as the mindset shaped by mental inhibitors and enablers forming an individual's inherent tendency to embrace technology adoption (Parasuraman, 2000). The factors determining technology adoption and adoption outcomes have been studied widely (Parasuraman, 2000), making the field of study well-established and ripe for quantitative analyses. Both TRI and TRI 2.0 have four categories: optimism, innovativeness, discomfort, and insecurity, which can be grouped into drivers (optimism and innovativeness) and inhibitors (discomfort and insecurity) (Parasuraman & Colby, 2015). In this research, TRI 2.0 was used.

The UTAUT is a framework consisting of multiple items used to describe employee technology acceptance and use (Venkatesh et al., 2003). The UTAUT was initially designed to describe employee technology acceptance and use (Venkatesh et al., 2012). In information systems research, the individual's acceptance of technology is among the most well-established streams of research (Venkatesh et al., 2012), and this maturity allows for quantitative research with readily available frameworks like UTAUT. UTAUT isolated the critical factors and conditions mostly in organisational contexts that predict the behavioural intention to use and the actual use of the technology (Venkatesh et al., 2012). It is worth noting that UTAUT has been used in the organisational context (Venkatesh et al., 2012). The addition of constructs in UTAUT2 has increased the generalisability of UTAUT to not only employees but also to include the broader definition of consumers (Venkatesh et al., 2012). Since the focus is on the individual working in an organisation, the concept model was adapted from UTAUT.

This research combines these two frameworks in an adapted form, as suggested by other research, which are discussed in detail below. Blut and Wang (2020) have indicated that usage intention and usage behaviour can be grouped as a single construct of technology usage. This simplification should not change any outcome since multiple studies (Budhathoki et al., 2024; Dwivedi et al., 2019; Khan et al., 2023; Venkatesh et al., 2003; Venkatesh & Zhang, 2010; Venkatesh et al., 2012) have also found that the relationship between behavioural intention to use is significantly positive. Thus, the concept model was adopted from UTAUT grouping behavioural intention and used as a single construct named adoption since the mediating effect of usage intention, which is associated with behavioural intention, is not the focus of this study. Blut and Wang (2020) have also shown that by grouping the four dimensions specified by TRI into two dimensions of motivators (innovativeness and optimism) and inhibitors (discomfort and insecurity), the construct of technology readiness is best conceptualised. This research adopted the TRI 2.0 model in the two dimensions of motivators (innovativeness and optimism) and inhibitors (discomfort and insecurity).

Lastly, the merging of the frameworks by pointing the independent variables of both frameworks to the same construct of adoption defined in both frameworks as the use of the product. This is necessary to analyse how trust moderates the relationship from technology readiness to adoption because, according to the literature (Blut & Wang, 2020; Chin et al., 2024; Flavián et al., 2022; Hwang & Good, 2014; Kim et al., 2023; Shamim et al., 2023; Shi et al., 2021; Yin et al., 2023), trust is expected to determine the strength of the relationship to adoption from the readiness motivators (innovativeness and optimism), readiness inhibitors (discomfort and insecurity), performance expectancy, effort expectancy, and social influence which are independent variables from both frameworks.

2.6. Key Relationships

The key relationships identified from TRI 2.0 (Parasuraman & Colby, 2015) and UTAUT (Venkatesh et al., 2003) are reviewed in this section. The goal is to get a better understanding of the relationships relevant to the study. Each relationship is reviewed together with the possible moderating effect of trust in the relationship. Thus, first, the literature in support of the relationship is reviewed, followed by the literature that opposes the relationship and finally, the literature in support and opposing the moderation of trust in the relationship.

2.6.1. Readiness Motivators and Adoption

In support of the relationship, Hwang and Good (2014), who did a study in the context of intelligent sensor-based services, found that technology readiness optimism, a factor of the readiness motivators (innovativeness and optimism), significantly and positively influences shopping intention at a retailer with intelligent sensor-based services, which is associated with behavioural intention and leads to adoption. Flavián et al. (2022), who did a study on analytical AI in the context of services, showed that the readiness motivator and technology readiness optimism significantly and positively influence the intention to use AI, which is associated with behavioural intention and leads to adoption.

In opposition to the relationship, Blut and Wang (2020), who did a study in the context of technology in an organisation, showed that readiness motivators (innovativeness and optimism) significantly but negatively influence usage intention, which is associated with behavioural intention that leads to adoption. This was an unexpected result for Blut and Wang (2020) because the significant negative influence was contrary to their predictions, and they checked the robustness of this unexpected result in their model against an alternative model testing motivators individually, which found an identical outcome. Flavián et al. (2022) have shown that the readiness motivator, technology readiness innovativeness, does not significantly influence the intention to use AI, which is associated with behavioural intention that leads to adoption. Blut and Wang (2020) showed that there is no significant influence of readiness motivators (innovativeness and optimism) on usage behaviour, which is associated with adoption. Blut and Wang (2020) did note that even though they did not find a direct influence from the readiness motivators (innovativeness and optimism) on usage behaviour, an influence through the mediators of their model: ease of use, usefulness perception, quality, perceived value and satisfaction. Thus, the opposing literature above from different contexts suggests that the relationship between the readiness motivators (innovativeness and optimism) and adoption changes with context.

The previous work (Lin & Hsieh, 2007; Yin et al., 2023) did not explicitly state that trust moderates the relationship between readiness motivators (innovativeness and optimism) and adoption. However, they did argue that trust in technology is linked to the relationship between technology readiness and adoption. Yin et al. (2023) tested for mediation between technology readiness and customer engagement behaviour, which is associated with behavioural intention which leads to adoption, and found that trust does not mediate the relationship between technology readiness optimism and engagement behaviour nor the relationship between technology readiness innovativeness and engagement behaviour, which is associated with behavioural intention which leads to adoption. Lin and Hsieh (2007) specifically expected that trust has a link to the relationship between technology readiness and behavioural intention, although they did not explicitly state moderation. Although there is no direct previous evidence for or against the moderation of trust in the relationship between readiness motivators (innovativeness and optimism), there is enough indirect evidence to suggest further investigation.

2.6.2. Readiness Inhibitors and Adoption

In support of the relationship, Hwang and Good (2014) found that the presence of negative information, technology readiness discomfort, a factor of the readiness inhibitors (discomfort and insecurity), negatively and significantly influences shopping intention at a retailer with intelligent sensor-based services, which is associated with behavioural intention which leads to adoption. In further support, Flavián et al. (2022) did a study in the AI services context, which showed that the readiness inhibitor, technology readiness insecurity, significantly and negatively influences the intention to use AI, which is associated with behavioural intention, which leads to adoption.

In opposition to the relationship, Flavián et al. (2022) did a study in the analytical AI services context, showing that the readiness inhibitor, technology readiness discomfort, does not significantly influence the intention to use AI, which is associated with behavioural intention, which leads to adoption. Also, in opposition, Blut and Wang (2020) did a study in the cutting-edge technology context. They found that readiness inhibitors (discomfort and insecurity) do not significantly influence usage behaviour, which is associated with use and adoption. In further opposition, Blut and Wang (2020) found that readiness inhibitors (discomfort and insecurity) significantly and positively influence usage intention, which is associated with behavioural intention, which leads to adoption. The significant positive influence of readiness inhibitors (discomfort and insecurity) on usage intention was unexpected to Blut and Wang (2020), as this relationship was expected to be a negative influence. Thus, the opposing literature above from different contexts suggests that the relationship between the readiness inhibitors (discomfort and insecurity) and adoption changes with context.

A study by Kaur and Arora (2021), in the context of online banking technology, found that trust positively and significantly moderates the relationship between perceived risk, which is associated with readiness inhibitors (discomfort and insecurity), and behavioural intention, which leads to adoption. Furthermore, Lin and Hsieh (2007), who did a study in the context of self-service technologies, expected that trust has a link to the relationship between technology readiness and behavioural intention, although not explicitly stating moderation. With some evidence for trust's moderation of the relationship between readiness inhibitors (discomfort and insecurity) and adoption, it is enough to investigate further.

2.6.3. Performance Expectancy and Adoption

In support of the relationship, Venkatesh et al. (2003) did a study in the context of information technology systems, Venkatesh and Zhang (2010) did a study in the context of technology systems, Venkatesh et al. (2012) did a study in the context of mobile internet consumers, Budhathoki et al. (2024) did a study in the context of ChatGPT in higher education, and Dwivedi et al. (2019) did a study in the context of information technology systems, showed that performance expectancy positively and significantly influences behavioural intention which leads to adoption. Furthermore, Blut and Wang (2020), who did a study in the context of technology in an organisation, showed that usefulness, which is associated with performance expectancy, positively and significantly influences usage behaviour, which is associated with behavioural intention, which leads to adoption. Furthermore, Khan et al. (2023) did a study in the context of AI in conservative industries who did a study in the context of technology in an organisation, which showed that performance expectancy positively and significantly influences AI acceptance intention, which is associated with behavioural intention, which leads to adoption. Thus, the alignment of the literature (Blut & Wang, 2020; Budhathoki et al., 2024; Dwivedi et al., 2019; Khan et al., 2023; Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012) from different contexts suggests that the relationship between performance expectancy and adoption is possibly generalisable over contexts.

Although Chin et al. (2024), who did a study in the context of AI-powered devices in smart homes, rejected the hypothesis that hypothesised the moderating role of trust in the relationship between perceived usefulness, which is associated with performance expectancy, and intention to use, which is associated with behavioural intention. It should be noted that with the confidence interval p smaller and equal to

0.05, the hypothesis by Chin et al. (2024) is accepted. Hence, Chin et al. (2024) support trust's moderation of performance expectancy and adoption. Even though Kim et al. (2023) did not explicitly suggest moderation, it was stated that trust is a critical factor associated with adoption. Kim et al. (2023), who did a study in the context of large language models, further noted that trust is the user's expectation that the technology should perform, which is associated with performance expectancy. In complement to the relationship, Shi et al. (2021), who did a study in the context of AI travel recommendations, showed that cognitive trust significantly mediates the relationship between performance efficacy, which is associated with performance expectancy, and intention to adopt, which is associated with behavioural intention which leads to adoption. With some evidence for trust's moderation of the relationship between performance expectancy and adoption, it is enough to investigate further.

2.6.4. Effort Expectancy and Adoption

In support of the relationship, Venkatesh et al. (2012) did a study in the context of mobile internet consumers, Budhathoki et al. (2024) did a study in the context of ChatGPT in higher education, and Dwivedi et al. (2019) did a study in the context of information technology systems, showed a significant positive relationship between effort expectancy and behavioural intention, which leads to adoption. Furthermore, Blut and Wang (2020), who did a study in the context of technology in an organisation, showed a significant positive relationship between ease of use, which is associated with effort expectancy, and usage intention, which is associated with behavioural intention, which leads to adoption. Furthermore, Khan et al. (2023) did a study in the context of AI in conservative industries who did a study in the context of technology in an organisation, which showed that effort expectancy positively and significantly influences AI acceptance intention, which is associated with behavioural intention, which leads to adoption.

In opposition to the relationship, Venkatesh and Zhang (2010), who did a study in the context of technology systems, found that the relationship between effort expectancy and behavioural intention, which leads to adoption, is not significant. Since there are both supporting (Blut & Wang, 2020; Budhathoki et al., 2024; Dwivedi et al., 2019; Khan et al., 2023; Venkatesh et al., 2012) and opposing (Venkatesh & Zhang, 2010) previous work, it suggests that the relationship is not generalisable in all technology contexts.

In support of trust's moderation in the relationship, Chin et al. (2024), who did a study in the context of AI-powered devices in smart homes, found that trust significantly and positively moderates the relationship between ease of use, which is associated with effort expectancy, and intention to use, which is associated with behavioural intention which leads to adoption. With some evidence for trust's moderation of the relationship between effort expectancy and adoption, it is enough to investigate further.

2.6.5. Social Influence and Adoption

In support of the relationship, Venkatesh et al. (2012) did a study in the context of mobile internet consumers, Budhathoki et al. (2024) did a study in the context of ChatGPT in higher education, and Dwivedi et al. (2019) did a study in the context of information technology systems, showed a significant positive relationship between social influence and behavioural intention, which leads to adoption.

In opposition to the relationship, Venkatesh and Zhang (2010), who did a study in the context of technology systems, and Venkatesh et al. (2003), who did a study in the context of information technology systems, who have found that the relationship between social influence and behavioural intention is not significant. Chin et al. (2024), who did a study in the context of AI-powered devices in smart homes, found that social identity, associated with social influence, has no significant influence on intention to use, which is associated with behavioural intention and leads to adoption. Since there are both supporting (Budhathoki et al., 2024; Dwivedi et al., 2019; Venkatesh et al., 2012) and opposing (Venkatesh & Zhang, 2010; Venkatesh et al., 2003) previous work, it suggests that the relationship is not generalisable in all technology contexts.

Chin et al. (2024), who did a study in the context of AI-powered devices in smart homes, in error found that trust significantly and positively moderates the relationship between social identity, which is associated with social influence, and intention to use, which is associated with behavioural intention which leads to adoption. The moderation test is not valid because Chin et al. (2024) could not significantly show a relationship between social identity and intention to use. As an alternative to how trust manifests, Shi et al. (2021) have shown that emotional trust, a factor of trust, significantly mediates the relationship between social influence and intention to adopt, which is associated with behavioural intention. Even though there is no significant evidence for trust's moderation of the relationship between effort, social influence, and adoption, the attempt by Chin et al. (2024) to test moderation is enough support for further investigation.

2.6.6. Facilitating Conditions and Adoption

In support of the relationship, Venkatesh et al. (2012), who did a study in the context of mobile internet consumers, and Dwivedi et al. (2019), who did a study in the context of information technology systems, showed a significant positive relationship between facilitating conditions and use. The significant support for the influence of facilitating conditions on adoption is limited in the papers reviewed.

In opposition to the relationship, Venkatesh and Zhang (2010), who did a study in the context of technology systems, Venkatesh et al. (2003), who did a study in the context of information technology systems, and Budhathoki et al. (2024), who did a study in the context of ChatGPT in higher education, showed no significant relationship between facilitating conditions and usage behaviour, which is associated with use and adoption. Since there are both supporting (Dwivedi et al., 2019; Venkatesh et al., 2012) and opposing (Budhathoki et al., 2024; Venkatesh & Zhang, 2010; Venkatesh et al., 2003) support, it suggests that the relationship is not generalisable in all technology contexts.

2.7. Conclusion of Literature Review

In the literature review, the three core constructs of this study, technology readiness, trust, and technology adoption, were explored through the body of existing knowledge to understand how they are perceived in the real world. The frameworks for AI technology readiness TRI 2.0 (Parasuraman & Colby, 2015) and for AI technology adoption UTAUT (Venkatesh et al., 2003) were explored, and how they will be adapted for this study were described. Finally, the details of each one of the relationships in the frameworks were reviewed, together giving a solid foundation to proceed to the next chapter, Research Question, where these relationships will be formalised into hypotheses.

3. Research Question

In this section, the main research question for this study is presented, and then each of the hypotheses to address the research question is introduced. The main research question for this study was: “Does trust moderate the influence of AI technology readiness on AI technology adoption in organisations?” From the Research Question Chapter onwards, the term readiness will be used for technology readiness; if readiness is not intended to be technology readiness, it will be stated as such. Also, the term adoption will be used for technology adoption; if adoption is not intended to be technology adoption, it will be stated as such. Since everything in the study is within the context of technology, it should facilitate reading and not lead to any confusion. The hypothesised hypothesis is defended from the literature below, followed by a concept model, and finally, the control variables used in the study are discussed.

3.1. Hypotheses

In this section, support from the literature is given for each Hypothesis. Thereafter, the Hypothesis is stated.

3.1.1. Hypothesis H1

The TRI 2.0 framework, as proposed by Parasuraman and Colby (2015), suggests a relationship where readiness motivators (optimism and innovativeness) have a positive influence on adoption (Blut & Wang, 2020; Flavián et al., 2022; Hwang & Good, 2014). Thus, it is hypothesised that:

> H1: Readiness motivators, which are optimism and innovativeness, positively influence adoption.

3.1.2. Hypothesis H2

Even though trust as a moderator in the relationship between readiness motivators (innovativeness and optimism) and adoption is not explicitly stated, trust is expected to influence the strength of the relationship between readiness and adoption. This is because trust not only directly influences adoption (Shamim et al., 2023) but also affects how readiness motivators (innovativeness and optimism) influence adoption (Yin et al., 2023). For instance, Yin and Hsieh (2023) stated that higher levels of readiness motivators (innovativeness and optimism) require higher levels of trust, suggesting that trust increases the influence of readiness on adoption. Thus, it is hypothesised that:

> H2: Trust positively moderates the influence of readiness motivators, which are optimism and innovativeness, on adoption.

3.1.3. Hypothesis H3

The TRI 2.0 framework, as proposed by Parasuraman and Colby (2015), suggests a relationship where readiness inhibitors (discomfort and insecurity) negatively influence adoption (Blut & Wang, 2020; Flavián et al., 2022; Hwang & Good, 2014). Thus, it is hypothesised that:

> H3: Readiness inhibitors, which are discomfort and insecurity, negatively influence adoption.

3.1.4. Hypothesis H4

Kaur and Arora (2021) have found that trust positively moderates the relationship between perceived risk, which is associated with readiness inhibitors (discomfort and insecurity), and behavioural intention, which is a factor of adoption, i.e., higher trust dampens the negative influence of perceived risk on behavioural intention. Even though trust as a moderator in the relationship between readiness inhibitors (discomfort and insecurity) and adoption is not explicitly stated, trust not only directly influences adoption (Shamim et al., 2023) but also affects how the readiness inhibitors (discomfort and insecurity) influence adoption (Lin & Hsieh, 2007). For instance, Lin and Hsieh (2007) stated that low trust affects insecurity, a factor of readiness inhibitors (discomfort and insecurity). Thus, it is hypothesised that:

> H4: Trust positively moderates the negative influence of readiness inhibitors, which are discomfort and insecurity, on adoption.

3.1.5. Hypothesis H5

The UTAUT framework suggests a relationship where performance expectancy positively influences use through behavioural intention (Budhathoki et al., 2024; Dwivedi et al., 2019; Khan et al., 2023; Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012). Blut and Wang (2020) grouped behavioural intention and use as adoption. Thus, it is hypothesised that:

H5: Performance expectancy positively influences adoption.

3.1.6. Hypothesis H6

According to Chin et al. 2024, trust positively affects behavioural intention and use because of the trust in the technology's ability to achieve the expected increase in performance. Thus, trust is expected to influence the strength of the relationship between performance expectancy and adoption (Chin et al., 2024; Kim et al., 2023). Thus, it is hypothesised that:

H6: Trust positively moderates the influence of performance expectancy on adoption.

3.1.7. Hypothesis H7

The UTAUT framework suggests a relationship where effort expectancy positively influences use through behavioural intention (Budhathoki et al., 2024; Dwivedi et al., 2019; Khan et al., 2023; Venkatesh et al., 2012). Blut and Wang (2020) grouped behavioural intention and use as adoption. Thus, it is hypothesised that:

H7: Effort expectancy positively influences adoption.

3.1.8. Hypothesis H8

According to Chin et al. 2024, trust positively affects behavioural intention and use because of the trust in the technology's ability to ease their job. Thus, trust is expected to positively influence the strength of the relationship between effort expectancy and adoption (Chin et al., 2024). Thus, it is hypothesised that:

H8: Trust positively moderates the influence of effort expectancy on adoption.

3.1.9. Hypothesis H9

The UTAUT framework suggests a relationship where social influence positively influences use through behavioural intention (Budhathoki et al., 2024; Dwivedi et al., 2019; Venkatesh et al., 2012). Blut and Wang (2020) grouped behavioural intention and use as adoption. Thus, it is hypothesised that:

H9: Social influence positively influences adoption.

3.1.10. Hypothesis H10

According to Chin et al. 2024, trust positively affects behavioural intention and use because of the role of trust in enabling a social presence that makes the interaction between humans and technology feel personal. Thus, trust is expected to positively influence the strength of the relationship between social influence and adoption (Chin et al., 2024; Kim et al., 2023). Thus, it is hypothesised that:

H10: Trust positively moderates the influence of Social influence on adoption.

3.1.11. Hypothesis H11

The UTAUT framework suggests a relationship where facilitating conditions positively influence use through behavioural intention (Dwivedi et al., 2019; Venkatesh et al., 2012). Blut and Wang (2020) grouped behavioural intention and use as adoption. Thus, it is hypothesised that:

H11: Facilitating conditions positively influence adoption.

3.2. Concept Model

The hypotheses are graphically represented in the concept model shown in Figure 1, which indicates the relationship between each factor and the moderator.

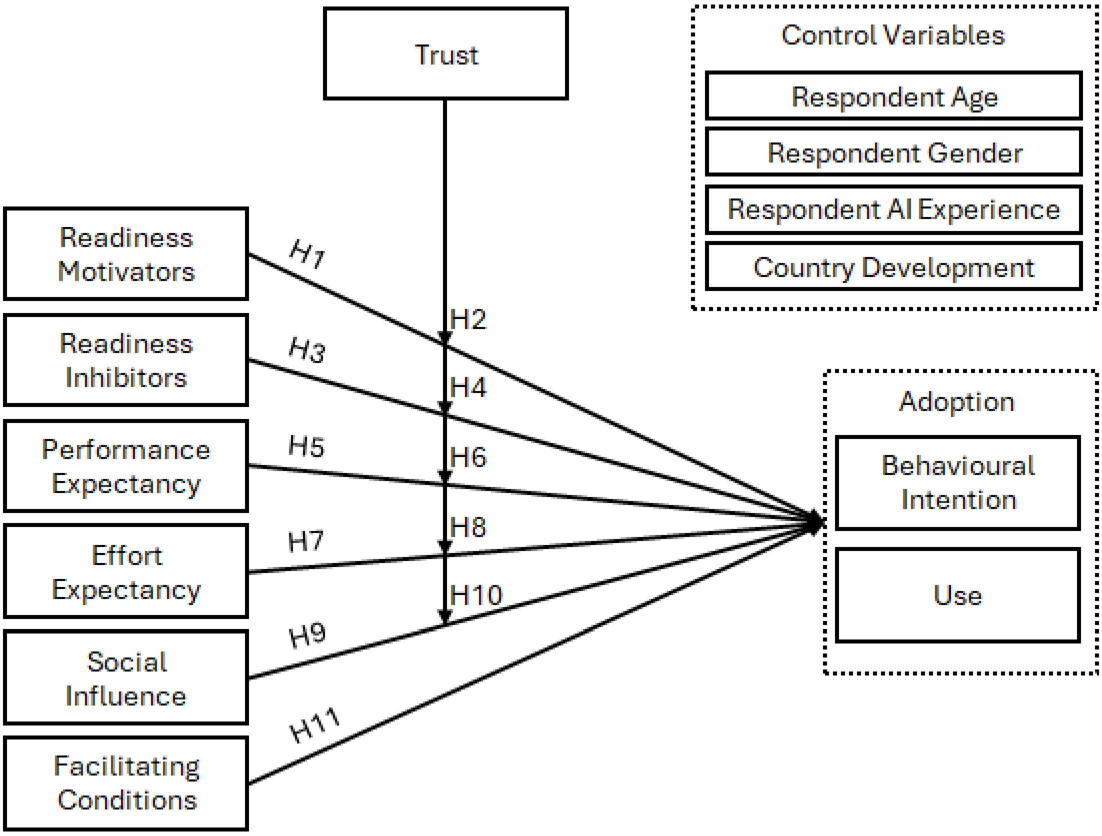


Figure 1: Concept Model of Proposed Research

Notes:

The model was adapted from UTAUT (Venkatesh et al., 2003) and TRI 2.0 (Parasuraman & Colby, 2015).

3.3. Control Variables

3.3.1. Country Development

Adopting technology has risks and opportunities, which can differ between developed and developing countries due to the availability of financial resources, skills, limited inter-organisational cooperation, and institutional voids (Shamim et al., 2023). These institutional voids include little support from institutions to assist in technology development and adoption, lack of regulation, and lack of standards (Shamim et al., 2023). However, this is in contrast with Budhathoki et al. (2024), who did a study in two countries, one developing and one developed. They found the same relationships to be significant in both countries: the relationships between performance expectancy and behavioural intention, effort expectancy and behavioural intention, social influence and behavioural intention, and facilitating conditions and use behaviour. Since there is evidence supporting and contrasting the need to have country development as a control variable, this study will control for the country's development.

3.3.2. Respondent Gender

Gender was used as a control variable by Parasuraman and Colby (2015), but no justification was provided. Venkatesh et al. (2012) argue that gender is a user characteristic moderating adoption because a male is more willing than a female to invest effort to bridge challenges to reach their goals. In contrast, Dwivedi et al. (2019) argue that gender should only be a control variable since gender is not a moderator in all contexts. In multiple other UTAUT-based studies, gender is only a control variable (Balakrishnan et al., 2022; Khan et al., 2023; Shi et al., 2021). Gender was a control variable for this study and was measured by the following options: male, female, non-binary, transgender, prefer not to reply, and not listed, which the respondents can uniquely specify (Kaur & Arora, 2021).

3.3.3. Respondent Age

Age was used as a control variable by Parasuraman and Colby (2015), but no justification was provided. It is argued that age is a user characteristic moderating adoption because an older person tends to find new or complex information harder to process, thus inhibiting their ability to learn new technology (Venkatesh et al., 2012). This difficulty could be due to reduced memory and cognitive skills, typical of ageing (Venkatesh et al., 2012). In contrast, Dwivedi et al. (2019) argue that age should only be a control variable since age is not a moderator in all contexts. In multiple other UTAUT-based studies, age is only a control variable (Balakrishnan et al., 2022; Khan et al., 2023; Shi et al., 2021). Age was a control variable in this study measured in years.

3.3.4. Respondent AI Experience

The UTAUT2 model argues that Experience is a user characteristic moderating adoption because greater familiarity with the technology and knowing the content of the support structures makes learning how to utilise the technology easier (Venkatesh et al., 2012). It has also been shown that less familiarity and experience with technology increases the need for facilitating conditions (Venkatesh et al., 2012). In contrast, Dwivedi et al. (2019) argue that experience should only be a control variable since experience is not a moderator in all contexts. In multiple other UTAUT-based studies, age is only a control variable (Khan et al., 2023; Shi et al., 2021). Experience was measured in terms of familiarity with AI tools and the period of use.

4. Research Methodology

The study aimed to determine if Trust moderates the relationship between Readiness and Adoption in organisations that use AI technology. More specifically, it first sought to measure the relationship between the following independent variables: Readiness Motivators (Optimism and Innovativeness), Readiness Inhibitors (Discomfort and Insecurity), Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions and the dependent variable: Adoption (Behavioural Intention and Use) quantitively. Secondly, the study sought to determine if these relationships hold in the presence of the following control variables: Respondent Age, Respondent Gender, Respondent AI Experience and the Respondent’s Country Development. Lastly, it sought to determine if Trust moderates the relationships between the following independent variables: Readiness Motivators (Optimism and Innovativeness), Readiness Inhibitors (Discomfort and Insecurity), Performance Expectancy, Effort Expectancy, and Social Influence and the dependent variable: Adoption (Behavioural Intention and Use). These relationships and the hypotheses are grounded in the existing literature (Parasuraman & Colby, 2015; Shi et al., 2021; Venkatesh & Zhang, 2010). It was decided to facilitate the reading of the variables and constructs in sentences by always using a capital letter for the first letter of each word of the variables and constructs.

The Research Methodology Chapter starts with the overarching research design, followed by the population, sampling, and unit of analysis of the research. The measurement instrument used follows it, and how the data is collected is discussed. Next, the significance level for the study is established. It was followed by a comprehensive section on the preparation of the data, which includes the handling of missing data and outliers, the coding of data, and the testing of the assumptions required for the statistical tests. Then, the integrity of the research was improved by exploratory factor analysis, validity testing and reliability testing. Next, the data was represented graphically for visual analysis. It was followed by the methods for the statistical data analysis, which is described in detail. Finally, the research’s quality assurance and limitations are discussed.

4.1. Research Design

The decisions regarding the research philosophy must align with the research and data collection strategies (Saunders & Lewis, 2018). This section begins with the overarching research philosophy and then drills down to the details of the methodology applied in this research.

4.1.1. Purpose of Research Design

The aim was to understand how the constructs, Readiness and Adoption, relate to each other and whether this relationship is moderated by Trust using descriptive data and statistical tests, i.e., correlation and regression, to improve the understanding of the relationship. Since the study relied on the collection of measurable and quantifiable data using a quantitive survey questionnaire that profiled the respondents and was processed using descriptive statistics, it constituted the descriptive component of the study (Saunders & Lewis, 2018; Saunders et al., 2016; Zikmund et al., 2013). However, the study was not only descriptive because the data was used to make inferences from the relationships between the variables using statistical tests, i.e., correlation and regression, which added an explanatory element to the research (Saunders & Lewis, 2018; Saunders et al., 2016). Thus, it was a descripto-explanatory study (Saunders et al., 2016). The acquired descriptive data were analysed with statistical tests, i.e., correlation or regression, for each hypothesis to respond to the research question (Saunders & Lewis, 2018).

4.1.2. Philosophy

The philosophy chosen for the research not only determines the assumptions and the methods chosen for the research but is also underpinned by the research philosophy adopted by the researcher (Saunders et al., 2016). This underpinning is essential as the researcher needs to be cognisant of the philosophical commitments made with the chosen research strategy because this significantly impacts not only our actions but also how the topic under investigation is understood (Saunders et al., 2016). The researcher's natural philosophy in life is more biased towards positivism, where more importance is given to facts which produce law-like generalisations rather than feelings or attitudes. Although it is argued that it is not possible to conduct research in an entirely value-free way, in line with the positivist philosophy, it was kept as value-free as possible by the researcher (Saunders et al., 2016).

The research comprised a research question that was answered by collecting data using a questionnaire, which was then processed to determine if the hypotheses were significant or not using statistical methods. The nature of the research was aligned with positivism because of the use of data to evaluate hypotheses through statistical methods to arrive at law-like generalisations (Saunders et al., 2016). Given the nature of the research's alignment with the positivist philosophy, positivism was chosen as the philosophy.

Positivist science is based on rigorous data collection, which describes constructs that describe the real world (Straub et al., 2004) through collected data to measure and describe the readiness, adoption and trust in the real world. Positivism assumes that the real world is objective and causal and that the existing relationships can be measured, enabling generalisations from statistical findings that were made (Straub et al., 2004). In this study, multiple relationships were investigated, from readiness to adoption and how some of these relationships are influenced by trust, using objective data collection through questionnaires and statistical analysis. Positivism is primarily used to empirically test the theory to increase the predictability of real-world phenomena (Orlikowski & Baroudi, 1991), e.g., in this study where the outcome could be used to predict how trust determines the strength of the influence from Readiness to Adoption. The research used a quantitative survey through a self-administered online questionnaire to prove a relationship between constructs to produce a law-like generalisation (Mishra et al., 2022; Saunders & Lewis, 2018). Furthermore, a positivist inquiry is value-free (Orlikowski & Baroudi, 1991), ensuring human interpretation and bias do not easily influence methods that promote unambiguous and accurate knowledge from data and facts, e.g. in this study, well-established questionnaires and statistical techniques were used for evaluating the relationship between the constructs (Saunders & Lewis, 2018).

Unfortunately, the positivist philosophy is not without its shortcomings. The shortcomings are the overemphasis on quantitive data, which makes it hard to capture a holistic view of respondents and the fact that reality cannot always be accurately defined by definite law-like generalisations (Saunders et al., 2016). To partially mitigate the difficulty of achieving law-like generalisations, control variables were introduced, a larger usable sample size of 213 (Saunders et al., 2016) was obtained, and generalisations were made noting the selected significance level (Saunders et al., 2016). Furthermore, the shortcoming of only relying on quantitative data from a mono-method survey, which did not allow the capturing of the underlying reasons for the choices that were made, was not mitigated.

4.1.3. Approach Selected

The research aims to test the relationship between constructs, Readiness and Adoption and whether this relationship is moderated by Trust, which was defined in the existing literature (Parasuraman & Colby, 2015; Venkatesh & Zhang, 2010; Shi et al., 2021). The relationship and moderation are captured in the hypotheses, which were tested in a structured process using statistical methods, i.e., correlation and regression. This process of developing a clear theoretical position, which is captured in hypotheses before proceeding with the data collection, is the deductive approach (Saunders et al., 2016). Thus, the deductive approach was selected because existing literature (Parasuraman & Colby, 2015; Venkatesh & Zhang, 2010; Shi et al., 2021) on the constructs under study was available prior to the research project, which informed the hypothesis formulation as per the expected outcomes captured (Saunders & Lewis, 2018; Saunders et al., 2016). Furthermore, the aim was to test the relationship between Readiness and Adoption and whether this relationship is moderated by trust quantitively. Readiness and Adoption have well-established and well-documented theoretical frameworks, TRI 2.0 (Parasuraman & Colby, 2015) and UTAUT (Venkatesh & Zhang, 2010), respectively, which were used to inform the hypotheses formulation (Saunders & Lewis, 2018). The deductive approach tests logically the identified cause-and-effect relationships using hypothesis through analysis (Orlikowski & Baroudi, 1991). The proposed conceptual model was formulated from TRI 2.0 (Parasuraman & Colby, 2015) and UTAUT (Venkatesh & Zhang, 2010). The survey questionnaire used to collect data was created by adopting and adapting questions that were aligned with the frameworks. The data was used for statistical null hypothesis testing. The outcome of the hypothesis testing determined if the data supported the conceptual model or recommended the need for further modification of the model (Saunders & Lewis, 2018).

4.1.4. Methodological Choices

The study was based on well-established constructs, as evidenced in the literature review, that can be measured using existing questionnaires (Parasuraman & Colby, 2015; Venkatesh & Zhang, 2010; Shi et al., 2021). Furthermore, only one method was chosen to collect the necessary data to address the research question. Thus, given that quantitive survey questions can be adopted and adapted from existing questionnaires and that they can collect sufficient data to respond to the research question, a quantitative mono method was chosen for this study (Saunders & Lewis, 2018). A survey was more suited to measuring constructs quantitatively over a large number of respondents (Saunders & Lewis, 2018). The disadvantage of using a mono method is the lack of another independent source of data to use for triangulation to improve the credibility of the research findings (Saunders & Lewis, 2018). To partially overcome this lack of independent data sources, findings were compared to what was found in previous research, which enabled highlighting results in alignment and contrast (Parasuraman & Colby, 2015; Venkatesh & Zhang, 2010; Shi et al., 2021). Another disadvantage of the mono-quantitive method was that when a relationship was significant, the reasons for the relationship were not available due to the lack of qualitative context (Saunders & Lewis, 2018). This shortcoming was not overcome, and when the reason for the relationship was not apparent, it was suggested as a topic for future research. Similar studies (Budhathoki et al., 2024; Dhiman et al., 2023; Vimalkumar et al., 2021) used a quantitative mono method.

4.1.5. Strategy

The research used the survey strategy using a self-administered questionnaire because it enabled the outcomes to be generalised, it was easily replicated, and it facilitated the measurement of the constructs, Readiness, Adoption and Trust, from a large population sample cost-effectively (Mikalef et al., 2020; Saunders & Lewis, 2018). The survey strategy facilitates data collection in a structured process using a questionnaire. For this study, the participants completed the questionnaire online (Saunders & Lewis, 2018). The survey strategy aligns well with the descripto-explanatory purpose of the research (Saunders & Lewis, 2018). Similar studies (Navarro et al., 2022; Vimalkumar et al., 2021) also used a self-administered questionnaire as a survey strategy.

4.1.6. Time Horizon

The study aimed to test the relationship between constructs, Readiness and Adoption and whether Trust moderates this relationship at a particular time because, for the scope of this research, the change of these relationships over time would not fit into the execution time of the research project. Thus, the time horizon of data collection was cross-sectional. The survey questionnaire was only completed once by each participant for the study (Orlikowski & Baroudi, 1991). Hence, it delivered a value for a snapshot in time for the measured variables (Saunders & Lewis, 2018). Similar studies (Rafdinal & Senalasari, 2021; Vimalkumar et al., 2021) have also used the cross-sectional time horizon. The cross-sectional choice was appropriate for this study because it provided a snapshot of the situation within the allowed time for the study. Even though it would not capture changes over time, it is an efficient method to get the required data to answer the research question, which is not focused on the change of the factors over time.

4.2. Population

The study aimed to test the relationship between constructs, Readiness and Adoption and whether Trust moderates this relationship in organisations. The legal age for an individual to be employed in any job by an organisation is 18 years and older in South Africa (Basic Conditions of Employment Act 75 of 1997, 1997). Even though this legal work age differs around the world, for both simplicity and ethical reasons discussed later, the minimum age for the study is chosen as 18 years. The population for the research was chosen as any person 18 years and older who works for an organisation. Any person who did not qualify would be excluded from the sample, e.g., individuals not working for an organisation, pensioners who no longer worked for an organisation, and students who did not also work for an organisation. However, owners who indicated that they were working for an organisation were not deleted because they are working in the organisation and are thus part of the population.

4.3. Sampling

The selected population for the study was large, and it was extremely difficult to get access to everyone with the allocated resources for this research, considering anyone who was working or contributing to an organisation qualified. Thus, sampling was needed (Saunders et al., 2016). Unfortunately, because no sampling frame was available to pick individuals statistically at random, only non-probability sampling methods can be used (Saunders et al., 2016). Fortunately, for this research, it was not a requirement that the inferences of the population should be statistically significant (Saunders et al., 2016). A sample size of 200 usable samples was targeted, which is discussed in more detail later. Allowing the use of convenience sampling and snowball sampling (Saunders et al., 2016). Since convenience sampling is not likely to represent the population well, it was only used to seed the snowball sampling (Saunders et al., 2016). Although snowball sampling also has a low probability of being representative of the population, the respondents could have the desired characteristics of the population (Saunders et al., 2016).

Thus, the study used convenience and snowball sampling (Saunders & Lewis, 2018). Snowball sampling was initiated by seeding it with convenience sampling. The researcher asked his personal network to participate in the survey. Then, the instructions on the survey requested each respondent to please request their contacts to participate, enabling snowball sampling. Even though it was not possible to make statistical inferences about the population since a non-probability sampling method was used, some generalisation was still possible but not on statistical grounds (Saunders et al., 2016).

The required sample size of the statistical methods determined the initial usable sample size target. The exploratory factor analysis sample size requirement varies with the factor representation achieved (Hair et al., 2019). A conservative factor representation target of at least 40% was chosen, which requires a usable sample size of 200 (Hair et al., 2019). A sample size of 200 usable samples was targetted for a significance level of $\alpha = 0.05$, assuming the model will have a moderate effect size (Hair et al., 2010). The multiple regression required a sample of at least 100 observations (Hair et al., 2019). Since not all surveys would be usable due to issues discussed in the data preparation section, the usable data collected were periodically checked to see if the target of 200 usable samples was achieved. The total usable samples collected were 213.

4.4. Unit of Analysis

In this study, an individual person is the unit of analysis (UA), the entity or level relevant to the outcomes. The collected data was analysed for each person and was not further grouped (Hair et al., 2010). In similar readiness and adoption studies, the individual respondent was also the UA (Navarro et al., 2022; Vimalkumar et al., 2021). Thus, the unit of analysis is an individual person.

4.5. Measurement Instrument

The questionnaire was adopted and adapted from multiple existing measurement instruments: the TRI 2.0 (Parasuraman & Colby, 2015) to evaluate Readiness, the UTAUT (Venkatesh et al., 2012) to measure Adoption levels of a population, and Shi et al. (2021) used questions to measure Trust.

4.5.1. Dependent Variables

The dependent variable, Adoption, consisted of two factors: Behavioural Intention and Use in the survey. These came from UTAUT (Venkatesh et al., 2012).

The study by Venkatesh et al. (2012) was focused on mobile internet use, whereas the current study was on AI technology tool use; thus, the Behavioural Intention questions in the questionnaire from Venkatesh et al. (2012) were adapted to 'AI technology tools (e.g., ChatGPT)' instead of 'mobile internet'. The seven-point Likert scale was used unchanged in the anchoring points of Strongly agree and strongly disagree. However, the researcher added the points in between since they were not given. Thus, the complete Likert scale had the following options: strongly agree, agree, somewhat agree, neither agree nor disagree, somewhat disagree, disagree, strongly disagree. The variables that were checked for validity with the correlation between item and item-total-score to be above 0.5 (Hair et al., 2010) and checked for internal consistency reliability or Cronbach alpha to be above 0.6 (Hair et al., 2010) reduced the risk of validity problems and reliability problems, respectively, which is discussed in more detail including of why it is important later in the chapter under sections 4.8.10 and 4.8.11. The internal consistency of the measurement instrument was 0.93, and the validity of each item was at least 0.84, reducing the risk of inconsistent findings later (Kline, 2016).

The Adoption questions from Venkatesh et al. (2012) related to mobile internet examples were updated with examples of AI technology tools: Spelling and grammar checker, e.g., Grammarly, Voice recognition, e.g., Dictate in Microsoft Word, Voice reader, e.g., Read Aloud in Microsoft Word, Assistant on your phone, e.g., Siri on Apple, Assistant on your PC, e.g., ClickUp, Large language model, e.g., ChatGPT, AI-driven picture/image tool, e.g., DALL.E, AI-driven video tool, e.g., SORA, AI-driven graphics design tool, e.g., Adobe Firefly, AI-driven engineering design tool, e.g., Design Assistant in SOLIDWORKS, AI-driven data analysis tool, e.g., Google Cloud Smart Analytics, AI-driven code assistant, e.g., Copilot, and the ability to specify three options which were not listed. The seven-point ordinal frequency scale was used unchanged in the anchoring points, which were several times per day and never. However, the researcher added the points in between since they were not given. Thus, the complete ordinal frequency scale had the following options: several times a day, daily, several times a week, weekly, monthly, less than monthly, and never. This scale was not checked for internal consistency reliability and validity by Venkatesh et al. (2012). Although each one of the items alone is of the ordinal type, when averaged together, they form a formative composite index of both variety and frequency, which can be treated as interval data and can be used in correlation and regression, given the required assumptions are met respectively (Diamantopoulos & Winklhofer, 2001; Venkatesh et al., 2012). The assumptions are discussed in the data analysis section.

4.5.2. Independent Variables

The independent variables were Readiness Motivators (Optimism and Innovativeness), Readiness Inhibitors (Discomfort and Insecurity), Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions.

The questions measuring the factors of Optimism and Innovativeness of Readiness Motivators (Innovativeness and Optimism) and the factors of Discomfort and Insecurity of Readiness Inhibitors (Discomfort and Insecurity) came from TRI 2.0 (Parasuraman & Colby, 2015). TRI (Parasuraman, 2000) was first developed and then refined to TRI 2.0 (Parasuraman & Colby, 2015). They defined technological readiness as how likely people are to use new technologies daily to achieve goals. The TRI and TRI 2.0 focus on whether users are mentally ready for the technology. TRI 2.0 measures readiness in four dimensions: insecurity, discomfort, innovativeness and optimism. The first two are inhibitors (Discomfort and Insecurity), and the latter two are motivators (Innovativeness and Optimism). The TRI 2.0 framework has been used in previous technology research by Kaushik and Agrawal (2021), Rafdinal and Senalasari (2021) and Navarro et al. (2022). TRI 2.0 was defined using a five-point Likert scale. The seven-point Likert scale was used to get more granularity and keep the questionnaire homogeneous. The Likert scale had the following options: strongly agree, agree, somewhat agree, neither agree nor disagree, somewhat disagree, disagree, and strongly disagree. The lowest internal consistency reliability for all the factors was 0.7, and the lowest validity was 0.59, reducing the risk of inconsistent findings later (Kline, 2016). It should, however, be noted that this was tested on the five-point Likert scale and not on the seven-point Likert scale.

The questions measuring the variables Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions came from UTAUT (Venkatesh et al., 2012).

Davis (1985) first developed the TAM. Venkatesh et al. (2003) merged TAM with multiple technology theories focused on adopting and utilising technology, which resulted in the UTAUT. UTAUT contains social influence, facilitating conditions, performance expectancy, and effort expectancy. Vimalkumar et al. (2021), Flavián et al. (2022), and Qasem (2021) used UTAUT in previous technology research. The seven-point Likert scale was used unchanged in the anchoring points. However, the researcher added the points in between since they were not given. The Likert scale had the following options: strongly agree, agree, somewhat agree, neither agree nor disagree, somewhat disagree, disagree, strongly disagree. Venkatesh et al. (2012) checked the internal consistency of each, which was above 0.75, and the validity of each item was above 0.75, reducing the risk of inconsistent findings later (Kline, 2016).

4.5.3. Moderating Variables

The moderating variables were Trust Cognitive Benevolence, Trust Cognitive Competence, Trust Cognitive Integrity and Trust Emotional. The study by Shi et al. (2021) used questions to measure Trust in 'autonomous vehicles' that were adapted to 'AI tools.' These questions had options from agree to disagree on a seven-point Likert scale. The seven-point Likert scale was adapted to keep the survey homogeneous to the following options: strongly agree, agree, somewhat agree, neither agree nor disagree, somewhat disagree, disagree, strongly disagree. Shi et al. (2021) checked the internal consistency reliability with Cronbach's alpha of each variable, which was at least 0.84, and the validity of each item was at least 0.81, reducing the risk of inconsistent findings later (Kline, 2016).

4.5.4. Control Variables

The control variables were Respondent Age, Respondent Gender, Country Development and Respondent AI Experience. Note that Country Development was derived from the country selected by the respondent and was discussed in detail under Data Enrichment. The corresponding defending literature is in the control variable section in the Research Question Chapter. To see the options for the control variable questions, please refer to the complete questionnaire attached in Appendix A.

4.5.5. Demographic Variables

The demographic questions, which were also control variables, were Respondent Age and Respondent Gender. Country Development was derived from the Country of the respondent. The remaining demographic questions were Race, Education, Department in Organisation and Employment Status. The demographic questions, except age, had an option for the respondents to enter a custom response, which was not listed as one of the options not to exclude any individual who might not fit one of the preloaded options. To see the options for the demographic questions, please refer to the complete questionnaire attached in Appendix A.

4.6. Data Collection

4.6.1. Online Survey

The survey was self-administered via the online survey platform Qualtrics. The use of an online survey for this research has the following advantages: global reach, speed, convenience, ease of data entry, low cost, large sample easier to obtain, and helping respondents not to skip questions by mistake (Evans & Mathur, 2018). The advantages outweigh the following disadvantages: perceptions of spam, skewed attributes of the internet population, respondent's lack of online experience, and low response rate (Evans & Mathur, 2018). The perception of spam risk was mitigated by including the email address of both the researcher and supervisor, which the respondent could use to verify the link. Furthermore, a credible survey platform was used to mitigate the perception of spam. The skewed attributes of the internet population and respondent lack of online experience were not mitigated but were listed as limitations. The risk of a low response rate was mitigated by requesting as many as possible contacts to forward the survey and follow up with their contacts to do the same. A limitation of the anonymous online survey was that it is not possible to know if someone completed the survey more than once, which could not be mitigated while keeping anonymity. The data on the online platform was exported and downloaded in an Excel file format.

4.6.2. Ethical Considerations

The purpose of ethical considerations in research is to preserve the rights of the participants and also to protect the researcher from harm (Saunders et al., 2016).

The study was conducted in the field of business management to determine if Trust moderates the influence of Readiness on Adoption. The Chosen population excluded individuals who were not 18 years and older, thus avoiding any age-related ethical issues. The online survey did not intend to cause embarrassment, stress, discomfort, pain or harm to participants (Saunders et al., 2016). The basis for starting the survey was voluntary informed consent (Saunders et al., 2016). Furthermore, the individuals enjoyed complete anonymity (Saunders et al., 2016). The questionnaire was submitted to the Masters Research Ethics Committee of the Gordon Institute of Business Science, and ethical clearance was obtained. The clearance confirmation is attached in Appendix B.

4.6.3. Survey Pre-test

A pre-test was done with 20 identified respondents, of whom 17 gave detailed feedback to minimise the questionnaire errors before it was sent out (Saunders & Lewis, 2018). The remaining three respondents reported that they did not detect anything wrong with the survey. The detailed feedback consisted of between one and four comments related to different aspects of the survey, which are discussed below. The input according to the number of respondents who mentioned it is discussed below, in descending order.

The most frequent feedback was related to grammar, spelling, and punctuation mistakes, which seven respondents highlighted. Four respondents mentioned that the survey was long. However, after analysing the average duration it took respondents to complete, which was only 18 minutes, it was decided to keep the length the same as the average response time was reasonable and less than the 20 minutes requested on the survey cover page. Three of the respondents commented that they did not like the quality questions verifying the attention of the respondent, contrasted with two respondents who said it was a good idea. The researcher decided to remove the quality questions for three reasons: to reduce the length of the survey, secondly that he felt people should be trusted to do their best when they are volunteering to complete, and lastly the comment by the supervisor that these types of questions are not typically used in surveys at the university. Two of the respondents mentioned that the term “intelligent machines” was not adequately defined, which was then replaced with “AI technology tools”. Two respondents mentioned that the survey has multiple questions that make it feel as if they are asking questions about the same thing, e.g. “The AI technology tool (e.g., ChatGPT) would execute its task to my best benefit.” And “The AI technology tool (e.g., ChatGPT) is interested in my benefits, not just its own.” However, this was not changed since it is the nature of the measuring tools used in the survey, which have at least three questions measuring each of the factors.

The following feedback was only given once by one of the respondents. Two questions were mentioned first: “Which level in the organisation are you on?” was not clear and was replaced with “What is your current job role within the organisation?” and second, the question "Which discipline do you work in?" was not a clear question corresponding to options given and was updated to "Which department do you currently work in?". The options for AI experience time ranges were unclear. Thus, they were updated. One respondent requested that examples of each type of AI tool be included to facilitate understanding. Therefore, examples were included next to each type of AI tool. One respondent mentioned that they could not monitor their progress through the survey, and adding a progress bar would assist with tracking the progress. Thus, a progress bar was added.

The researcher detected the following issues. First, while reviewing the feedback, it was realised that four questions from TRI 2.0 were omitted from the online platform but were submitted as part of the questionnaire for ethical clearance. The omitted questions were added to the online questionnaire. It was detected that in some places where the term “AI tools” was used, ChatGPT was shown as an example, but in other questions, it was not. Thus, ChatGPT was added as an example everywhere next to the term “AI tools” in the questions.

4.6.4. Survey Distribution

The Qualtrics link was circulated to all the researcher's WhatsApp, email, Facebook, and LinkedIn contacts to complete if they qualified. Each contact was asked to forward the link to their contacts. At the end of the survey, there were three questions to remind and push the respondents to assist with survey distribution. The three questions were: “Please indicate the number of people with whom you are willing to share the survey.”, “Could you please follow up with the people to whom you shared the survey link within two days?” and “Could you please confirm to the person who shared the survey that you have completed it?”. The responses to these questions were not as crucial to the researcher as the effect of responsibility, which it created with the respondents to share if they would say yes. Since the surveys were anonymous, the researcher could not do anything with the responses to distribute the survey further. The data capturing of survey submissions by respondents was in the cloud and automated by Qualtrics, i.e., all the responses were saved online after the respondent completed the online form without any intervention of the researcher, and data was downloaded from the platform in a structured Excel file.

The survey by Mikalef et al. (2020) was circulated online, and the response rate was 43%, whereas only 40% were usable. As a mitigation to the anticipated low response rate, the data collection process was started with as many contacts as possible, and each respondent was requested to confirm when they had completed the survey or if they had chosen not to. A risk was that even though a person committed to completing the survey, they might forget. Thus, to mitigate this risk, if no confirmation of completion was received, a follow-up message was sent.

The survey was first circulated on 26 August 2024, and the data was exported on 16 September 2024. Thus, it was in circulation for 22 days. A total of 476 responses were recorded, of which 213 were usable due to the deletion of incomplete surveys, missing data and outliers. Since snowball sampling was used, the number of times the survey was circulated could not be recorded, and thus, no response rate was calculated.

4.6.5. Data Storage and Retention

Data storage and retention are crucial for a research project to ensure data is available for later perusal if required. The infrastructure used is Microsoft OneDrive, which ensures that security measures, updates, backup, recovery, access and permission can be appropriately managed. The researcher is responsible for managing this data on OneDrive. The data storage period was selected as at least ten years as per the institution's requirement.

4.7. Significance Level

For this research, a significance level of $\alpha = 0.05$ was selected for all statistical analyses in line with conventional guidelines (Hair et al., 2019).

4.8. Data Preparation

A total of 213 responses were used, and 476 responses were collected. The difference is due to missing data, respondents outside of the population, and the deletion of outliers. These are subsequently discussed in detail, and a table summarising the response deletion process to arrive at the 213 usable samples can be found in Appendix C.

4.8.1. Missing Data

The number of responses with less than 50% missing data, which were possible to complete by imputation (Hair et al., 2019), was only 11% of the final usable response count of 213. Thus, because the usable sample size was more significant than the target sample size and the imputation would only increase the sample by 11%, it was decided to go with the simple complete case approach (Hair et al., 2019). Thus, all the missing responses were deleted after checking the deletion criteria (Hair et al., 2019), which is discussed below.

The 46 cases from respondents who failed to start the survey can be deleted from the sample since they contain no data and are categorised as cases with high missing data (Hair et al., 2019). Thus, the 46 responses of respondents who failed to start answering were deleted.

If the reason for partially stopping the answering process is known and understood, the response can be deleted (Hair et al., 2019). All the responses that stopped partially were at the end of the page of the online survey, which had six pages with questions. The respondents who stopped responding at the end of a page were distributed over all six pages, giving the researcher strong evidence that these respondents failed to proceed to the next page of the online survey at the respective page. Thus, the 64 responses of respondents who stopped answering partially through the process were deleted.

If the responses with skipped questions cannot be proven to be random but the responses with skipped questions are less than 10% of the responses, the responses with missing questions can be deleted (Hair et al., 2019). Four respondents skipped one question, and one respondent skipped one question for an unknown reason. The five responses where respondents skipped up to two questions are 1% of the responses, which is less than 10% and thus can be deleted even if randomness is not proved (Hair et al., 2019).

The above process was facilitated using a missing data table, which listed all the responses with missing data in Appendix D. The survey had six pages of questions, which were highlighted using different grey contrasts. The pattern noted was that the questions with answers (black dots) always ended at the end of a page of the online survey. In contrast, none of the single missing responses (red blocks) were on the same item nor had any obvious pattern. Although randomness could not be adequately tested with such few instances, a pattern could not be identified.

4.8.2. Respondents Outside of Population

The responses that did not fit the defined universe were deleted since their data was irrelevant to the study. The 55 responses from respondents who did not fit the defined population for the study due to not working for an organisation were deleted in alignment with the exclusion criteria as defined by the study's population.

4.8.3. Checking the Response Time of Respondents

In previous research, they checked the response time required to complete the survey; if this was unrealistically fast, the respondent was removed from the sample (Parasuraman & Colby, 2015). After the deletion of missing data for this survey, the fastest time recorded was 4:42 minutes, which is possible for a person to complete as the researcher was able to complete the survey in 4:35 minutes. Thus, no additional data was deleted because of a response duration that was too short.

4.8.4. Data Grouping and Enrichment

In the demographics section of the survey, the respondents had a choice to enter a custom response. When the same custom response was given by four or more respondents, a new category was created consisting of the corresponding custom responses. All the custom responses with less than four responses were grouped under a category called other.

One of the demographic questions was Country, the respondent's country name. One of the study's control variables was Country Development, the state of the country's development, which had two possible groupings: developing and developed. The Country variable was used to populate the Country Development variable utilising the classification of the International Monetary Fund (2023).

4.8.5. Data Structure and Coding

The variables used to group the items in the questionnaire were aligned with what was done in the literature, from which the questions were adapted and adopted (Parasuraman & Colby, 2015; Venkatesh & Zhang, 2010; Shi et al., 2021). In Table 1, a shortened abbreviation for each variable was assigned to assist in presenting concise tables. The variable type indicates whether it is a control, independent, or dependent variable, the number of items or questions it represents, whether the data type is nominal or interval, and the description as per the literature from where the questions were adapted and adopted.

The large number of variables with abbreviations made it hard for the first-time reader to remember. Thus, even though against convention, to facilitate reading while referring to the tables containing only the abbreviations, both the variable name, starting each word with a capital letter, and the abbreviations in brackets are presented in the text for the rest of the Research Methodology Chapter and the Results Chapter. Thereafter, for the Discussion of Results Chapter and Conclusions and Recommendations Chapter, only the variable names, starting each word with a capital letter, are used to facilitate identification of the variable names.

Table 1: Data Structure

Data Structure				
Variable	Description	Variable Type	Items	Data Type
AGE	Respondent Age	Control	1	Ordinal
GEN	Respondent Gender	Control	1	Nominal
CD	Country Development	Control	1	Nominal
AIXP	Respondent AI Experience	Control	2	Ordinal
TRO	Technology Readiness Optimism	Independent	4	Interval
TRIV	Technology Readiness Innovativeness	Independent	4	Interval
TRD	Technology Readiness Discomfort	Independent	4	Interval
TRIS	Technology Readiness Insecurity	Independent	4	Interval
UTPE	Performance Expectancy	Independent	4	Interval
UTEE	Effort Expectancy	Independent	4	Interval
UTSI	Social Influence	Independent	3	Interval
UTFC	Facilitating Conditions	Independent	4	Interval
TCB	Trust Cognitive Benevolence	Moderating	3	Interval
TCC	Trust Cognitive Competence	Moderating	4	Interval
TCI	Trust Cognitive Integrity	Moderating	4	Interval
TE	Trust Emotional	Moderating	3	Interval
ADBI	Behavioural Intention	Dependent	3	Interval
ADU	Use	Dependent	13	Interval
Replaced ADU after EFA:				
ADUD	Use Defined Tasks	Dependent	4	Interval
ADUG	Use General Tasks	Dependent	3	Interval
ADUS	Use Specialised Tasks	Dependent	4	Interval

The abbreviations for each variable were defined as Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD), Respondent AI Experience (AIXP), Readiness Optimism (TRO), Readiness Innovativeness (TRIV), Readiness Discomfort (TRD), Readiness Insecurity (TRIS), Performance Expectancy (UTPE), Effort Expectancy (UTEE), Social Influence (UTSI), Facilitating Conditions (UTFC), Trust Cognitive Benevolence (TCB), Trust Cognitive Competence (TCC), Trust Cognitive Integrity (TCI), Trust Emotional (TE), Behavioural Intention (ADBI), and Use (ADU). The Use (ADU) variable was split into three variables after factor analysis, which are discussed in detail later. The three variables are Use Defined Tasks (ADUD), Use General Tasks (ADUG), and Use Specialised Tasks (ADUS). The data was coded for each item or question. The coding is shown in Table 34 in Appendix E.

4.8.6. Outliers

The outliers needed to be identified because they were suspected to affect the tests for normality negatively. A method for dealing with influential outliers is deletion (Aguinis et al., 2013). Although it is recommended to report results with and without the outliers, it was decided to only report without them since the parametric tests are sensitive to the normality assumption. Deleting the outliers improved the normality, at least in terms of kurtosis. A box and whisker plot was used to identify each independent and dependent variable's outliers, corresponding to 1.5 times the interquartile range (IQR) (Aguinis et al., 2013). The box is the upper and lower quartile. The whiskers represent the upper quartile plus 1.5 times IQR and the lower quartile minus 1.5 times IQR. Thus, in the box and whisker plot, the outliers are indicated below and above the whiskers. The median is the line in the box, and the mean is shown by the cross in the box. A total of 93 outliers were identified and deleted, and the corresponding response IDs are shown in Appendix C. After the deletion of the outliers, 213 responses remained.

In Figure 2, the box and whisker plot before the deletion of outliers is shown on the left, and the box and whisker plot after the deletion of outliers is shown on the right. The values for the plots were scaled to a range of one to seven for better graphical representation and comparison.

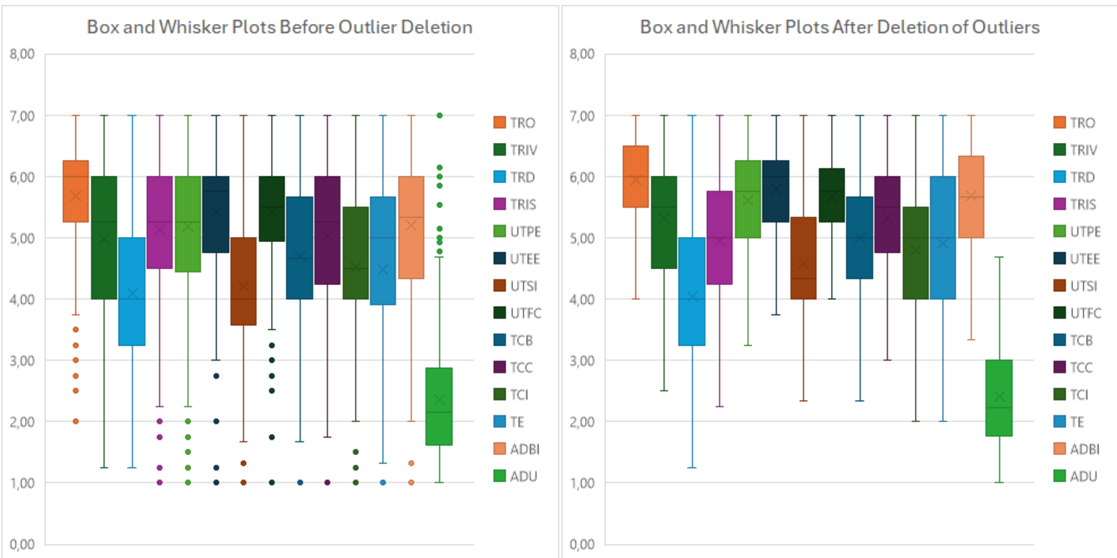


Figure 2: Box and Whisker Plots

4.8.7. Normality

Normality is an assumption for many methods used in multivariate analysis (Hair et al., 2019). It is also assumed to be true for exploratory factor analysis, reliability testing using Pearson's correlation, and regression analysis (Hair et al., 2019). Thus, the test for normality using the Shapiro-Wilk and Kolmogorov-Smirnov tests was done (Hair et al., 2019). The results for the normality tests before and after outlier deletion are shown in Table 2 and Table 3, respectively. For both normality tests, the p-value must be equal to or greater than 0.05, which rejects the hypothesis that the difference between the variable under test and the normal distribution is significant, i.e., the variable under test has a normal distribution. In Table 2 and Table 3, if the p-value is less than the minimum for normality, the value is marked in red. For none of the variables, both the normality tests passed even after the outliers were deleted.

Furthermore, in Table 2 and Table 3, the skewness and kurtosis of the distributions are evaluated using the Z-score, which needs to be between -1.96 and 1.96 (Hair et al., 2019). The deletion of the outliers brought the kurtosis of all variables within range, but the skewness of nine variables remained out of range.

It was suggested that even when extremely non-normal distributions are used, tests which assume normality can still perform well with large sample sizes (Maxwell & Delaney, 2004). Thus, even though none of the variables were statistically normal, the tests that needed the normality assumption were still used. As mitigation to the risk, the effect of testing without normality for each test was discussed in the following sections.

Table 2: Descriptive Statistics and Normality Before Outlier Deletion

Descriptive Statistics and Normality: Pre-outlier Deletion																	
	Descriptive Stat.				Kolmogorov-Smirnova			Shapiro-Wilk			Skewness			Kurtosis			
Variable	Min.	Max.	Mean	Std. Dev.	Stat.	df	Sig.	Stat.	df	Sig.	Value	Std. Error	Z-score	Value	Std. Error	Z-score	Normal
TRO	2,00	7,00	5,68	1,00	0,14	306	0,00	0,93	306	0,00	-0,90	0,14	-6,45	0,71	0,28	2,54	No
TRIV	1,25	7,00	4,99	1,34	0,12	306	0,00	0,95	306	0,00	-0,64	0,14	-4,57	-0,31	0,28	-1,12	No
TRD	1,25	7,00	4,10	1,25	0,06	306	0,01	0,99	306	0,01	-0,05	0,14	-0,34	-0,58	0,28	-2,05	No
TRIS	1,00	7,00	5,13	1,23	0,12	306	0,00	0,95	306	0,00	-0,74	0,14	-5,32	0,11	0,28	0,38	No
UTPE	1,00	7,00	5,18	1,32	0,11	306	0,00	0,94	306	0,00	-0,81	0,14	-5,77	0,47	0,28	1,69	No
UTEE	1,00	7,00	5,42	1,19	0,13	306	0,00	0,92	306	0,00	-1,04	0,14	-7,44	1,35	0,28	4,82	No
UTSI	1,00	7,00	4,20	1,32	0,17	306	0,00	0,96	306	0,00	-0,30	0,14	-2,17	-0,20	0,28	-0,72	No
UTFC	1,00	7,00	5,42	0,97	0,13	306	0,00	0,95	306	0,00	-0,89	0,14	-6,33	1,50	0,28	5,36	No
TCB	1,00	7,00	4,70	1,17	0,11	306	0,00	0,96	306	0,00	-0,68	0,14	-4,84	0,76	0,28	2,71	No
TCC	1,00	7,00	5,03	1,14	0,11	306	0,00	0,93	306	0,00	-0,96	0,14	-6,84	1,50	0,28	5,34	No
TCI	1,00	7,00	4,52	1,19	0,13	306	0,00	0,95	306	0,00	-0,68	0,14	-4,89	0,77	0,28	2,75	No
TE	1,00	7,00	4,49	1,43	0,16	306	0,00	0,94	306	0,00	-0,62	0,14	-4,45	-0,16	0,28	-0,57	No
ADBI	1,00	7,00	5,21	1,38	0,13	306	0,00	0,93	306	0,00	-0,86	0,14	-6,15	0,39	0,28	1,39	No
ADU	1,00	7,00	2,36	1,01	0,13	306	0,00	0,90	306	0,00	1,36	0,14	9,70	2,48	0,28	8,85	No

Table 3: Descriptive Statistics and Normality After Outlier Deletion

Descriptive Statistics and Normality: Pre-outlier Deletion																	
	Descriptive Stat.				Kolmogorov-Smirnova			Shapiro-Wilk			Skewness			Kurtosis			
Variable	Min.	Max.	Mean	Std. Dev.	Stat.	df	Sig.	Stat.	df	Sig.	Value	Std. Error	Z-score	Value	Std. Error	Z-score	Normal
TRO	4,00	7,00	5,94	0,76	0,12	213	0,00	0,94	213	0,00	-0,44	0,17	-2,61	-0,30	0,34	-0,91	No
TRIV	2,50	7,00	5,31	1,09	0,11	213	0,00	0,96	213	0,00	-0,54	0,17	-3,20	-0,26	0,34	-0,77	No
TRD	1,25	7,00	4,05	1,22	0,07	213	0,01	0,99	213	0,12	0,05	0,17	0,29	-0,37	0,34	-1,11	No
TRIS	2,25	7,00	4,95	1,17	0,10	213	0,00	0,97	213	0,00	-0,40	0,17	-2,41	-0,53	0,34	-1,57	No
UTPE	3,25	7,00	5,60	0,95	0,12	213	0,00	0,95	213	0,00	-0,33	0,17	-1,98	-0,62	0,34	-1,86	No
UTEE	3,75	7,00	5,79	0,80	0,13	213	0,00	0,95	213	0,00	-0,34	0,17	-2,04	-0,41	0,34	-1,23	No
UTSI	2,33	7,00	4,57	1,04	0,17	213	0,00	0,95	213	0,00	0,27	0,17	1,62	-0,49	0,34	-1,46	No
UTFC	4,00	7,00	5,66	0,73	0,09	213	0,00	0,97	213	0,00	-0,21	0,17	-1,24	-0,39	0,34	-1,16	No
TCB	2,33	7,00	4,99	0,88	0,11	213	0,00	0,98	213	0,00	-0,21	0,17	-1,25	-0,12	0,34	-0,35	No
TCC	3,00	7,00	5,32	0,86	0,11	213	0,00	0,97	213	0,00	-0,27	0,17	-1,59	-0,48	0,34	-1,42	No
TCI	2,00	7,00	4,80	0,95	0,10	213	0,00	0,97	213	0,00	-0,23	0,17	-1,36	-0,29	0,34	-0,86	No
TE	2,00	7,00	4,91	1,06	0,16	213	0,00	0,95	213	0,00	-0,40	0,17	-2,36	-0,26	0,34	-0,78	No
ADBI	3,33	7,00	5,67	0,91	0,13	213	0,00	0,95	213	0,00	-0,32	0,17	-1,89	-0,64	0,34	-1,90	No
ADU	1,00	4,69	2,41	0,80	0,10	213	0,00	0,96	213	0,00	0,66	0,17	3,93	-0,12	0,34	-0,36	No
	Replaced ADU after EFA:																
ADUD	1,00	6,00	2,29	1,17	0,14	213	0,00	0,90	213	0,00	1,04	0,17	6,22	0,64	0,34	1,92	No
ADUG	1,00	7,00	2,93	1,40	0,12	213	0,00	0,95	213	0,00	0,61	0,17	3,66	-0,29	0,34	-0,88	No
ADUS	1,00	5,00	1,71	0,91	0,22	213	0,00	0,78	213	0,00	1,58	0,17	9,42	2,20	0,34	6,56	No

4.8.8. Data Transformation

Even though data transformation is a viable option to improve the statistical characteristics of the data, it should be based on theoretical foundations to maintain interpretation simplicity (Hair et al., 2019). Previous studies did not have a theoretical basis for transforming the data, and the study's outcome needs to be explained (Parasuraman & Colby, 2015; Venkatesh & Zhang, 2010; Shi et al., 2021). Transforming the data would complicate explanations and interpretations (Hair et al., 2019). Even though the transformations would complicate explanations and interpretations, transformations were attempted.

The data transformation was attempted according to the guidelines aligned to skewness and kurtosis, and none of the simple transformations fixed the normality of the variables except for one (Hair et al., 2019). After the application of the $log_{10}()$ transformation, the Use variable was normalised, but the researcher could not explain the transformation. Success was achieved regarding normality with the Box-Cox transformation, but explaining the results when Box-Cox is used is even more complicated. Thus, to avoid complications from these explanations, it was decided not to apply any transformations to the data due to the non-normality. Therefore, non-parametric statistical tests were used, which do not have normality as an assumption, and for the tests that do require normality, the effect of non-normality was considered for each, discussed in more detail later.

4.8.9. Exploratory Factor Analysis

Exploratory factor analysis (EFA) is used to identify the factors of a set of items without forcing it to a pre-existing structure (Reio & Shuck, 2015). The researcher should never create a summated scale without assessing its unidimensionality with EFA (Hair et al., 2010). Even though EFA is typically only used for newly developed questionnaires, it can also be used when adopted and adapted survey questions (Beavers et al., 2013). For EFA, the researcher is responsible for ensuring that the variables analysed together have a solid conceptual foundation (Hair et al., 2019); e.g., the diameter and height of a tree are conceptually different, but they correlate since both increase as the tree grows. Furthermore, the EFA cannot detect if the researcher has grouped dependent and independent variables, which would not deliver appropriate results (Hair et al., 2019). Thus, in this research, EFA was done only between variables shown in the previous research (Parasuraman & Colby, 2015; Venkatesh & Zhang, 2010; Shi et al., 2021) to correspond to the same factors within constructs. When EFA's statistical assumptions of normality, homoscedasticity, and linearity are not valid, it should only reduce the method's ability to show observed correlations; thus, for this research, it was decided to continue with EFA (Hair et al., 2019).

EFA was executed using principal component analysis of all the variables to ensure that at least one variable achieves a correlation of 0.3 with another (Hair et al., 2019); otherwise, deletion of the item should be considered (Hair et al., 2019). The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) was also calculated and had to achieve a value of at least 0.5 (Hair et al., 2019). Barlett's Test of Sphericity had to achieve a p-value smaller or equal to 0.05 (Hair et al., 2019). The factors were limited to factors exceeding an eigenvalue of one, and the corresponding cumulative loading of the factors was noted for each test.

The EFA was run on the items grouped according to constructs (Parasuraman & Colby, 2015; Venkatesh & Zhang, 2010; Shi et al., 2021). The results are summarised in Table 4.

Table 4: Exploratory Factor Analysis Results

EFA Analysis						
Variable	Correlation Matrix	KMO	KMN p-value	New Factor	Items	Cumulative Loading
Target	at least one > 0,3	≥ 0,5	≤ 0,05	-	-	-
TRO	All Yes	0,74	0,00	n/a	TRO1-4	57,57%
TRIV	All Yes	0,79	0,00	n/a	TRIV1-4	67,77%
TRD	All Yes	0,70	0,00	n/a	TRD1-4	59,93%
TRIS	All Yes	0,68	0,00	n/a	TRIS1-4	57,30%
UTPE	All Yes	0,82	0,00	n/a	UTPE1-4	77,99%
UTEE	All Yes	0,81	0,00	n/a	UTEE1-4	77,08%
UTSI	All Yes	0,70	0,00	n/a	UTSI1-3	73,91%
UTFC	All Yes	0,65	0,00	n/a	UTFC1-4	53,60%
TCB	All Yes	0,64	0,00	n/a	TCB1-3	65,13%
TCC	All Yes	0,84	0,00	n/a	TCC1-4	76,95%
TCI	All Yes	0,80	0,00	n/a	TCI1-4	69,39%
TE	All Yes	0,74	0,00	n/a	TE1-3	87,26%
ADBI	All Yes	0,70	0,00	n/a	ADBI1-3	80,11%
	No			A	ADU1	
	Yes			B	ADU2-5	
ADU	Yes	0,77	0,00	C	ADU7-11	59,48%
	Yes			D	ADU6,12	
	No				ADU13	
After deletion of ADU1 and ADU13:						
				ADUD	ADU2-5	
ADU	All Yes	0,77	0,00	ADUG	ADU6,7,12	58,53%
				ADUS	ADU8-11	

All the groupings of items which constitute the variables, except Adoption (ADU), were found to have the correct number of factors, with loadings ranging from 53.60% to 87.26%. Two Adoption (ADU) items did not achieve the required correlation of 0.3 with any other item. The highest of ADU1 was 0.17, and the highest of ADU13 was 0.26, which informed the decision to delete both ADU1 and ADU13. The EFA was rerun on the remaining items, ADU2 through ADU12, and all the items achieved a correlation of at least 0.3 with another item. The KMO was larger than 0.5, and the p-value was smaller than 0.05. The items were grouped into three factors or variables that replaced adoption (ADU). The first consisted of ADU2 to ADU5, named Use Defined Tasks (ADUD), because the AI executes highly defined tasks, e.g., voice recognition, voice reader, phone assistant, and personal computer assistant.

The second consisted of ADU6, ADU7, and ADU12, named Use General Tasks (ADUG) because the AI executes broader and more general tasks, e.g., large language model, AI-driven image tool, and AI-driven code assistant. The third consisted of ADU8 to ADU11, named Use Specialised Tasks (ADUS), because the AI executes more specialised tasks, e.g., AI-driven video tool, AI-driven graphics design tool, AI-driven engineering design tool, and AI-driven data analytics tool. Their cumulative loading was 58.53%.

4.8.10. Validity

Validity indicates a set of measures' ability to correctly represent a concept under study, i.e., indicating how systematic or nonrandom error was excluded during measurement (Hair et al., 2010). Validity indicates how well a measure describes the concept, whereas reliability indicates how consistent the measure is (Hair et al., 2010). Internal consistency is a method used to measure validity; it applies to the consistency of the variables included in a scale calculated by adding multiple items (Hair et al., 2010). Since all the added items measure the same factor, they must have a high correlation (Hair et al., 2010). The validity was assessed using the bivariate correlation of each item with the item-total-score for each factor (Hair et al., 2010). The correlation of each item with the item-total score should be at least 0.5 (Hair et al., 2010), with the significance level chosen for this research being 0.05. Validity was tested for all the items that were added together to form a variable, calculating the bivariate Pearson's correlation. The results are shown in Table 5.

Table 5: Validity Test Results

Validity Test Results								
		Correlation with Item-Total Score						
Variable	Items	Item1	Item2	Item3	Item4	Item p-values	Sample Size	Decision
TRO	TRO1-4	0,72	0,71	0,80	0,80	0,00	213	Proceed
TRIV	TRIV1-4	0,81	0,87	0,82	0,79	0,00	213	Proceed
TRD	TRD1-4	0,75	0,75	0,82	0,78	0,00	213	Proceed
TRIS	TRIS1-4	0,77	0,78	0,74	0,72	0,00	213	Proceed
UTPE	UTPE1-4	0,85	0,89	0,89	0,91	0,00	213	Proceed
UTEE	UTEE1-4	0,86	0,89	0,89	0,87	0,00	213	Proceed
UTSI	UTSI1-3	0,83	0,89	0,86	-	0,00	213	Proceed
UTFC	UTFC1-4	0,73	0,75	0,75	0,64	0,00	213	Proceed
TCB	TCB1-3	0,80	0,84	0,78	-	1,00	213	Proceed
TCC	TCC1-4	0,88	0,88	0,91	0,84	2,00	213	Proceed
TCI	TCI1-4	0,82	0,82	0,82	0,82	3,00	213	Proceed
TE	TE1-3	0,95	0,93	0,91	-	4,00	213	Proceed
ADBI	ADBI1-3	0,84	0,91	0,93	-	5,00	213	Proceed
ADUD	ADU2-5	0,71	0,70	0,74	0,75	6,00	213	Proceed
ADUG	ADU6,7,12	0,81	0,73	0,76	-	7,00	213	Proceed
ADUS	ADU8-11	0,75	0,79	0,73	0,77	8,00	213	Proceed

The validity of all the items or questions has been successfully established, with the bivariate Pearson correlation with each item-total-score. All the items correlated at least 0.5 with their corresponding item-total-score at a significance with the p-value smaller or equal to 0.05. Thus, the validity of the items or questions is significant.

4.8.11. Reliability

Reliability is how well a variable measures what it intends to measure (Hair et al., 2010). Thus, when multiple measurements are taken and are considered reliable, their values will be consistent (Hair et al., 2010). Reliability was assessed using the reliability coefficients, or Cronbach's alphas, where the minimum from theory was set at 0.6 (Hair et al., 2010) and in previous research was set at 0.7 (Parasuraman & Colby, 2015; Venkatesh & Zhang, 2010).

The reliability was assessed by calculating Cronbach's alpha for each variable, which consisted of the sum of multiple items. All the items except Facilitating Conditions

(UTFC), Use Defined Tasks (ADUD) and Use General Tasks (ADUG) had Cronbach's alphas larger than 0.7, which aligns with theory and previous research. For Facilitating Conditions (UTFC), Use Defined Tasks (ADUD) and Use General Tasks (ADUG), they had 0.66, 0.68 and, 0.64, respectively. Although they are lower than the minimum selected by previous research (Parasuraman & Colby, 2015; Venkatesh & Zhang, 2010), it is still higher than the minimum of 0.6 in theory (Hair et al., 2010). Thus, it was decided to proceed without deleting. The detailed reliability test results are shown in Table 6, and the results for Facilitating Conditions (UTFC), Use Defined Tasks (ADUD) and Use General Tasks (ADUG) are marked in blue.

Table 6: Reliability Test Results

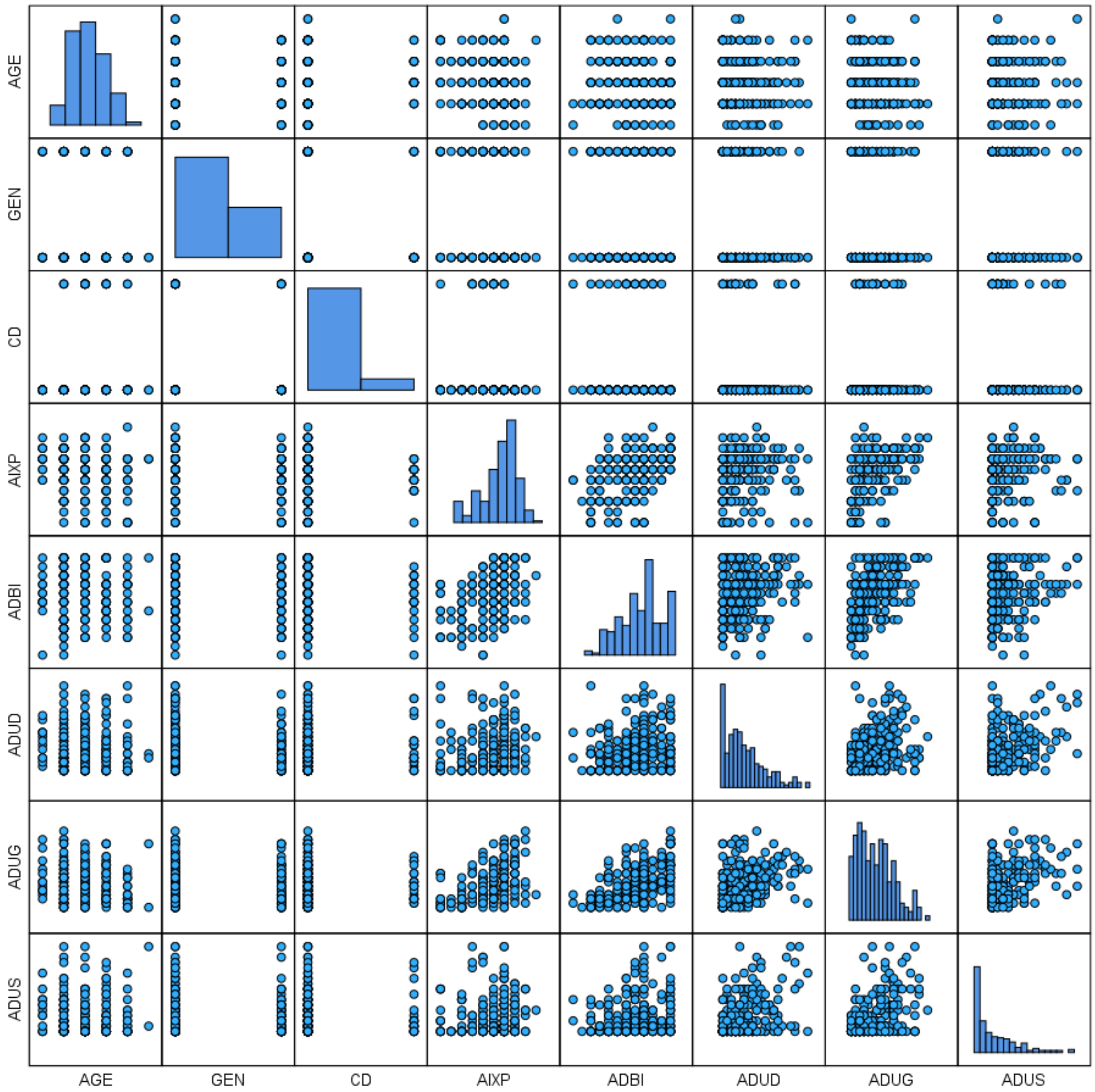
Reliability Test Results				
Variable	**Sample Size**	**Items**	**Cronbach's Alpha**	**Decision**
TRO	213	4	0,74	Proceed
TRIV	213	4	0,84	Proceed
TRD	213	4	0,78	Proceed
TRIS	213	4	0,74	Proceed
UTPE	213	4	0,91	Proceed
UTEE	213	4	0,90	Proceed
UTSI	213	3	0,82	Proceed
UTFC	213	4	0,66	Proceed
TCB	213	3	0,72	Proceed
TCC	213	4	0,90	Proceed
TCI	213	4	0,85	Proceed
TE	213	3	0,93	Proceed
ADBI	213	3	0,87	Proceed
ADUD	213	4	0,68	Proceed
ADUG	213	3	0,64	Proceed
ADUS	213	4	0,74	Proceed

4.8.12. Preliminary Examination of the Data

Multivariate techniques require the researcher to understand, evaluate, and interpret complex results (Hair et al., 2019). The increased complexity demands a thorough understanding of the data and the relationship between the variables (Hair et al., 2019). The use of graphical techniques is a valuable aid in increasing the researcher’s understanding, e.g., univariate profiling to examine the shape of the distributions with histograms and bivariate profiling to explore the relationship between variables using scatter plots (Hair et al., 2019).

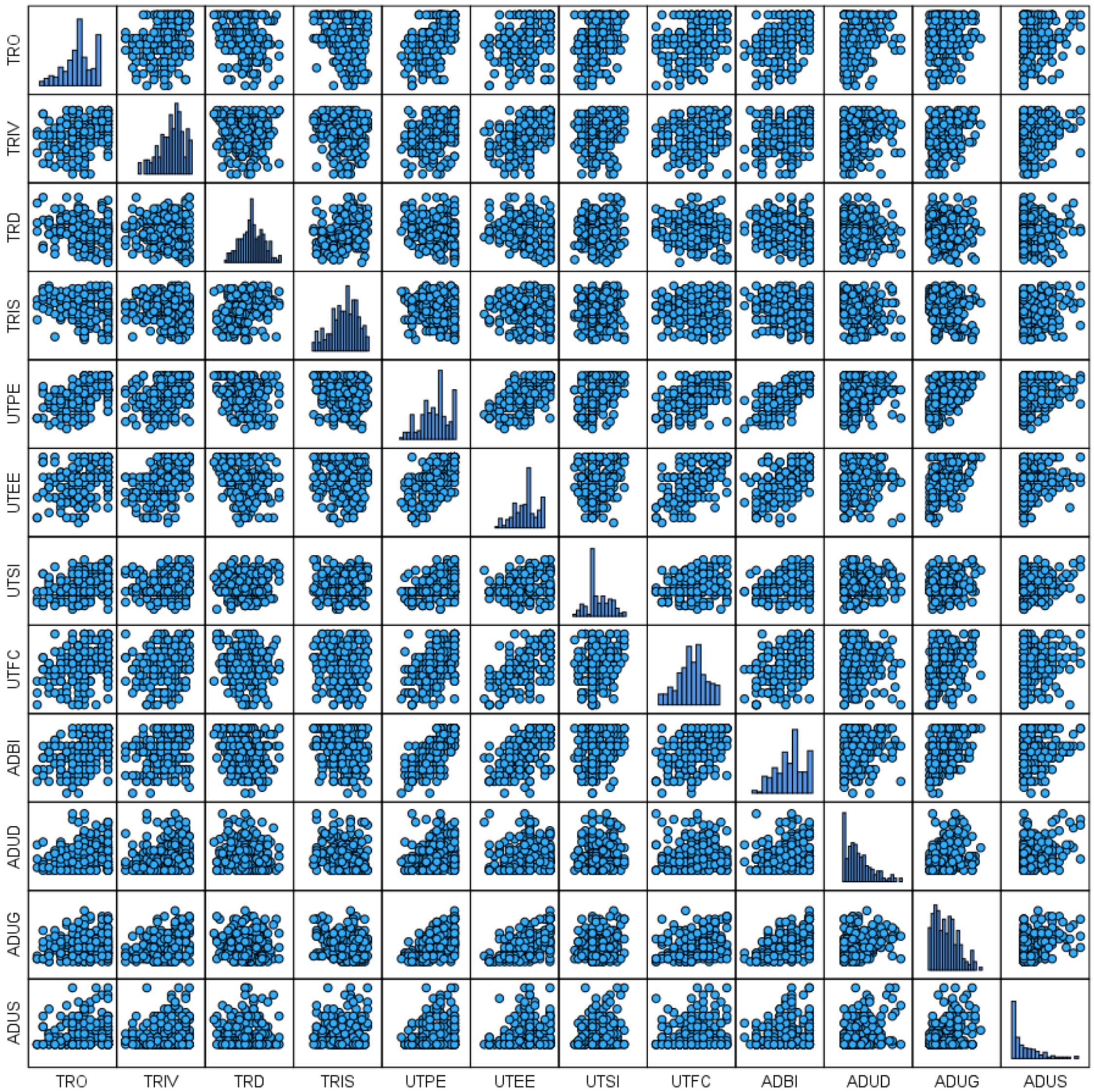
In Table 7, the scatterplot matrix shows the control and dependent variables. The histograms also show that Respondent AI Experience (AIXP), Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS) are generally not normally distributed in alignment with normality calculations. Graphically, there are correlations between all the dependent variables. Graphically, there is no visible correlation between Respondent Age (AGE) and any of the dependent variables. Graphically, there is some correlation between Respondent Gender (GEN) and Use General Tasks (ADUG), but not the other dependent variables. Graphically, there is some correlation between Country Development (CD) and three of the dependent variables, Use Define Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), but not with Behavioural Intention (ADBI). Graphically, there is some correlation between Respondent AI Expereince (AIXP) and all four dependent variables: Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS).

Table 7: Scatterplot Matrix - Control and Dependent Variables



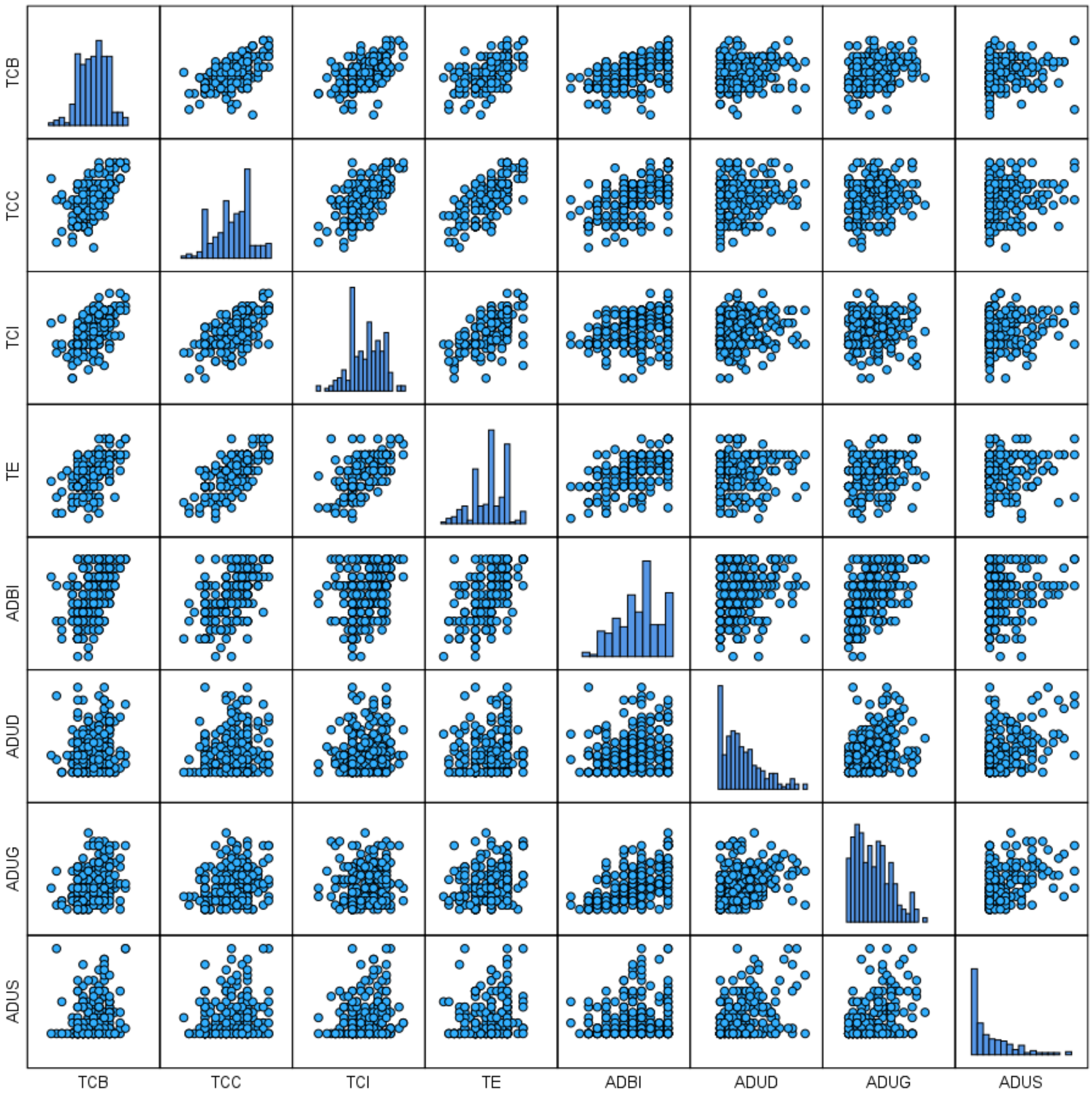
In Table 8, the scatterplot matrix with the independent and dependent variables is shown. The histograms visually confirm the non-normality of the distributions except Readiness Insecurity (TRIS), which tends towards a normal distribution in alignment with normality calculations. The variables Readiness Optimism (TRO), Readiness Innovativeness (TRIV), Readiness Discomfort (TRD), Readiness Insecurity (TRIS), Social Influence (UTSI) and Facilitating Conditions (UTFC) do not show a clear indication of correlation with the dependent variables graphically. Performance Expectancy (UTPE) and Effort Expectancy (UTEE) show some correlation with all the dependent variables.

Table 8: Scatterplot Matrix - Independent and Dependent Variables



In Table 9, the scatterplot matrix for the moderating and dependent variables is shown. The histograms visually confirm the result of non-normality. There are visual correlations between all the trust variable pairs: Trust Cognitive Benevolence (TCB) and Trust Cognitive Competence (TCC), Trust Cognitive Benevolence (TCB) and Trust Cognitive Integrity (TCI), Trust Cognitive Benevolence (TCB) and Trust Emotional (TE), Trust Cognitive Competence (TCC) and Trust Cognitive Integrity (TCI), Trust Cognitive Competence (TCC) and Trust Emotional (TE), and Trust Cognitive Integrity (TCI) and Trust Emotional (TE). This correlation between the variables of the moderator could lead to multicollinearity if it is attempted to test the influence of two simultaneously, i.e., have an interaction term with two of them together (Kutner et al., 2005). Although multicollinearity is a concern at this point, multicollinearity will be tested as part of the regression analysis. There are visual indications of correlation between Trust Cognitive Benevolence (TCB) and Behavioural Intention (ADBI), Trust Cognitive Competence (TCC) and Behavioural Intention (ADBI), Trust Cognitive Integrity (TCI) and Behavioural Intention (ADBI), and Trust Emotional (TE) and Behavioural Intention (ADBI). None of the others have a graphical indication of correlation.

Table 9: Scatterplot Matrix - Moderating and Dependent Variables



4.8.13. Linearity

Linearity is determined by the pattern of association between each pair of variables and whether the association can be appropriately approximated by a straight line (Hair et al., 2019). Visual inspection of the scatter plot of variable pairs can be used to determine if there are any non-linear relationships (Hair et al., 2019). The scatterplots in Table 7, Table 8, and Table 9 do not reveal any apparent nonlinear relationship or any nonlinear patterns. Thus, the assumption of linearity holds.

4.8.14. Homoscedasticity

Homoscedasticity is the condition when the variance of the errors, also known as residuals of the independent variables under test, are equal (Hair et al., 2019; Kutner et al., 2005). Levene's test for Homoscedasticity was used to test the assumption of homoscedasticity used in linear regression (Hair et al., 2019). With a p-value larger than 0.05, there is no significant evidence that variances are not equal. Thus, they are equal (Hair et al., 2019). Levene's test for Homoscedasiticity relative to the mean in SPSS was used. The results are shown in Table 10, where the p-values smaller and equal to 0.05 are marked in red, indicating that there is a significant difference in the variance of errors and, thus, not homoscedastic. The p-values marked in black are the remaining ones for which the assumption of homoscedasticity holds. Even though some variables are not homoscedastic, it was chosen to continue because as long as the researcher is cognisant that when the assumption of homoscedasticity does not hold, it could negatively influence the accuracy of the confidence intervals for regression coefficients (Hayes, 2018).

Table 10: Levene's Test for Homoscedasticity

	Levene's Test for Homoscedasticity					
	Categorical Variables					
	AGE		GEN		CD	
Metric Variable	Statistic	p-value	Statistic	p-value	Statistic	p-value
AIXP	2,41	0,04	0,86	0,36	4,14	0,04
TRO	0,19	0,97	1,00	0,32	1,78	0,18
TRIV	3,36	0,01	4,47	0,04	1,15	0,29
TRD	2,78	0,02	0,11	0,74	5,88	0,02
TRIS	0,70	0,62	0,23	0,63	5,01	0,03
UTPE	0,71	0,62	0,82	0,37	1,04	0,31
UTEE	0,19	0,97	0,24	0,63	0,43	0,51
UTSI	0,43	0,83	0,01	0,92	0,01	0,94
UTFC	1,92	0,09	2,17	0,14	0,10	0,75
TCB	1,26	0,28	0,12	0,73	2,20	0,14
TCC	1,69	0,14	0,24	0,63	5,26	0,02
TCI	0,99	0,42	2,34	0,13	5,57	0,02
TE	1,27	0,28	0,68	0,41	1,87	0,17
ADBI	1,57	0,17	1,86	0,17	1,17	0,28
ADUD	0,80	0,55	5,39	0,02	0,37	0,54
ADUG	3,63	0,00	0,35	0,55	1,56	0,21
ADUS	2,10	0,07	2,49	0,12	0,08	0,77

4.8.15. Standardisation of Variables

Although standardisation of variables is not a requirement for regression (Hayes, 2018), it improves the interpretation and calculation in the regression analysis. It involves the centring and scaling of variables (Kutner et al., 2005). The first reason for variable standardisation is to maintain the same variable value ranges in the matrix during calculation since the calculation of the inverse matrix is much less susceptible to roundoff errors (Kutner et al., 2005). Secondly, standardisation facilitates the comparison of regression coefficients because they are likely to have similar ranges (Kutner et al., 2005).

Centring involves taking each one of the observations of a variable and subtracting the mean from it (Kutner et al., 2005). Centring helps reduce multicollinearity substantially, especially in the case of moderation, where the interaction term is added, and there is a correlation between the independent variable and the moderator (Kutner et al., 2005). The variables are centred around the mean to avoid problems during regression analysis (Kutner et al., 2005). Centring influences the y-intercept of regression, but it does not affect the unstandardised regression coefficient (Kline, 2016). Centring the variables prior to analysis allows for the interpretation of the coefficients (Hayes, 2018).

All the independent variables and dependent variables were centred, as discussed above. However, since the control variables are categorical, they cannot be centred since calculating the mean from categories does not make sense. Not scaling the control variables should not cause severe collinearity issues because, for the control variable regression, no interaction terms were added.

The process of scaling typically involves dividing each observation by the standard deviation of the variable, resulting in the variables being represented in the units of the standard deviation of the observations (Kutner et al., 2005). Scaling using the standard deviation would negatively influence our ability to interpret the coefficients of the regression (Hayes, 2018). Hence, to avoid having a variable that differs by massive ranges, all the variables were kept to their original ranges in the questionnaire, i.e., most of them correspond to the seven-point Likert scale with values from one to seven. Thus, the maximum difference in range was one versus six, e.g. Respondent Gender (GEN) versus Readiness Optimism (TRO). The maximum difference of six is not multiple factors different and should not cause problems. Furthermore, not scaling avoids coefficient interpretation problems (Kutner et al., 2005).

4.8.16. Interaction Terms

The interaction terms for moderation are calculated by multiplying each one of the independent variables with the moderating variable, i.e., there was an interaction term for each independent variable (Hayes, 2018). The interaction terms were calculated from the centred variables.

4.9. Data Analysis

The study's results were captured in the next chapter, Chapter Five. The first step was to show the demographic data results, followed by the results structured per hypothesis. For each of the uneven hypotheses, the bivariate relationship of the independent and dependent variables must be tested for direction and significance. Next, determine if the independent variables significantly influence the dependent variable even in the presence of the control variables. For each of the even hypotheses, determine if the moderator has a significant positive or negative influence on the relationship between the independent variables and the dependent variable. The statistical tests used to assess each of the hypotheses are summarised in Table 11, which will be discussed in detail in the following sections.

Table 11: Statistical Tests per Hypotheses

Statistical Tests				
Hypothesis	Independent Variable	Dependent Variable	Moderator	Statistical Test
H1	Readines Motivators (TRO, TRIV)	Adoption (ADBI, ADUD, ADUG, ADUS)	n/a	Spearman's rank rorrelation coefficient
H3	Readiness Inhibitors (TRD, TRIS)			
H5	Performance Expectancy (UTPE)			
H7	Effort Expectancy (UTEE)			
H9	Social Influence (UTSI)			
H11	Facilitating Conditions (UTFC)			
H2	Readines Motivators (TRO, TRIV)		Trust (TCB, TCC, TCI, TE)	Hierarchical multiple regression
H4	Readiness Inhibitors (TRD, TRIS)			
H6	Performance Expectancy (UTPE)			
H8	Effort Expectancy (UTEE)			
H10	Social Influence (UTSI)			

4.9.1. Bivariate Relationships

In the previous section, it was shown that the data is not normal. Thus, the nonparametric Spearman's rank correlation coefficient was selected because it does not require the assumption of normality (Kothari, 2004; Kutner et al., 2005). The value of Spearman rank correlation coefficient ranges from -1 to 1, corresponding to a perfect negative and perfect positive correlation, respectively and the values in between the various degrees of correlation and with a value of zero, there is no association between the variables (Kothari, 2004; Kutner et al., 2005). The significance is set at the same p smaller or equal to 0.05 as for the rest of the study.

The assumption for Spearman's rank correlation is that the test requires more than 30 samples, whereas this study has 213 samples, which satisfies the requirement. The test checks for a monotonic relationship, i.e., when one variable increases, the other increases, not necessarily linearly. The test uses either ordinal, interval, or ratio data types, and this study has interval data that will be used in the correlation, which satisfies the data type requirement (Kothari, 2004).

Spearman's Rank correlation was calculated using SPSS bivariate correlation using the Spearman option. Relationships were marked in red when they were not significant and when p was larger than 0.05.

4.9.2. Influence of Control Variables

Hierarchical multiple regression was used to determine if the control variables influenced the dependent variable (Bernerth et al., 2018; Hayes, 2018). The main advantages of regression, which informed its selection, are its relative simplicity of understanding, its widespread use by researchers, its widespread implementation by software, including SPSS, and its tendency to approximate reality well when used thoughtfully (Hayes, 2018).

The assumptions for regression are discussed next. The first is linearity, which was tested. Linearity is essential because if it is violated, it depreciates the interpretation of the regression coefficient (Hayes, 2018). The second is normality, which was tested for, and the test indicated that none of the variables are normal. Normality is the least essential assumption in regression since research through simulation showed that only severe violations of normality affected the validity of the inferences made from regression unless the sample is small (Hayes, 2018). It was suggested that even when highly non-normal distributions are used, tests that assume normality can still perform well with large sample sizes (Maxwell & Delaney, 2004). The Third is homoscedasticity; after testing, the sample data was shown to be not homoscedastic. Thus, non-homoscedastic data could negatively influence the accuracy of the confidence intervals for regression coefficients (Hayes, 2018). The fourth is independence, where it is assumed that the errors in estimation are independent (Hayes, 2018). Independence is well explained by considering something independent, such that knowing some information about one thing does not give any information about the other (Hayes, 2018). The independence was not tested, but when it is violated, it negatively affects the accuracy of the confidence intervals for regression (Hayes, 2018). Even though not all the assumptions were checked and achieved, the researcher is cognisant of the possible detrimental effects on the results, and thus, it was chosen to continue (Hayes, 2018).

The calculation was executed in SPSS using the linear regression function. The test was run for each dependent variable separately. The dependent variable under the test was entered into the dependent variable box. All the control variables went into the independent box block one, and both the control variables and independent variables under test went into the independent box block 2. The statistical settings checked were estimates, model fit, R^2 change, descriptives, part and partial correlations, and collinearity diagnostics. The settings under options selected: Use a probability of F entry 0.05 and removal 0.10, include constant in the equation, and exclude cases pairwise.

The collinearity was checked using the collinearity statistics: if tolerance is less than 0.10 or variance inflation factor (VIF) is above 10.00, multicollinearity is possible. If multicollinearity is possible, one of the independent variables should be removed.

The standardised beta-weights are taken from the unstandardised 'B' given by SPSS as these are the correct betas (Friedrich, 1982). The R^2 values were converted to percentages by multiplying them by 100.

The R^2 value of the model explained the percentage of variance in the dependent variable, which is explained by the variables entered in the corresponding model box. In model one, the R^2 value is the percentage of the variance of the dependent variable, which is explained by the control variables collectively, and this is significant if the p-value is smaller and equal to 0.05. The ANOVA indicates the significance of the whole model if the p-value is smaller and equal to 0.05. Secondly, the R^2 from model two is the percentage of the variance of the dependent variable, which is explained by the control variables and independent variables under test together and is significant if the p-value is smaller and equal to 0.05. Thirdly, the change in R^2 from model one to model two is the percentage of the variance of the dependent variable, which is explained by the addition of the independent variables under test and is significant if the p-value is smaller and equal to 0.05. Thus, the change in R^2 is the percentage of variance explained by the independent variable in the presence of the control variables when the test is significant. Stated differently, if significant, the independent variables explained (R^2x100)% of the change in variance of the dependent variable even in the presence of the control variables. In the coefficients table, the unstandardised coefficient 'B' represents the slope, i.e., the actual change in the dependent variable for each unit of change in the independent variable. At the same time, a smaller p-value equal to 0.05 indicates that the interaction is significant.

4.9.3. Influence of Moderator

To determine the influence of the moderating variables in the relationship between the independent variables and the dependent variable (Hayes, 2018), the test used is hierarchical multiple regression (Hayes, 2018). It looks for evidence of moderation to determine if the relationship between the independent variable and the dependent variable changes systematically as a function of the proposed moderator (Hayes, 2018). The reasons for selection are the same as discussed under control variable influence.

The assumptions are the same as discussed under control variable influence. Thus, it was chosen to continue because it was suggested that it is acceptable to do so even in the absence of normality (Maxwell & Delaney, 2004). The Assumptions for statistical tests are not only there to check if they were violated, but rather when they are violated to ensure the researcher is cognisant during interpretation that there is a possibility that the results of the analysis might be wrong (Hayes, 2018).

The calculation was executed in SPSS using the linear regression function. The test was run for each dependent variable separately. The dependent variable under the test was entered into the dependent variable box. All the independent variables and the independent variables under test went into the independent box block one. The independent variables and the independent variables under test, together with the corresponding independent interaction terms, went into the independent box block two. The statistical settings checked were estimates, model fit, R^2 change, descriptives, part and partial correlations, and collinearity diagnostics. The settings under options selected: Use a probability of F entry 0.05 and removal 0.10, include constant in the equation, and exclude cases pairwise.

The collinearity was checked for multicollinearity, as discussed under control variable influence. The standardised weights are taken from the unstandardised 'B' given by SPSS, as these are the correct betas (Friedrich, 1982). The R^2 values were converted to percentages by multiplying them by 100.

The R^2 value of the model explained the percentage of variance in the dependent variable, which is explained by the variables entered in the corresponding model box. By comparing the R^2 in the model summary between model one and model two, the increase in R^2 corresponds to the additional percentage of the variance of the dependent variable, which is explained by the interaction terms, which represent moderation. The increase in R^2 for model two is significant when the p-value is smaller or equal to 0.05. Furthermore, the p-value in the ANOVA table indicates that the whole model is significant when the p-value is smaller than or equal to 0.05. In the coefficients table, the unstandardised coefficient 'B' represents the slope, i.e., the actual change in the dependent variable for each unit of change in the independent variable. At the same time, a smaller p-value equal to 0.05 indicates that the interaction is significant.

4.10. Quality Assurance

Quality was controlled by measuring reliability and validity (Hair et al., 2010; Parasuraman & Colby, 2015; Saunders & Lewis, 2018; Venkatesh & Zhang, 2010). The target reliability and validity were achieved, and it should be noted that only established proven questionnaires were used. Errors in the survey were minimised by running a pre-test survey.

In previous research (Parasuraman & Colby, 2015), the response time to complete the survey was checked, and if this was unrealistically fast, the response was removed from the sample. No such cases were detected or deleted in this research.

Parasuraman and Colby (2015) compared the demographic of their sample to the demographic of census data to check for any bias that might exist in the sample. The same was done for this research and is further elaborated in later sections.

4.11. Limitations

A limitation of the study is the sampling bias, which causes some categories of a population to be either over or under-represented (Mercer et al., 2017). The sampling bias led to the results not being representative of the population, affecting the generalisability of the results (Mercer et al., 2017). The type of sampling bias that was most prominent in this study was selection bias due to the sampling methods used (Mercer et al., 2017). Convenience sampling and snowball sampling favour individuals who are close to the researcher over other people in the population, excluding certain demographic groups to some extent. The data collection was initiated using the researchers's professional and personal network, which likely introduced bias because it is not representative and not a probabilistic sample. This bias should be alleviated if snowball sampling significantly exceeds convenience sampling. Since non-probabilistic sampling is used, the following variables should be monitored for possible biases due to over or under-representation: Respondent Age, Respondent Gender, Respondent Race, Country Development, Department in Organisation, Industry, Employment Status and Qualification Level, which is further discussed in Chapter Six (Venkatesh et al., 2012). The generalisability of any outcome from the study should be done in line with the countries' development state from which the data was recorded (Shamim et al., 2023; Venkatesh et al., 2012).

Even though using an online survey is widely adopted in literature (Vimalkumar et al., 2021), the survey is being conducted using technology, a personal computer or smartphone, which introduces some bias since the people answering the question are likely to have experience in adoption already. The skewed attributes of the internet population and respondents' lack of online experience (Evans & Mathur, 2018) were not mitigated.

Even though some previous research (Parasuraman & Colby, 2015) randomised the questions to minimise the effect of the questions' order, other previous research (Shi et al., 2021; Venkatesh & Zhang, 2010; Wu et al., 2023) did not. In this research, the questions were not randomised. Thus, there could be a bias in the data due to the order of the questions.

Common method bias is likely when a single measurement instrument is used to measure both the dependent and independent variables, especially when it is self-reported by the respondent (Podsakoff et al., 2003). In this study, only a survey was used, which was completed by the respondent; hence, common method bias is a risk that could influence the validity of the statistical tests (Podsakoff et al., 2003). The only control that was implemented against common method bias was the guarantee of anonymity of the respondent (Podsakoff et al., 2003). Although precautions are taken to ensure respondents stay anonymous, some might still not be honest regarding their readiness and adoption (Damerji & Salimi, 2021). Thus, results from statistical tests could be under or overstated due to the common method bias.

The TRI 2.0 framework has limitations related to Discomfort and Insecurity, both inhibitor dimensions, that are not representable as homogeneous attributes (Parasuraman & Colby, 2015). As mitigation, they were determined as factors in the exploratory factor analysis and passed the reliability and validity tests.

The survey was only circulated at one point in time due to the period of the research project, and thus, it was not able to measure the change over time, as was done by Venkatesh et al. (2012). The study focused on the variables being measured quantitatively by the models and may miss other factors not included in the models (Budhathoki et al., 2024). Even though not all the assumptions required for the statistical tests were statistically checked and achieved, the researcher was cognisant of the possible detrimental effects on the results (Hayes, 2018). A limitation of the anonymous online survey was that it is not possible to know if someone completed the survey more than once, which could not be mitigated while keeping anonymity.

5. Results

The Results Chapter presents the study's results. First, the sample is described in terms of its demographics. Then, the results of the hypothesis testing follow.

5.1. Sample Description

The sample has 213 usable responses after deletion; for details on deletion, refer to data preparation in the Research Methodology Chapter. First, the results for the sample demographics are documented, followed by the descriptive statistics.

5.1.1. Geographical Demographics

The geographical demographics consist of the country of residence of the respondent and whether that country is developing or developed. The distribution of respondents from each country is shown in Figure 3. Other consists of countries with a representation of less than 2%.

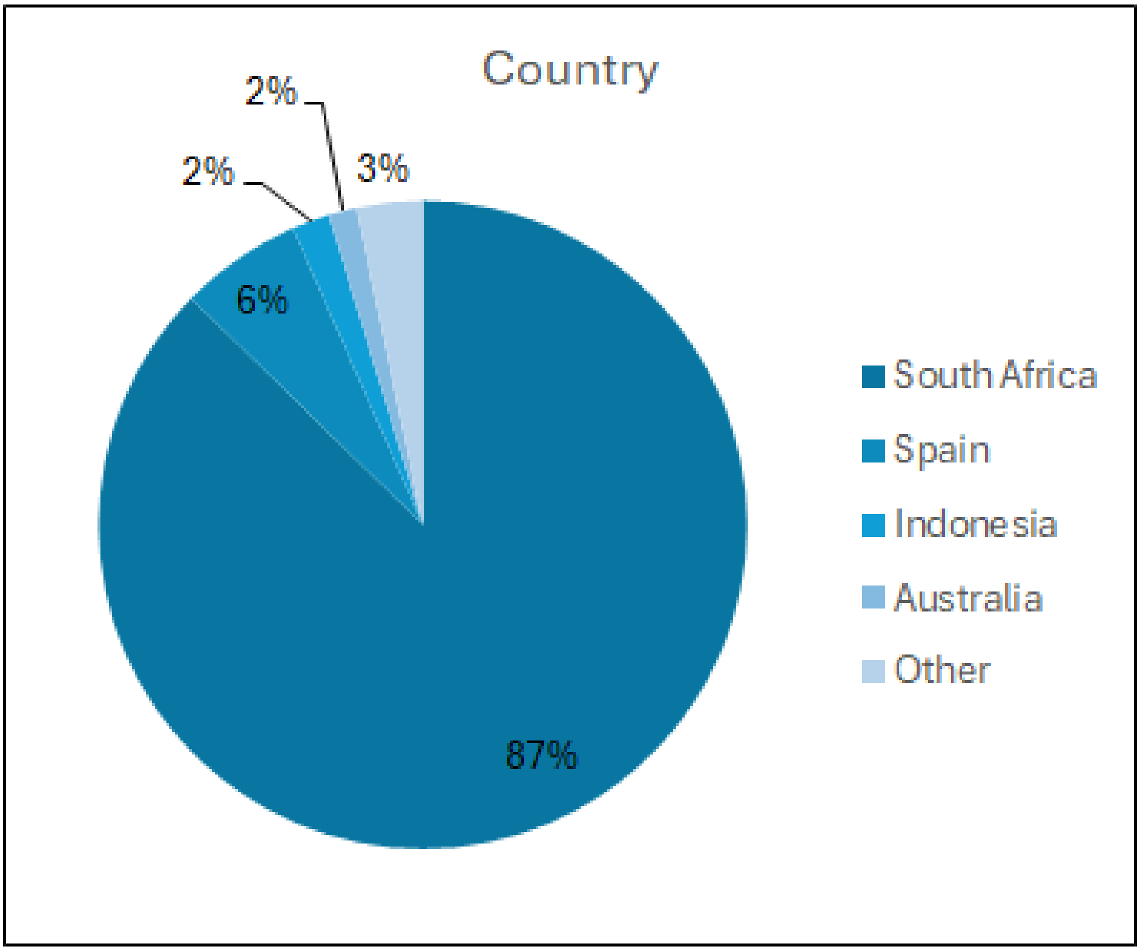


Figure 3: Country Distribution of Respondents

The Country Development distribution of the respondents, which is either developing or developed countries, is shown in Figure 4.

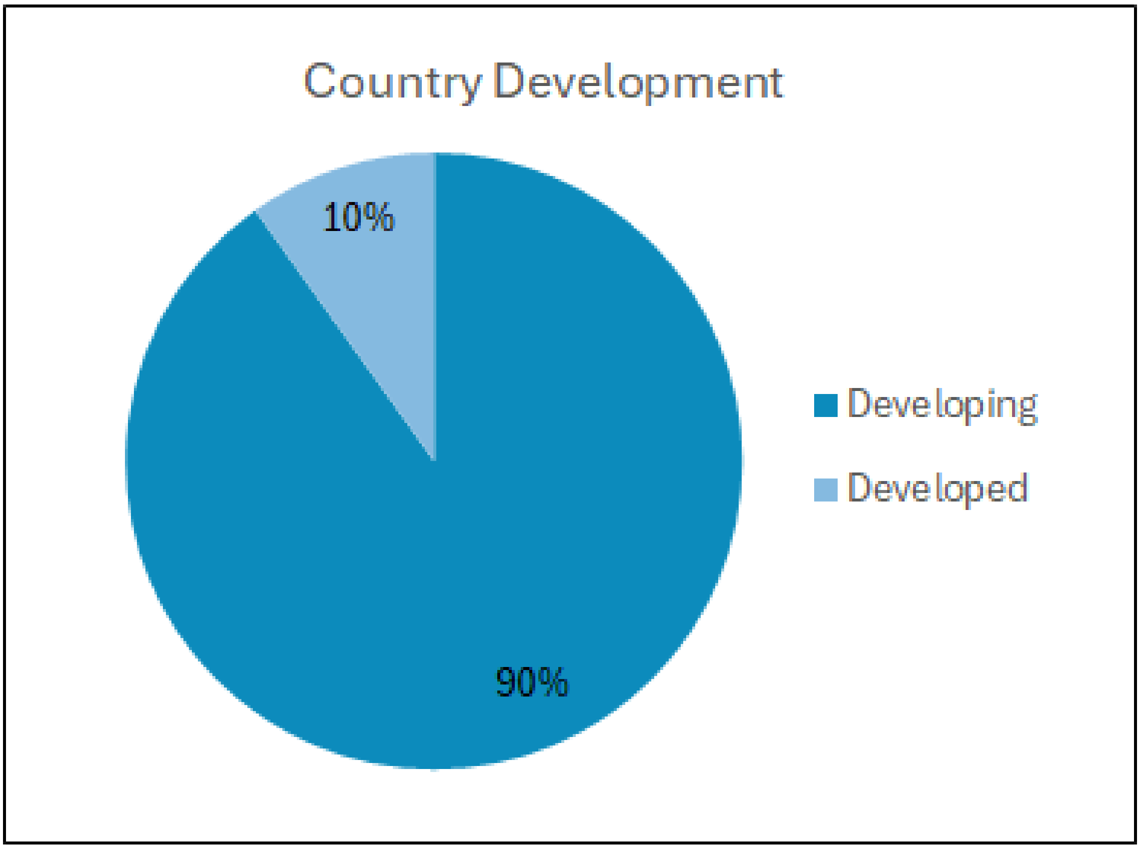


Figure 4: Country Development Distribution of the Respondents

5.1.2. Basic Demographics

The Respondent Age distribution is shown in Figure 5. It is worth noting that there were respondents 65 years and older, beyond the typical retirement age. However, they specifically indicated that they are still working for an organisation and were thus included in the study.

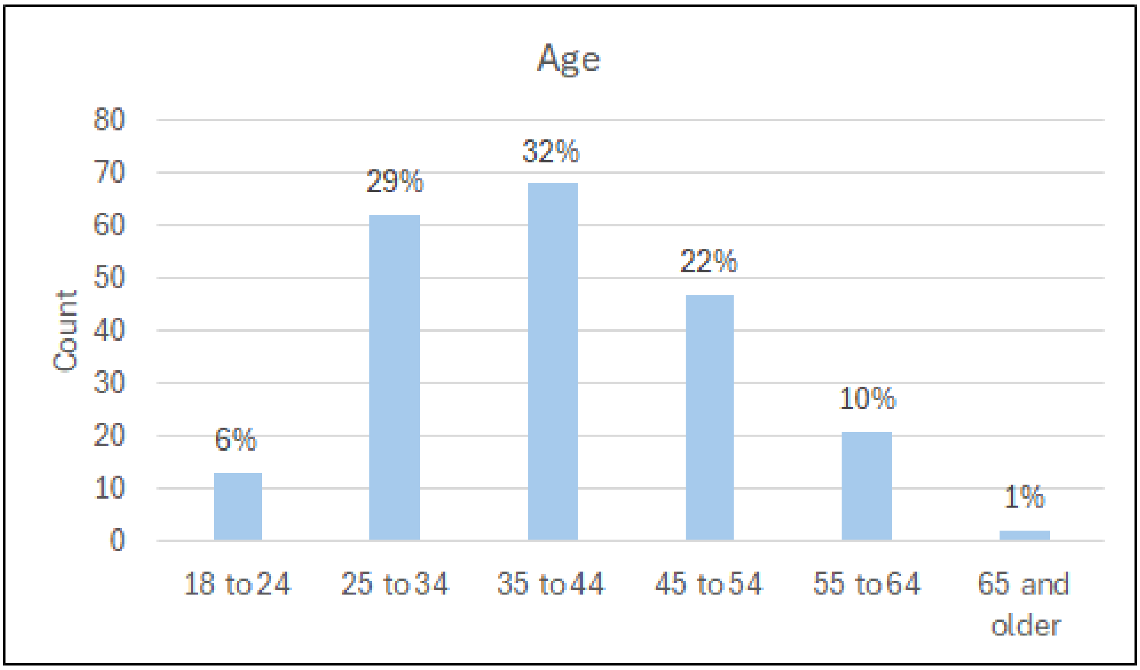


Figure 5: Age Distribution of Respondents

The Respondent Gender distribution is shown in Figure 6.

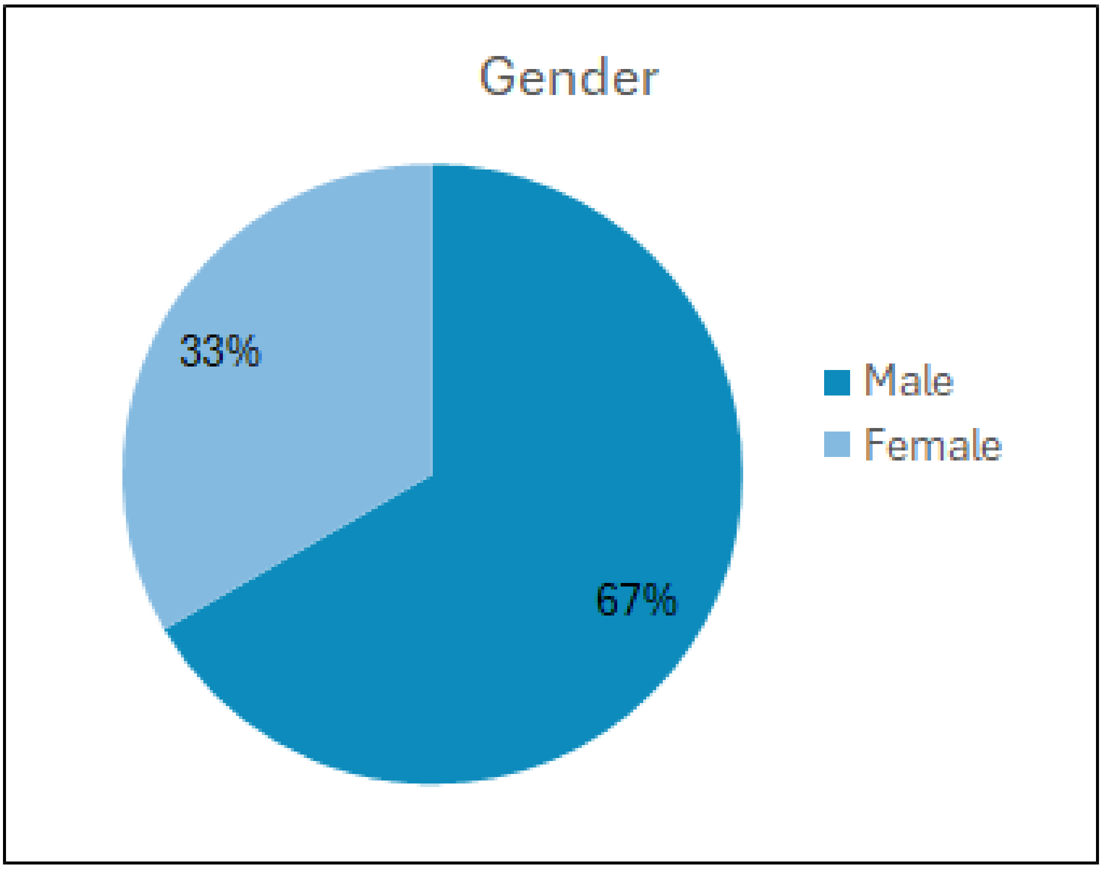


Figure 6: Gender Distribution of Respondents

The race distribution of the respondents is shown in Figure 7. Other consisted of races which represented less than 2% of the sample.

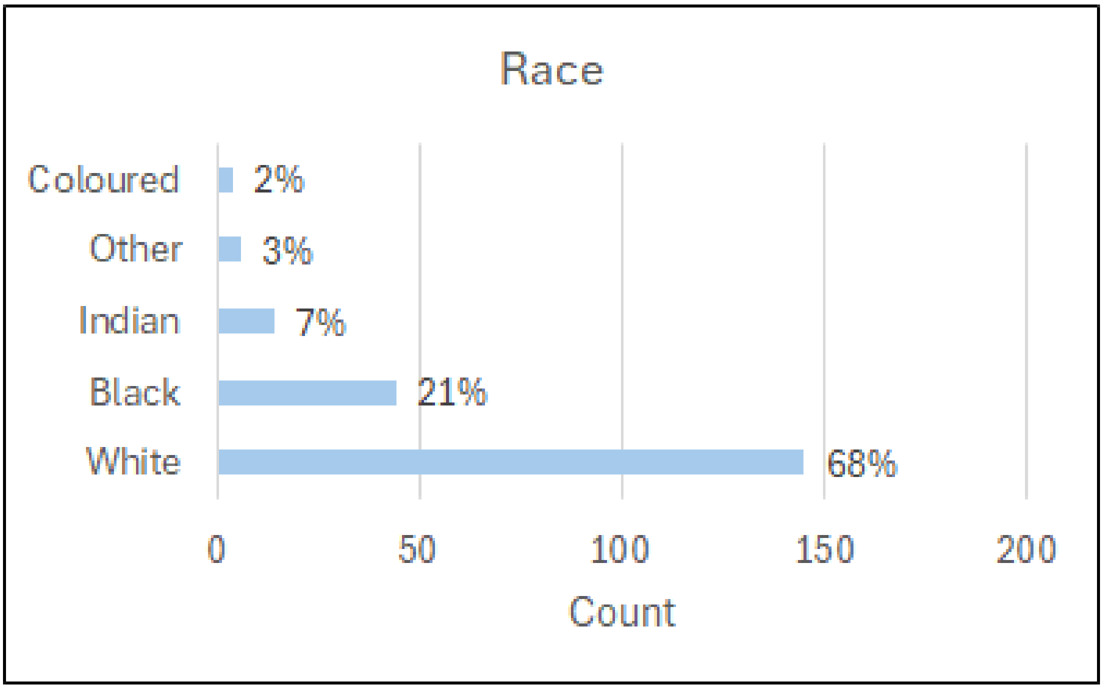


Figure 7: Race Distribution of Respondents

5.1.3. Socioeconomic Demographics

The education level distribution of respondents is shown in Figure 8. The other group is formed of smaller groupings, which constitute less than 2% of the sample.

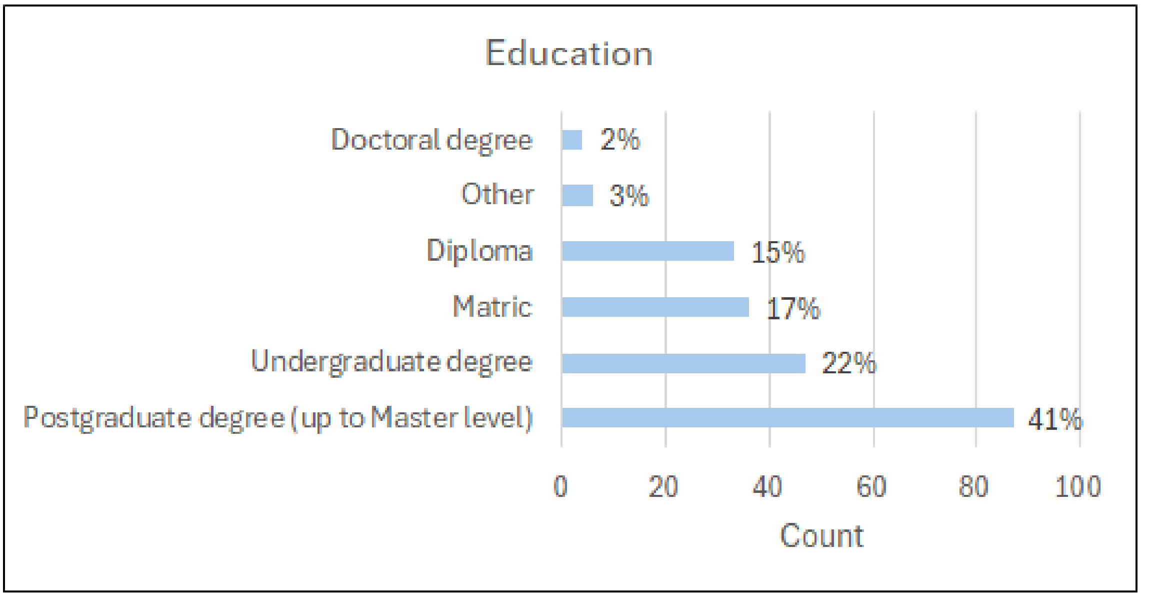


Figure 8: Education Level Distribution of Respondents

Figure 9 shows the employment status distribution of the respondents. The other group is formed of smaller groupings, which constitute less than 2% of the sample.

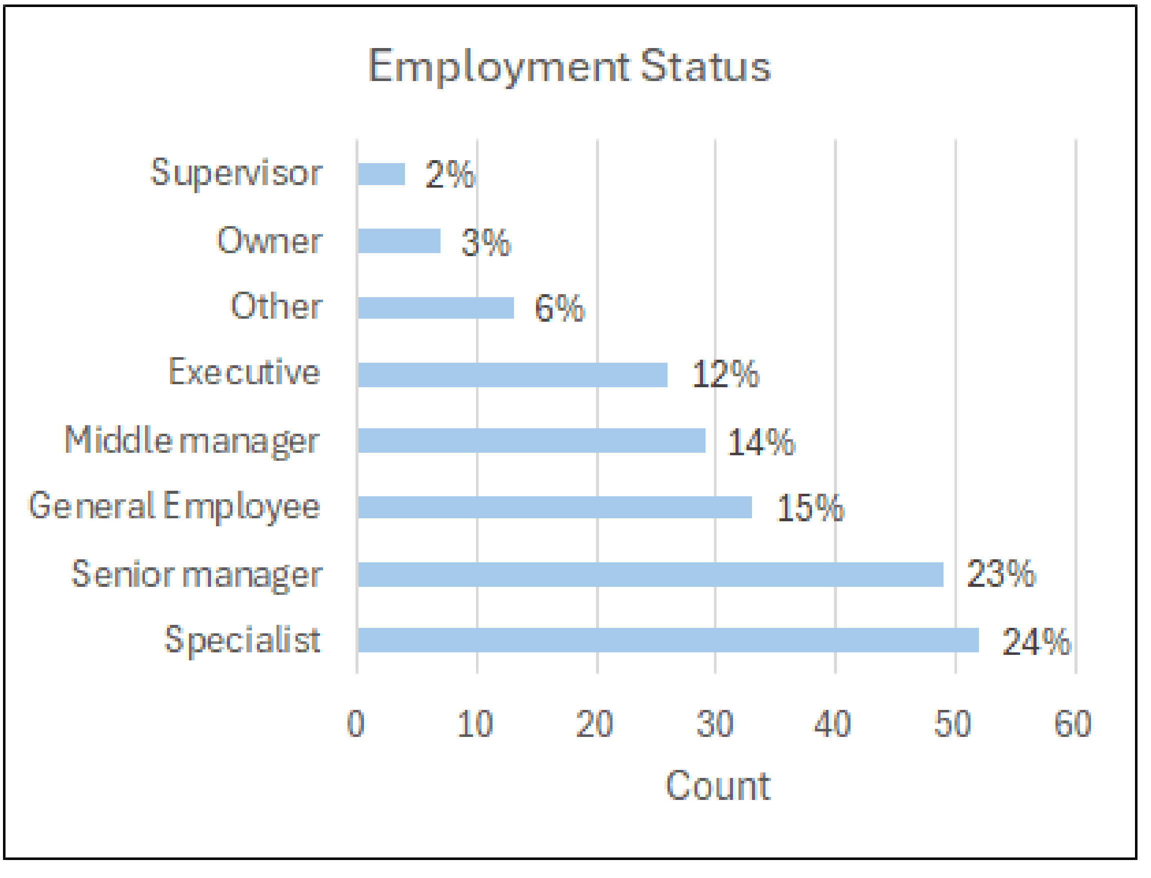


Figure 9: Employment Status Distribution of Respondents

5.1.4. Organisational Demographics

The distribution of the industry in which respondents worked is shown in Figure 10. The other group is formed of smaller groupings, which constitute less than 2% of the sample.

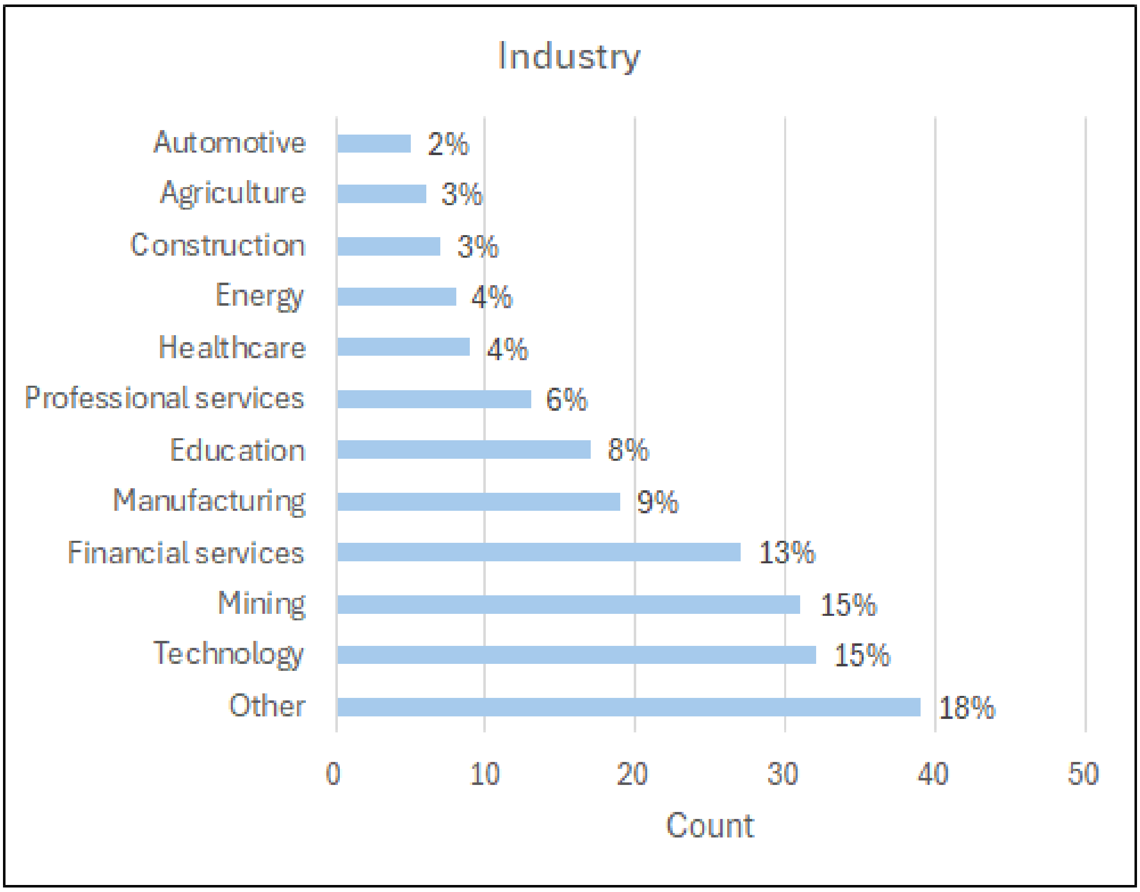


Figure 10: Distribution of Industry in which Respondents Worked

The distribution of the departments where respondents worked is shown in Figure 11. The other group is formed of smaller groupings, which constitute less than 2% of the sample.

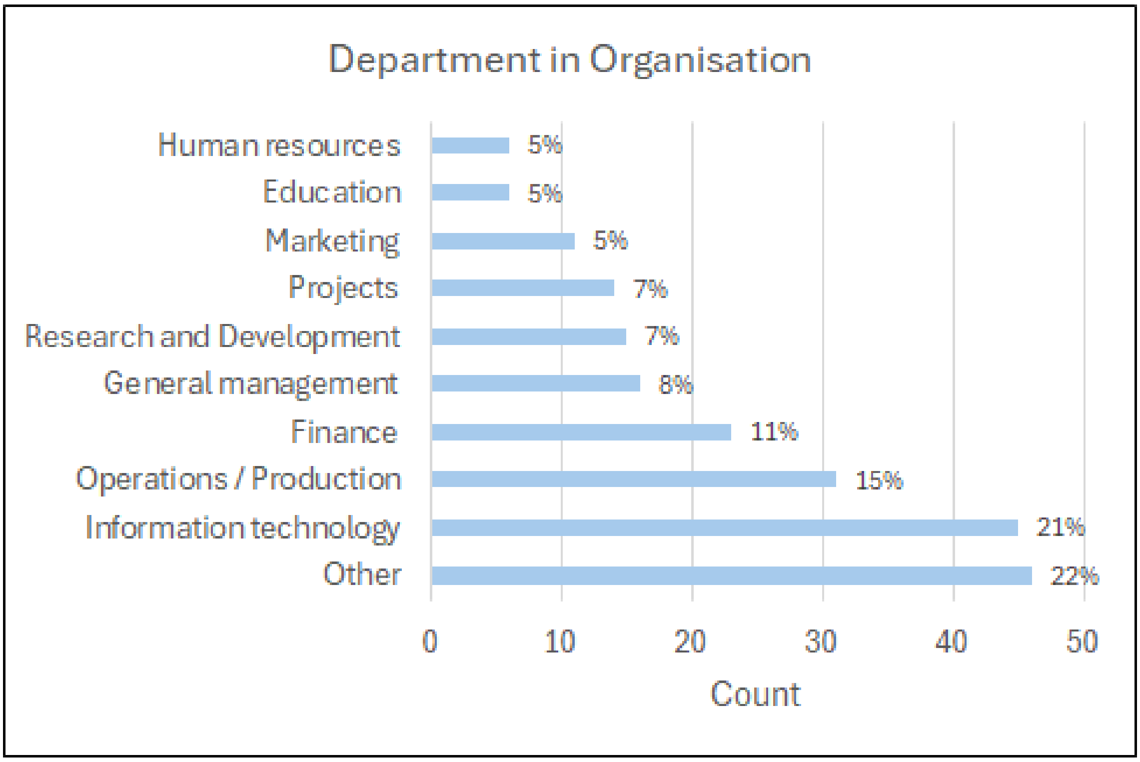


Figure 11: Distribution of the Department where Respondents Worked

5.1.5. Descriptive Statistics

The descriptive statistics for the sample are shown in Table 12, which includes the minimum value, maximum value, mean, and standard deviation for each variable where applicable. Furthermore, the distribution characteristics are described by the skewness and kurtosis, each giving a value and Z-score for every variable. The Z-scores which fall outside the range of -1.96 and 1.96 to be considered normal are marked in red (Hair et al., 2019). It is worth noting that the means of the independent and dependent variables are not aligned and range from 1.71 to 5.94. The total average of all the individual means is 4.66, which is 1.16 above the centre of the seven-point Likert scale. This suggests that respondents tended to give positive answers across all responses. This positive tendency is supported by the maximum values, which were chosen for 14 out of the 16 variables, and the minimum value, which was only selected for three out of the 16 variables. The variables contained no outliers, as these were deleted during data preparation.

Table 12: Descriptive Statistics

Descriptive Statistics								
	Descriptive Stat.				Skewness		Kurtosis	
Variable	Min.	Max.	Mean	Std. Dev.	Value	Z-score	Value	Z-score
TRO	4,00	7,00	5,94	0,76	-0,44	-2,61	-0,30	-0,91
TRIV	2,50	7,00	5,31	1,09	-0,54	-3,20	-0,26	-0,77
TRD	1,25	7,00	4,05	1,22	0,05	0,29	-0,37	-1,11
TRIS	2,25	7,00	4,95	1,17	-0,40	-2,41	-0,53	-1,57
UTPE	3,25	7,00	5,60	0,95	-0,33	-1,98	-0,62	-1,86
UTEE	3,75	7,00	5,79	0,80	-0,34	-2,04	-0,41	-1,23
UTSI	2,33	7,00	4,57	1,04	0,27	1,62	-0,49	-1,46
UTFC	4,00	7,00	5,66	0,73	-0,21	-1,24	-0,39	-1,16
TCB	2,33	7,00	4,99	0,88	-0,21	-1,25	-0,12	-0,35
TCC	3,00	7,00	5,32	0,86	-0,27	-1,59	-0,48	-1,42
TCI	2,00	7,00	4,80	0,95	-0,23	-1,36	-0,29	-0,86
TE	2,00	7,00	4,91	1,06	-0,40	-2,36	-0,26	-0,78
ADBI	3,33	7,00	5,67	0,91	-0,32	-1,89	-0,64	-1,90
ADU	1,00	4,69	2,41	0,80	0,66	3,93	-0,12	-0,36
	Replaced ADU after EFA:							
ADUD	1,00	6,00	2,29	1,17	1,04	6,22	0,64	1,92
ADUG	1,00	7,00	2,93	1,40	0,61	3,66	-0,29	-0,88
ADUS	1,00	5,00	1,71	0,91	1,58	9,42	2,20	6,56

5.2. Assessment of Research Hypotheses

In this section, the results of the tests for hypotheses H1 to H11 are captured. For each test, only the model-level regression results were captured in the main report; please refer to Appendix F and Appendix G, which contains the detailed betas for the regression of control variables and regression of moderation.

5.2.1. Hypothesis H1

The results for Hypothesis H1 are first presented without the presence of control variables and then in the presence of control variables.

5.2.1.1. Hypothesis H1

H1 hypothesised that Readiness Motivators, which are Optimism and Innovativeness, positively influence Adoption. The variables dealt with in H1 are the Readiness Motivators represented by Readiness Optimism (TRO) and Readiness Innovativeness (TRIV), Adoption represented by Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), and the control variables Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD) and Respondent AI

Experience (AIXP). The results of Spearman's correlation are shown in Table 13, where the independent variables (IV) are listed in the first column and the dependent variables (DV) in the subsequent columns. Both Readiness Optimism (TRO) and Readiness Innovativeness (TRIV) have a significant positive correlation with each of the dependent variables: Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS). The correlation strengths are between 18% and 49%, with the p-value smaller and equal to 0.05. Thus, the null hypothesis is rejected, and H1 is confirmed, demonstrating that with an increase in Readiness Motivators (Innovativeness and Optimism), Adoption also increases. The strongest correlations were Readiness Optimism (TRO) and Behavioural Intention (ADBI) with 49%, Readiness Innovativeness (TRIV) and Use General Tasks (ADUG) with 38%, and Readiness Innovativeness (TRIV) and Behavioural Intention (ADBI) with 27%.

Table 13: Spearman's Correlation Results for Hypothesis H1

	Spearman's Correlation							
	Dependent Variable							
	ADBI		ADUD		ADUG		ADUS	
IV	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
TRO	0,49	0,00	0,19	0,01	0,24	0,00	0,18	0,01
TRIV	0,27	0,00	0,19	0,01	0,38	0,00	0,26	0,00

5.2.1.2. Influence of Control Variables for Hypothesis H1

The results for the regression of the control variables are shown in Table 14. The results for the collinearity check indicated no collinearity. For Behavioural Intention (ADBI), the addition of Readiness Optimism (TRO) and Readiness Innovativeness (TRIV) to the model in step two explains an additional 13% of the variance of Behavioural Intention (ADBI) in the presence of the control variables and is significant. For Use Defined Tasks (ADUD), the addition of Readiness Optimism (TRO) and Readiness innovativeness (TRIV) to the model in step two explains an additional 3% of the variance of Use Defined Tasks (ADUD) in the presence of the control variables and is significant. For Use General Tasks (ADUG), the addition of Readiness Optimism (TRO) and Readiness Innovativeness (TRIV) to the model in step two explains an additional 5% of the variance of Use General Tasks (ADUG) in the presence of the control variables and is significant.

For Use Specialised Tasks (ADUS), the addition of Readiness Optimism (TRO) and Readiness Innovativeness (TRIV) to the model in step two explains an additional 6% of the variance of Use Specialised Tasks (ADUS) in the presence of the control variables. Thus, the Readiness Motivators (Innovativeness and Optimism) influence Adoption even after controlling for Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD) and Respondent AI Experience (AIXP).

The control variables significantly explained the variance of Behavioural Intention (ADBI), Use Defined Tasks (ADUD), and Use General Tasks (ADUG) with 25%, 5%, and 24%, respectively. The control variables did not explain the variance of Use Specialised Tasks Significantly. Each of the control variable checks have the same result since step one of all the hypotheses is the same. Thus, this was not repeated for each Hypothesis.

Table 14: Regression Results with Control Variables for Hypothesis H1

Hierarchical Multiple Regression								
			Collinearity Statistics		Model Fit Statistics			ANOVA
DV	Step	IV	Tol. Min	VIF Max	R^2	ΔR^2	p-value	p-value
ADBI	1	*	0,92	1,09	0,25		0,00	0,00
	2	*,**	0,74	1,34	0,38	0,13	0,00	0,00
ADUD	1	*	0,92	1,09	0,05		0,04	0,04
	2	*,**	0,74	1,34	0,08	0,03	0,03	0,01
ADUG	1	*	0,92	1,09	0,24		0,00	0,00
	2	*,**	0,74	1,34	0,29	0,05	0,00	0,00
ADUS	1	*	0,92	1,09	0,01		0,70	0,70
	2	*,**	0,74	1,34	0,07	0,06	0,00	0,01

*AGE, GEN, CD, AIXP
**TRO, TRIV

5.2.2. Hypothesis H2

H2 hypothesised that Trust positively moderates the influence of Readiness Motivators, which are Optimism and Innovativeness, on Adoption. The variables dealt with in H1 are the Readiness Motivators represented by Readiness Optimism (TRO) and Readiness Innovativeness (TRIV), Adoption represented by Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), and the control variables Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD) and Respondent AI Experience (AIXP).

The results for the moderation of hypothesis H2 are shown in Table 15. The results for the collinearity check indicated no collinearity. For Behavioural Intention (ADBI), Use Defined Tasks (ADUD), and Use General Tasks (ADUG), the addition of the moderation interaction terms in model two resulted in a p-value larger than 0.05, indicating that the increase in the explanation of the variance for Behavioural Intention (ADBI), Use Defined Tasks (ADUD), and Use General Tasks (ADUG) is insignificant. For Use Specialised Tasks (ADUS), the addition of the moderation interaction terms to the model in step two explains an additional 7% of the variance of Use Specialised Tasks (ADUS) and is significant. Thus, the null hypothesis is confirmed, and H2 is rejected, demonstrating that Trust does not moderate the relationship between Readiness Motivators (Innovativeness and Optimism) and all the factors of Adoption; however, Trust does moderate the relationship between Readiness Optimism (TRO) and Readiness Innovativeness (TRIV) to Use Specialised Tasks (ADUS).

Table 15: Regression Results for Hypothesis H2

Hierarchical Multiple Regression								
			Collinearity Statistics		Model Fit Statistics			ANOVA
DV	Step	IV	Tol. Min	VIF Max	R^2	ΔR^2	p-value	p-value
ADBI	1	*	0,39	2,56	0,44		0,00	0,00
	2	*,**	0,19	5,14	0,45	0,01	0,75	0,00
ADUD	1	*	0,39	2,56	0,06		0,04	0,04
	2	*,**	0,19	5,14	0,13	0,06	0,08	0,02
ADUG	1	*	0,39	2,56	0,25		0,00	0,00
	2	*,**	0,19	5,14	0,30	0,05	0,12	0,00
ADUS	1	*	0,39	2,56	0,10		0,00	0,00
	2	*,**	0,19	5,14	0,17	0,07	0,04	0,00

*TCB, TCC, TCI, TE, TRO, TRIV

**TROxTCB, TROxTCC, TROxTCI, TROxTE, TRIVxTCB, TRIVxTCC, TRIVxTCI, TRIVxTE

5.2.3. Hypothesis H3

The results for Hypothesis H3 are first presented without the presence of control variables and then in the presence of control variables.

5.2.3.1. Hypothesis H3

H3 hypothesised that Readiness Inhibitors, which are Discomfort and Insecurity, negatively influence Adoption. The variables dealt with in H3 are the Readiness Inhibitors (Discomfort and Insecurity) represented by Readiness Discomfort (TRD) and Readiness Insecurity (TRIS), Adoption represented by Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), and the control variables Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD) and Respondent AI Experience (AIXP).

The results of the Spearman's correlation are shown in Table 16. Both Readiness Discomfort (TRD) and Readiness Insecurity (TRIS) have a significant negative correlation with each of the dependent variables, Behavioural Intention (ADBI) and Defined Tasks (ADUD). Only Readiness Insecurity (TRIS) has a significant negative correlation with Use General Taks (ADUG). In contrast, the correlation between Readiness Discomfort (TRD) and Use of General Taks (ADUG) is insignificant. Both Readiness Discomfort (TRD) and Readiness Insecurity (TRIS) have an insignificant correlation with Use Specialised Tasks (ADUS). Thus, the null hypothesis is accepted, and H3 is rejected, demonstrating that an increase in Readiness Inhibitors (Discomfort and Insecurity) is not associated with a decrease in all the factors of Adoption. However, the significant correlation strengths are between -14% and -24%, with the p-value smaller and equal to 0.05. Thus, an increase in Readiness Discomfort (TRD) is associated with a decrease in Behavioural Intention (ADBI) and Use Defined Tasks (ADUD). Furthermore, an increase in Readiness Insecurity (TRIS) is associated with a decrease in Behavioural Intention (ADBI), Use Defined Tasks (ADUD), and Use General Tasks (ADUG).

Table 16: Spearman's Correlation Results for Hypothesis H3

	Spearman's Correlation							
	Dependent Variable							
	ADBI		ADUD		ADUG		ADUS	
IV	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
TRD	-0,17	0,01	-0,15	0,03	-0,10	0,17	-0,03	0,68
TRIS	-0,20	0,00	-0,24	0,00	-0,14	0,04	0,02	0,75

5.2.3.2. Influence of Control Variables for Hypothesis H3

The results for the regression of the control variables are shown in Table 17. The results for the collinearity check indicated no collinearity. For Use Define Tasks (ADUD), the addition of Readiness Discomfort (TRD) and Readiness Insecurity (TRIS) to the model in step two explains an additional 5% of the variance of Use Defined Tasks (ADUD) in the presence of the control variables and is significant.

For Behavioural Intention (ADBI), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), the addition of Readiness Discomfort (TRD) and Readiness Insecurity (TRIS) to the model in step two does not improve the explanation of the variance of Behavioural Intention (ADBI), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS) respectively in the presence of the control variables because they are insignificant. Thus, the Readiness Motivators (Innovativeness and Optimism) do not influence all the factors of Adoption after controlling for Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD) and Respondent AI Experience (AIXP).

Table 17: Regression Results with Control Variables for Hypothesis H3

Hierarchical Multiple Regression								
			Collinearity Statistics		Model Fit Statistics			ANOVA
DV	Step	IV	Tol. Min	VIF Max	R^2	ΔR^2	p-value	p-value
ADBI	1	*	0,92	1,09	0,25		0,00	0,00
	2	*,**	0,85	1,18	0,26	0,01	0,16	0,00
ADUD	1	*	0,92	1,09	0,05		0,04	0,04
	2	*,**	0,85	1,18	0,10	0,05	0,01	0,00
ADUG	1	*	0,92	1,09	0,24		0,00	0,00
	2	*,**	0,85	1,18	0,25	0,01	0,37	0,00
ADUS	1	*	0,92	1,09	0,01		0,70	0,70
	2	*,**	0,85	1,18	0,01	0,00	0,76	0,84

*AGE, GEN, CD, AIXP
**TRD, TRIS

5.2.4. Hypothesis H4

H4 hypothesised that Trust positively moderates the negative Influence of Readiness Inhibitors, which are Discomfort and Insecurity, on Adoption. The variables dealt with in H4 are the Readiness Inhibitors represented by Readiness Discomfort (TRD) and Readiness Insecurity (TRIS), Adoption represented by Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), and the control variables Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD) and Respondent AI Experience (AIXP).

Since Hypothesis H3, which hypothesised that Readiness Inhibitors (Discomfort and Insecurity) negatively influence adoption, was rejected, Hypothesis H4 is also rejected. Even though the Hypothesis was rejected, the regression was still calculated to see if there was a factor relationship which is moderated, as shown in Table 18. Although the regression indicates that Trust moderates the relationship between Readiness Discomfort (TRD) and Readiness Insecurity (TRIS) and Use General Tasks (ADUG), the influence of Readiness Discomfort (TRD) and Readiness Insecurity (TRIS) on Use General Tasks (ADUG) was neither significant with or without the presence of the control variables as shown before. Thus, Trust does not moderate the relationships between Readiness Discomfort (TRD) and Readiness Insecurity (TRIS) with any of the factors of Adoption.

Table 18: Regression Results for Hypothesis H4

Hierarchical Multiple Regression								
			Collinearity Statistics		Model Fit Statistics			ANOVA
DV	Step	IV	Tol. Min	VIF Max	R^2	ΔR^2	p-value	p-value
ADBI	1	*	0,40	2,49	0,40		0,00	0,00
	2	*,**	0,25	3,94	0,41	0,02	0,74	0,00
ADUD	1	*	0,40	2,49	0,07		0,01	0,01
	2	*,**	0,25	3,94	0,11	0,04	0,40	0,05
ADUG	1	*	0,40	2,49	0,17		0,00	0,00
	2	*,**	0,25	3,94	0,24	0,07	0,02	0,00
ADUS	1	*	0,40	2,49	0,06		0,07	0,07
	2	*,**	0,25	3,94	0,07	0,02	0,88	0,36

*TCB, TCC, TCI, TE, TRD, TRIS

**TRDxTCB, TRDxTCC, TRDxTCI, TRDxTE, TRISxTCB, TRISxTCC, TRISxTCI, TRISxTE

5.2.5. Hypothesis H5

The results for Hypothesis H5 are first presented without the presence of control variables and then in the presence of control variables.

5.2.5.1. Hypothesis H5

H5 hypothesised that Performance Expectancy positively influences Adoption. The variables dealt with in H5 are Performance Expectancy (UTPE) and Adoption, represented by Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), and the control variables Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD), and Respondent AI Experience (AIXP). The results of the Spearman's correlation are shown in Table 19. Performance Expectancy (UTPE) has a significant positive correlation with each of the dependent variables: Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG), and Use Specialised Tasks (ADUS). The correlation strengths are between 24% and 77%, with the p-value smaller and equal to 0.05. Thus, the null hypothesis is rejected, and H5 is confirmed, demonstrating that with an increase in Performance Expectancy, the Adoption also increases. The strongest correlations were between Performance Expectancy (UTPE) and Behavioural Intention (ADBI) at 77% and Behavioural Intention (ADBI) and Use General Tasks (ADUG) at 52%.

Table 19: Spearman's Correlation Results for Hypothesis H5

	Spearman's Correlation							
	Dependent Variable							
	ADBI		ADUD		ADUG		ADUS	
IV	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
UTPE	0,77	0,00	0,25	0,00	0,52	0,00	0,24	0,00

5.2.5.2. Influence of Control Variables for Hypothesis H5

The results for the regression of the control variables are shown in Table 20. The results for the collinearity check indicated no collinearity. For Behavioural Intention (ADBI), the addition of Performance Expectancy (UTPE) to the model in step two explains an additional 37% of the variance of Behavioural Intention (ADBI) in the presence of the control variables and is significant. For Use Defined Tasks (ADUD), the addition of Performance Expectancy (UTPE) to the model in step two explains an additional 2% of the variance of Use Defined Tasks (ADUD) in the presence of the control variables and is significant. For Use General Tasks (ADUG), the addition of Performance Expectancy (UTPE) to the model in step two explains an additional 12% of the variance of Use General Tasks (ADUG) in the presence of the control variables and is significant. For Use Specialised Tasks (ADUS), the addition of Performance Expectancy (UTPE) to the model in step two explains an additional 5% of the variance of Use Specialised Tasks (ADUS) in the presence of the control variables. Thus, the Performance Expectancy (UTPE) influences Adoption even after controlling for Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD) and Respondent AI Experience (AIXP).

Table 20: Regression Results with Control Variables for Hypothesis H5

Hierarchical Multiple Regression								
			Collinearity Statistics		Model Fit Statistics			ANOVA
DV	Step	IV	Tol. Min	VIF Max	R^2	ΔR^2	p-value	p-value
ADBI	1	*	0,92	1,09	0,25		0,00	0,00
	2	*,**	0,76	1,32	0,63	0,37	0,00	0,00
ADUD	1	*	0,92	1,09	0,05		0,04	0,04
	2	*,**	0,76	1,32	0,07	0,02	0,02	0,01
ADUG	1	*	0,92	1,09	0,24		0,00	0,00
	2	*,**	0,76	1,32	0,36	0,12	0,00	0,00
ADUS	1	*	0,92	1,09	0,01		0,70	0,70
	2	*,**	0,76	1,32	0,06	0,05	0,00	0,03

*AGE, GEN, CD, AIXP
**UTPE

5.2.6. Hypothesis H6

H6 hypothesised that Trust positively moderates the influence of Performance Expectancy on Adoption. The variables dealt with in H6 are Performance Expectancy (UTPE) and Adoption, represented by Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), and the control variables Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD), and Respondent AI Experience (AIXP). The results for the moderation of hypothesis H6 are shown in Table 21. The results for the collinearity check indicated no collinearity.

For Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), the addition of the moderation interaction terms in model two resulted in a p-value larger than 0.05, indicating that the increase in the explanation of the variance for Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS) respectively is insignificant. Thus, the null hypothesis is confirmed, and H6 is rejected, demonstrating that Trust does not moderate the relationship between Performance Expectancy (UTPE) and any of the factors of Adoption.

Table 21: Regression Results for Hypothesis H6

Hierarchical Multiple Regression								
			Collinearity Statistics		Model Fit Statistics			ANOVA
DV	Step	IV	Tol. Min	VIF Max	R^2	ΔR^2	p-value	p-value
ADBI	1	*	0,39	2,55	0,64		0,00	0,00
	2	*,**	0,36	2,78	0,64	0,01	0,62	0,00
ADUD	1	*	0,39	2,55	0,05		0,06	0,06
	2	*,**	0,36	2,78	0,06	0,01	0,72	0,18
ADUG	1	*	0,39	2,55	0,31		0,00	0,00
	2	*,**	0,36	2,78	0,32	0,01	0,63	0,00
ADUS	1	*	0,39	2,55	0,08		0,01	0,01
	2	*,**	0,36	2,78	0,09	0,02	0,50	0,02

*TCB, TCC, TCI, TE, UTPE

**UTPExTCB, UTPExTCC, UTPExTCI, UTPExTE

5.2.7. Hypothesis H7

The results for Hypothesis H7 are first presented without the presence of control variables and then in the presence of control variables.

5.2.7.1. Hypothesis H7

H7 hypothesised that Effort Expectancy positively influences Adoption. The variables dealt with in H7 are Effort Expectancy (UTEE), Adoption represented by Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), and the control variables Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD) and Respondent AI Experience (AIXP). The results of the Spearman’s correlation are shown in Table 22.

Effort Expectancy (UTEE) has a significant positive correlation with each of the dependent variables: Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS). The correlation strengths are between 18% and 58%, with the p-value smaller and equal to 0.05. Thus, the null hypothesis is rejected, and H7 is accepted, demonstrating that with an increase in Effort Expectancy (UTEE), Adoption also increases. The strongest correlations were between Effort Expectancy (UTEE) and Behavioural Intention (ADBI) at 58% and between Effort Expectancy (UTEE) and Use General Tasks (ADUG) at 51%.

Table 22: Spearman's Correlation Results for Hypothesis H7

	Spearman's Correlation							
	Dependent Variable							
	ADBI		ADUD		ADUG		ADUS	
IV	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
UTEE	0,58	0,00	0,18	0,01	0,51	0,00	0,25	0,00

5.2.7.2. Influence of Control Variables for Hypothesis H7

The results for the regression of the control variables are shown in Table 23. The results for the collinearity check indicated no collinearity. For Behavioural Intention (ADBI), the addition of Effort Expectancy (UTEE) to the model in step two explains an additional 14% of the variance of Behavioural Intention (ADBI) in the presence of the control variables and is significant. For Use Defined Tasks (ADUD), the addition of Effort Expectancy (UTEE) to the model in step two explains none of the variance of Use Defined Tasks (ADUD) in the presence of the control variables and is insignificant. For Use General Tasks (ADUG), the addition of Effort Expectancy (UTEE) to the model in step two explains an additional 9% of the variance of Use General Tasks (ADUG) in the presence of the control variables and is significant. For Use Specialised Tasks (ADUS), the addition of Effort Expectancy (UTEE) to the model in step two explains 5% of the variance of Use Specialised Tasks (ADUS) in the presence of the control variables and is significant. Thus, Effort Expectancy (UTEE) does not influence all the factors of Adoption after controlling for Respondent Age (AGE), Gender (GEN), Country Development (CD) and AI Experience (AIXP).

Table 23: Regression Results with Control Variables for Hypothesis H7

Hierarchical Multiple Regression								
			Collinearity Statistics		Model Fit Statistics			ANOVA
DV	Step	IV	Tol. Min	VIF Max	R^2	ΔR^2	p-value	p-value
ADBI	1	*	0,92	1,09	0,25		0,00	0,00
	2	*,**	0,64	1,57	0,39	0,14	0,00	0,00
ADUD	1	*	0,92	1,09	0,05		0,04	0,04
	2	*,**	0,64	1,57	0,05	0,00	0,61	0,07
ADUG	1	*	0,92	1,09	0,24		0,00	0,00
	2	*,**	0,64	1,57	0,33	0,09	0,00	0,00
ADUS	1	*	0,92	1,09	0,01		0,70	0,70
	2	*,**	0,64	1,57	0,06	0,05	0,00	0,04

*AGE, GEN, CD, AIXP

**UTEE

5.2.8. Hypothesis H8

H8 hypothesised that Trust positively moderates the influence of Effort Expectancy on Adoption. The variables dealt with in H8 are Effort Expectancy (UTEE), Adoption represented by Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), and the control variables Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD) and Respondent AI Experience (AIXP). The results for the moderation of hypothesis H8 are shown in Table 24. The results for the collinearity check indicated no collinearity.

For Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), the addition of the moderation interaction terms in model two resulted in a p-value larger than 0.05, indicating that the increase in the explanation of the variance for Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS) respectively is insignificant. Thus, the null hypothesis is confirmed, and H8 is rejected, demonstrating that Trust does not moderate the relationship between Effort Expectancy (UTEE) and any of the factors of Adoption.

Table 24: Regression Results for Hypothesis H8

Hierarchical Multiple Regression								
			Collinearity Statistics		Model Fit Statistics			ANOVA
DV	Step	IV	Tol. Min	VIF Max	R^2	ΔR^2	p-value	p-value
ADBI	1	*	0,39	2,59	0,50		0,00	0,00
	2	*,**	0,33	3,06	0,51	0,02	0,13	0,00
ADUD	1	*	0,39	2,59	0,03		0,24	0,24
	2	*,**	0,33	3,06	0,04	0,01	0,62	0,41
ADUG	1	*	0,39	2,59	0,32		0,00	0,00
	2	*,**	0,33	3,06	0,33	0,02	0,34	0,00
ADUS	1	*	0,39	2,59	0,08		0,01	0,01
	2	*,**	0,33	3,06	0,08	0,01	0,77	0,03

*TCB, TCC, TCI, TE, UTEE

**UTEExTCB, UTEExTCC, UTEExTCI, UTEExTE

5.2.9. Hypothesis H9

The results for Hypothesis H9 are first presented without the presence of control variables and then in the presence of control variables.

5.2.9.1. Hypothesis H9

H9 hypothesised that Social Influence positively influences Adoption. The variables dealt with in H9 are Social Influence (UTSI), Adoption represented by Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), and the control variables Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD) and Respondent AI Experience (AIXP). The results of the Spearman's correlation are shown in Table 25.

Social Influence (UTSI) has a significant positive correlation with Behavioural Intention (ADBI), Use Defined Tasks (ADUD), and Use Specialised Tasks (ADUS) with correlation strengths of 24%, 14% and 17%, respectively, with the p-values smaller and equal to 0.05. The correlation between Social Influence (UTSI) and Use General Tasks (ADUG) was insignificant. Thus, the null hypothesis is accepted, and H7 is rejected, demonstrating that an increase in Social Influence (UTSI) did not lead to a rise in all the factors of Adoption.

Table 25: Spearman's Correlation Results for Hypothesis H9

	Spearman's Correlation							
	Dependent Variable							
	ADBI		ADUD		ADUG		ADUS	
IV	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
UTSI	0,24	0,00	0,14	0,04	0,11	0,11	0,17	0,01

5.2.9.2. Influence of Control Variables for Hypothesis H9

The results for the regression of the control variables are shown in Table 26. The results for the collinearity check indicated no collinearity. For Behavioural Intention (ADBI), the addition of Social Influence (UTSI) to the model in step two explains an additional 6% of the variance of Behavioural Intention (ADBI) in the presence of the control variables and is significant. For Use Defined Tasks (ADUD), the addition of Social Influence (UTSI) to the model in step two is insignificant in its prediction of Use Defined Tasks (ADUD). For Use General Tasks (ADUG), the addition of Social Influence (UTSI) to the model in step two explains an additional 2% of the variance of Use General Tasks (ADUG) in the presence of the control variables and is significant. For Use Specialised Tasks (ADUS), the addition of Social Influence (UTSI) to the model in step two explains an additional 4% of the variance of Use Specialised Tasks (ADUS) in the presence of the control variables. Thus, Social Influence (UTSI) does not influence all the factors of Adoption after controlling for

Respondent Age (AGE), Gender (GEN), Country Development (CD) and AI Experience (AIXP).

Table 26: Regression Results with Control Variables for Hypothesis H9

Hierarchical Multiple Regression								
			Collinearity Statistics		Model Fit Statistics			ANOVA
DV	Step	IV	Tol. Min	VIF Max	R^2	ΔR^2	p-value	p-value
ADBI	1	*	0,92	1,09	0,25		0,00	0,00
	2	*,**	0,92	1,09	0,31	0,06	0,00	0,00
ADUD	1	*	0,92	1,09	0,05		0,04	0,04
	2	*,**	0,92	1,09	0,06	0,02	0,07	0,02
ADUG	1	*	0,92	1,09	0,24		0,00	0,00
	2	*,**	0,92	1,09	0,26	0,02	0,03	0,00
ADUS	1	*	0,92	1,09	0,01		0,70	0,70
	2	*,**	0,92	1,09	0,05	0,04	0,00	0,04

*AGE, GEN, CD, AIXP

**UTSI

5.2.10. Hypothesis H10

H10 hypothesised that Trust positively moderates the influence of Social Influence on Adoption. The variables dealt with in H10 are Social Influence (UTSI), Adoption represented by Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), and the control variables Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD) and Respondent AI Experience (AIXP).

Since hypothesis H9, which hypothesised that Social Influence positively influences adoption, was rejected, hypothesis H10 was also rejected. Even though the hypothesis was rejected, the regression was still calculated to see if there was a factor relationship which is moderated, as shown in Table 27. The results for the collinearity check indicated no collinearity. For Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG), and Use Specialised Tasks (ADUS), the addition of the moderation interaction terms in model two resulted in a p-value larger than 0.05, indicating that the increase in the explanation of the variance for Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG), and Use Specialised Tasks (ADUS) is insignificant. Thus, the null hypothesis is confirmed, and H10 is rejected, demonstrating that Trust does not moderate the relationship between Social Influence (UTSI) and any of the factors of Adoption.

Table 27: Regression Results for Hypothesis H10

Hierarchical Multiple Regression								
			Collinearity Statistics		Model Fit Statistics			ANOVA
DV	Step	IV	Tol. Min	VIF Max	R^2	ΔR^2	p-value	p-value
ADBI	1	*	0,40	2,48	0,39		0,00	0,00
	2	*,**	0,31	3,20	0,40	0,01	0,34	0,00
ADUD	1	*	0,40	2,48	0,04		0,14	0,14
	2	*,**	0,31	3,20	0,06	0,02	0,35	0,18
ADUG	1	*	0,40	2,48	0,16		0,00	0,00
	2	*,**	0,31	3,20	0,16	0,01	0,82	0,00
ADUS	1	*	0,40	2,48	0,07		0,01	0,01
	2	*,**	0,31	3,20	0,10	0,03	0,25	0,01

*TCB, TCC, TCI, TE, UTSI

**UTSIxTCB, UTSIxTCC, UTSIxTCI, UTSIxTE

5.2.11. Hypothesis H11

The results for Hypothesis H11 are first presented without the presence of control variables and then in the presence of control variables.

5.2.11.1. Hypothesis H11

H11 hypothesised that Facilitating Conditions positively influence Adoption. The variables dealt with in H11 are the Facilitating Conditions (UTFC), Adoption represented by Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS), and the control variables Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD) and Respondent AI Experience (AIXP). The results of the Spearman's correlation are shown in Table 28.

Facilitating Conditions (UTFC) has a significant positive correlation with each of the dependent variables: Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS). The correlation strengths are between 15% and 50%, with the p-value smaller and equal to 0.05. Thus, the null hypothesis is rejected, and H11 is accepted, demonstrating that with an increase in Facilitating Conditions (UTFC), the Adoption also increases. The strongest correlations were between Facilitating Conditions (UTFC) and Behavioural

Intention (ADBI) at 50% and between Facilitating Conditions (UTFC) and Use General Tasks (ADUG) at 31%.

Table 28: Spearman's Correlation Results for Hypothesis H11

	Spearman's Correlation							
	Dependent Variable							
	ADBI		ADUD		ADUG		ADUS	
IV	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
UTFC	0,50	0,00	0,15	0,03	0,31	0,00	0,19	0,01

5.2.11.2. Influence of Control Variables for Hypothesis H11

The results for the regression of the control variables are shown in Table 29. The results for the collinearity check indicated no collinearity. For Behavioural Intention (ADBI), the addition of Facilitating Conditions (UTFC) to the model in step two explains an additional 11% of the variance of Behavioural Intention (ADBI) in the presence of the control variables and is significant. For Use Defined Tasks (ADUD), the addition of Facilitating Conditions (UTFC) to the model in step two explains none of the variance of Use Defined Tasks (ADUD) in the presence of the control variables and is insignificant. For Use General Tasks (ADUG), the addition of Facilitating Conditions (UTFC) to the model in step two explains an additional 2% of the variance of Use General Tasks (ADUG) in the presence of the control variables and is significant. For Use Specialised Tasks (ADUS), the addition of Facilitating Conditions (UTFC) to the model in step two does not improve the explanation of the variance of Use Specialised Tasks (ADUS) in the presence of the control variables because it is insignificant. Thus, the Facilitating Conditions (UTFC) do not influence all the factors of Adoption after controlling for Respondent Age (AGE), Respondent Gender (GEN), Country Development (CD) and Respondent AI Experience (AIXP).

Table 29: Regression Results with Control Variables for Hypothesis H11

Hierarchical Multiple Regression								
			Collinearity Statistics		Model Fit Statistics			ANOVA
DV	Step	IV	Tol. Min	VIF Max	R^2	ΔR^2	p-value	p-value
ADBI	1	*	0,92	1,09	0,25		0,00	0,00
	2	*,**	0,78	1,28	0,36	0,11	0,00	0,00
ADUD	1	*	0,92	1,09	0,05		0,04	0,00
	2	*,**	0,78	1,28	0,05	0,00	0,76	0,07
ADUG	1	*	0,92	1,09	0,24		0,00	0,00
	2	*,**	0,78	1,28	0,26	0,02	0,03	0,00
ADUS	1	*	0,92	1,09	0,01		0,70	0,70
	2	*,**	0,78	1,28	0,03	0,02	0,06	0,32

*AGE, GEN, CD, AIXP

**UTFC

5.2.12. Results Summary of Hypotheses

A results summary of the hypotheses is provided in Table 30. The dependent variables are the main headings of the columns, Adoption, and its four factors: Behavioural Intention (ADBI), Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS). In each heading column, there are three tests: test for the relationship between the variables, test for the relationship between the variables in the presence of the control variables, and the moderating influence of Trust on the relationship. The row headings are the independent variables: Readiness Motivators (TRO & TRIV), Readiness Inhibitors (TRD & TRIS), Performance Expectancy (UTPE), Effort Expectancy (UTEE), Social Influence (UTSI), and Facilitating Conditions (UTFC). The matrix of the table shows the outcome of each test on the corresponding independent and dependent variable pair. The legend is shown at the bottom of the table, depicting whether the outcome of each test was significant or insignificant with an icon.

Table 30: Results Summary of Hypotheses

	Dependent Variables														
	Adoption			**Factors of Adoption**											
				Behav-ioural Intention (ADBI)			**Use Defined Tasks (ADUD)**			**Use General Tasks (ADUG)**			**Use Specialised Tasks (ADUS)**		
Independent Variables	**Relationship**	**Relationship with Controls**	**Trust Moderates**	**Relationship**	**Relationship with Controls**	**Trust Moderates**	**Relationship**	**Relationship with Controls**	**Trust Moderates**	**Relationship**	**Relationship with Controls**	**Trust Moderates**	**Relationship**	**Relationship with Controls**	**Trust Moderates**
Readiness Motivators (TRO & TRIV)	✓	✓	⊗	✓	✓	⊗	✓	✓	⊗	✓	✓	⊗	✓	✓	✓
Readiness Inhibitors (TRD & TRIS)	⊗	⊗	⊗	✓	✓	⊗	✓	⊗	⊗	⊗	⊗	⊗	⊗	⊗	⊗
Performance Expectancy (UTPE)	✓	✓	⊗	✓	✓	⊗	✓	✓	⊗	✓	✓	⊗	✓	✓	⊗
Effort Expectancy (UTEE)	✓	⊗	⊗	✓	✓	⊗	✓	⊗	⊗	✓	✓	⊗	✓	✓	⊗
Social Influence (UTSI)	⊗	⊗	⊗	✓	✓	⊗	✓	⊗	⊗	⊗	✓	⊗	✓	✓	⊗
Facilitating Conditions (UTFC)	✓	⊗	n/a	✓	✓	n/a	✓	⊗	n/a	✓	✓	n/a	✓	⊗	n/a

Legend: ✓ Significant | ⊗ Insignificant

5.3. Chapter Conclusion

The Results Chapter presented the study's results. First, the sample demographics were described, followed by the results of the hypotheses tested. The chapter was finalised by presenting a summary of the results for all hypotheses in a concise table to allow for a holistic view of the outcomes and facilitate the discussion of the results. In the next chapter, Discussion of Results, the results will be discussed in detail.

6. Discussion of Results

The study aimed to determine if Trust moderates the relationship between Readiness and Adoption of AI technology by individuals in organisations. More specifically, it first sought to measure the relationship between the following independent variables: Readiness Motivators, constituted by Readiness Optimism (TRO) and Readiness Innovativeness (TRIV), Readiness Inhibitors, consisting of Readiness Discomfort (TRD) and Readiness Insecurity (TRIS), Performance Expectancy (UTPE), Effort Expectancy (UTEE), Social Influence (UTSI) and Facilitating Conditions (UTFC) and the dependent variable Adoption, consisting initially only of Behavioural Intention (ADBI) and Use quantitively. However, Use was divided into Use Defined Tasks (ADUD), Use General Tasks (ADUG) and Use Specialised Tasks (ADUS) by the exploratory factor analysis.

Secondly, the study sought to determine if these relationships hold in the presence of the following control variables: Respondent Age (AGE), Respondent Gender (GEN), Respondent AI Experience (AIXP) and Country Development (CD). Lastly, it sought to determine if Trust moderates the relationships between the independent variables and the dependent variables, except for the relationship between Facilitating Conditions and Adoption. The factors of Trust were Trust Cognitive Benevolence (TCB), Trust Cognitive Competence (TCC), Trust Cognitive Integrity (TCI), and Trust Emotional (TE). These relationships and the hypotheses are grounded in the existing literature (Blut & Wang, 2020; Budhathoki et al., 2024; Chin et al., 2024; Flavián et al., 2022; Hwang & Good, 2014; Kim et al., 2023; Parasuraman & Colby, 2015; Shamim et al., 2023; Shi et al., 2021; Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012; Yin et al., 2023).

In the Discussion of Results Chapter, the demographic data is discussed and contextualised first, followed by the results of the statistical tests, which are compared to the previous research discussed in the Literature Review Chapter and how it aligns, extends, or contrasts the findings of the academic literature. The structure of the Discussion Chapter aligns with the Results Chapter, where the hypotheses guide the discussion. The uneven hypotheses hypothesise the relationship between the independent variable and the dependent variable, e.g. H1. Then, the even hypotheses hypothesise the moderating role of Trust in the corresponding relationship, e.g., H2. For the uneven hypotheses, the correlation results testing for the relationship were discussed; then, the control variables regression results were discussed to check if the relationship holds in the presence of the control variables. Then, for the even hypotheses, the regression test for moderation will be discussed.

The variable names and abbreviations were introduced above. Even though against convention, to facilitate reading the variable names, starting each word with a capital letter is used to facilitate identification of the variable names, and the abbreviation for the name will not be shown in brackets for the Discussion of Results Chapter.

6.1. Sample Discussion

The purpose of this section is to understand the context of the responses. Furthermore, to understand any biases in the sample and the generalisability of the sample.

The 213 responses were not representative of the population for all the demographic categories due to sampling bias, which was introduced due to the use of convenience and snowball sampling methods. The most substantial biases are discussed briefly. The country's level of development is strongly biased towards developing countries, which had 90% representation, with South Africa having 87% representation. The age group was concentrated between 25 and 54, with a total of 83% representation. The majority of respondents were males, with 67% representation. The race of the majority of respondents were white, with 68% representation. Most respondents had a postgraduate degree, with 41% representation. Most of the respondents were working as either a senior manager or a specialist, with a total of 47% representation. In terms of the industry and department in the organisation, the representation was more distributed. The highest category in industry technology represented 15%, and the highest category in the department in the organisation was information technology, representing 21%. Selection bias due to the poorly represented demographics hampers the ability to extrapolate over the defined population (Mercer et al., 2017). However, the results are representative of the typical respondent, as indicated in the paragraph below.

Since the responses in this study contained excessive white males from South Africa and were not representative of the population across the demographic of South Africa (Statistics South Africa, 2024), which is much more diversified in terms of race with male and female balanced, the sample was biased towards a particular demographic profile. The profile, which describes the demographics of the typical respondent to this study, would be a white male with a postgraduate degree aged 25 to 54 employed either as a senior manager or specialist working in South Africa. Understanding the typical profile of the respondents facilitated the researcher in understanding the context in which the data was collected and facilitated explaining some of the results.

6.2. Discussion of Control Variables

The direct influence of control variables on the dependent variables Behavioural Intention, Use Defined Tasks, Use General Tasks and Use Specialised Tasks is the same for all the hypotheses in this study. Hence, the control variables are discussed together below.

In previous research (Balakrishnan et al., 2022; Dwivedi et al., 2019; Khan et al., 2023; Parasuraman & Colby, 2015; Shamim et al., 2023; Shi et al., 2021; Venkatesh et al., 2012) concerns were raised that Country Development, Respondent Gender, Respondent Age and Respondent AI Experience might influence the dependent variable Adoption, consisting of Behavioural Intention, and Use. Thus, Country Development, Respondent Gender, Respondent Age and Respondent AI Experience were introduced as control variables for the even number hypotheses testing for the relatioship between the independent and dependent variables.

It is worth noting that the control variables were required since the control variables explained the variance of some of the factors of Adoption significantly, i.e. 25% of Behavioural Intention, 5% of Use Defined Tasks, and 24% of Use General Tasks, which aligns with the concerns raised in previous research (Balakrishnan et al., 2022; Dwivedi et al., 2019; Khan et al., 2023; Parasuraman & Colby, 2015; Shamim et al., 2023; Shi et al., 2021; Venkatesh et al., 2012) that Respondent Age, Respondent Gender, Country Development and Respondent AI Experience influences Adoption. However, none of the control variables had significantly explained the variance of Use Specialised Tasks. Previous research (Balakrishnan et al., 2022; Dwivedi et al., 2019; Khan et al., 2023; Parasuraman & Colby, 2015; Shamim et al., 2023; Shi et al., 2021; Venkatesh et al., 2012) are extended with the finding that the Adoption of more specialised use cases of technology is less influenced by Respondent Age, Respondent Gender, Country Development and Respondent AI Experience.

In alignment with the results, Blut and Wang (2020), who did a study in the context of technology in an organisation, found a significant positive influence of Respondent Age and experience, which is associated with AI Experience, on usage intention, which is associated with Behavioural Intention. Although Blut and Wang (2020) did not specify Respondent Age and experience, which is associated with AI Experience, as control variables, they were defined as antecedents with a direct influence on their dependent variables: usage intention, which is associated with Behavioural Intention, and usage behaviour, which is associated with Use. Since the antecedents, Respondent Age and experience, were tested for a direct influence on the dependent variables, it was possible to check whether these influences were significant. Furthermore, in alignment with the results, Flavián et al. (2022), who did a study on analytical AI in the context of services, found that Respondent Age has a significant positive influence on the intention to use AI, which is associated with Behavioural Intention. Thus, these studies (Blut & Wang, 2020; Flavián et al., 2022), which showed that Respondent Age and Respondent AI Experience have a significant direct influence on Behavioural Intention and Use, support the need for the control variables Respondent Age and Respondent AI Experience.

In contrast with the results, Blut and Wang (2020), who did a study in the context of technology in an organisation, showed that experience, which is associated with Respondent AI Experience, and Respondent Age have no significant influence on usage behaviour, which is associated with Use. Further contrasting the results, Flavián et al. (2022), who did a study on analytical AI in the context of services, found that Respondent Gender has no significant influence on the intention to use AI, which is associated with Behavioural Intention. Thus, in the studies (Blut & Wang, 2020; Flavián et al., 2022), the direct influence of the control variables, Respondent AI Experience, Respondent Age, and Respondent Gender on the dependent variables were not significant, demonstrating a reduced need for Respondent Age, Respondent Gender and Respondent AI Experience as control variables in some contexts.

Furthermore, in contrast with the results, Venkatesh and Zhang (2010), who did a study in the context of technology systems, showed a significant positive relationship between Performance Expectancy and Behavioural Intention in both a developing and a developed country. Furthermore, in contrast, Venkatesh and Zhang (2010) showed a non-significant relationship between Effort Expectancy and Behavioural Intention in both a developing and a developed country. Furthermore, in contrast, Venkatesh and Zhang (2010) showed a non-significant relationship between Effort Expectancy and Behavioural Intention in both a developing and a developed country. Thus, these relationships tested for significance by Venkatesh and Zhang (2010) in a developed and developing country with the same outcome demonstrate a reduced need for Country Development as a control variable in some contexts.

Furthermore, in contrast with the results, the evidence from the literature (Venkatesh & Zhang, 2010; Venkatesh et al., 2012) showed that Respondent Gender and Respondent Age significantly and positively moderate the relationship between Performance Expectancy and Adoption. Furthermore, in contrast with the results, the evidence from the literature (Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012) showed that Respondent Gender, Respondent Age, and Respondent Experience, which is associated with AI Experience, significantly and negatively moderate the relationship between Effort Expectancy and Adoption. Furthermore, in contrast with the results, the literature (Venkatesh et al., 2012) found that Respondent Gender, Respondent Age, and Respondent Experience significantly and negatively moderate the relationship between Social Influence and Behavioural Intention. Furthermore, in contrast with the results, previous literature (Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012) found that Respondent Age and Respondent Experience, which is associated with AI Experience, significantly moderate the relationship between Facilitating Conditions and Adoption. Thus, it would suggest that Respondent Gender, Respondent Age, and Respondent AI Experience are not control variables but moderators in the respective relationships in some contexts.

Since there is literature (Blut & Wang, 2020; Flavián et al., 2022) supporting and literature (Blut & Wang, 2020; Flavián et al., 2022; Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012) not supporting the need for control variables in the technology context, it is concluded that the results showing the need for control variables, Respondent Gender, Respondent Age, and Respondent AI Experience and Country Development is likely restricted to the AI adoption context. Thus, the control variables are needed to ensure that the influence evaluated on the dependent variables is indeed that of the independent variables. Without the control variables, the results would not be valid since they would also be influenced by the control variables and not only the independent variables under study. Note that the control variables and dependent variables are the same for all the hypotheses.

6.3. Discussion of Research Hypotheses

The discussion of the research hypotheses section was to interpret and critically analyse the results presented in the previous Results Chapter. The discussion critically analysed how the data either supported or contradicted the hypothesis, highlighting unexpected trends or deviations. Comparisons to determine generalisability were drawn between the sample results and what was found by existing literature, which is referenced in each comparison. Furthermore, it was important for the discussions to contextualise the findings in terms of the existing literature, exploring the possible reasons for any observed patterns. Finally, the model presented in the Research Question Chapter was updated.

The reliability and validity were shown to be acceptable (Hair et al., 2010). However, not all the assumptions for the statistical tests used were met. The distributions were non-normal and not homoscedastic. The lack of normality and homoscedasticity drove the decision to use Spearman’s rank correlation, which is robust with non-normal distributions that are not homoscedastic. Thus, the results from the correlation are robust. In terms of the regression, even though it was suggested (Hayes, 2018; Maxwell & Delaney, 2004) that tests requiring normality would still perform well with non-normal data, care should be taken when the assumption for homoscedasticity does not hold since it could negatively affect the accuracy of the confidence interval for regression coefficients (Hayes, 2018). Thus, if the regression results differ from the previous studies, further studies might be needed as the results might be affected by the non-adherence of assumptions.

In terms of context, this study focussed on the Adoption of AI technology by individuals working in organisations. However, not enough previous work was found within this specific context. Hence, previous work from a broader context was included to enable comparison to more previous research, even if the context is not well aligned. To overcome the shortcomings of the misalignment of context, the context of each previous author is noted when referenced.

The contextual reasoning was as follows: when the results are in alignment with multiple technology contexts, even outside the AI technology context, they are likely generalisable within the context of technology. However, if the results do not align with other studies outside of the context, the generalisability is likely confined to the context of AI technology in an organisation. Furthermore, when the results do not align with other studies within the context of AI technology in an organisation, it would be an indication that some limitation is biasing either of the study's results or there is a factor that has an influence that was not considered.

6.3.1. Hypothesis H1

Hypothesis H1 is first discussed without the presence of control variables and then in the presence of control variables.

6.3.1.1. Hypothesis H1

H1 hypothesised that Readiness Motivators (Optimism and Innovativeness) positively influence Adoption. The results showed that there was a significant positive relationship between the Readiness Motivators (Optimism and Innovativeness) and all the factors of Adoption. The factors of Adoption are Behavioural Intention, Use Defined Tasks, Use General Tasks, and Use Specialised Tasks. The correlation does not allow for causality to be concluded but needs to be taken from previous literature (Blut & Wang, 2020; Flavián et al., 2022; Hwang & Good, 2014; Parasuraman & Colby, 2015), it was established that Readiness Motivators (Innovativeness and Optimism) influence Adoption. Thus, the positive influence of the Readiness Motivators (Optimism and Innovativeness) on all the factors of Adoption is significant. Thus, Hypothesis H1 is accepted without considering the control variables. The results are further discussed and compared to the literature in the next section in the presence of control variables.

6.3.1.2. Hypothesis H1 with Control Variables

The Readiness Motivators, Readiness Optimism and Readiness Innovativeness significantly explained the variance of all the factors of Adoption, which are Behavioural Intention, Use Defined Tasks, Use General Tasks, and Use Specialised Tasks, even in the presence of the control variables Respondent Age, Respondent Gender, Country Development and Respondent AI Experience. More specifically, it explained 13% of Behavioural Intention, 3% of Use Defined Tasks, 5% of Use General Tasks, and 6% of Use Specialised Tasks. An increase in either of the

Readiness Motivators (Optimism and Innovativeness) drives an increase in the Adoption of AI technology in an organisation. Thus, Hypothesis H1 is accepted in the presence of the control variables.

The results in the presence of the control variables align with the results without the control variables in terms of polarity and significance. Thus, Hypothesis H1 is robust in the presence of the control variables Respondent Age, Respondent Gender, Respondent AI Experience, and Country Development.

The results align with Hwang and Good (2014), who did a study in the context of intelligent sensor-based services and found that Readiness Optimism, a factor of the Readiness Motivators, positively and significantly influences shopping intention at a retailer with intelligent sensor-based services, which is associated with Behavioural Intention. In further alignment, Flavián et al. (2022), who did a study on analytical AI in the context of services, showed that the factor of Readiness Motivators, Readiness Optimism, significantly and positively influences the intention to use AI, which is associated with Behavioural Intention.

However, in contrast to the results, Flavián et al. (2022), who did a study on analytical AI in the context of services, have shown that the Readiness Motivator, Readiness Innovativeness, does not significantly influence the intention to use AI, which is associated with Behavioural Intention. Furthermore, in contrast to the results, Blut and Wang (2020), who did a study in the context of technology in an organisation, showed there is no significant influence of Readiness Motivators (Optimism and Innovativeness) on usage behaviour, which is associated with Use. Blut and Wang (2020) did note that even though they did not find a direct influence from the readiness Motivators (Optimism and Innovativeness) on usage behaviour, an influence through the mediators of their model: ease of use, usefulness perception, quality, perceived value and satisfaction. However, the results do not align with Blut and Wang (2020), who did a study in the context of technology in an organisation, which showed that Readiness Motivators (Optimism and Innovativeness) significantly but negatively influence usage intention, which is associated with Behavioural Intention. The significant negative relationship between Readiness Motivators to Behavioural Intention is unexpected since the literature (Blut & Wang, 2020; Flavián et al., 2022; Hwang & Good, 2014) consulted hypothesised that the relationship between Readiness Motivators to Behavioural intention should be positive. Blut and Wang (2020) also noted that the significant negative influence was contrary to their predictions and checked the robustness of this unexpected result in their model against an alternative model testing motivators individually, which found an identical outcome. Thus, since the results show that Readiness Motivators (Innovativeness and Optimism) significantly and positively influence Adoption, but the literature discussed above from the broader technology context does not align, it suggests that the significant positive influence of Readiness Motivators (Innovativeness and Optimism) on Adoption is likely only generalisable to AI technology in an organisation, but further replication studies are required to confirm. The positive significant relationship between Readiness Motivators (Optimism and Innovativeness) and Adoption emphasises the importance of getting individuals in an organisation ready, i.e. driving a positive view of AI technology and driving their openness to use new technology (Parasuraman & Colby, 2015; Blut & Wang, 2020; Flavián et al., 2022), for the adoption of AI technology in an organisation.

6.3.2. Hypothesis H2

H2 hypothesised that Trust positively moderates the influence of Readiness Motivators (Optimism and Innovativeness) on Adoption. However, Trust only significantly and positively moderated the relationship between the Readiness Motivators (Optimism and Innovativeness) with the Use Specialised Tasks factor of Adoption. Trust did not significantly moderate the relationship between the Readiness Motivators (Optimism and Innovativeness) with Behavioural Intention, Use Defined Tasks and Used General Tasks. Thus, since not all the relationships between Motivators (Optimism and Innovativeness) and the factors of Adoption are significantly moderated by Trust, Hypothesis H2 is rejected.

In partial contrast, the existing literature (Lin & Hsieh, 2007; Yin et al., 2023) did not state that Trust moderated the relationship between Readiness Motivators (Innovativeness and Optimism) and adoption but did argue that Trust in technology is linked to the relationship between readiness and Adoption. Furthermore, in contrast to the results, Lin and Hsieh (2007), who did a study in the context of self-service technologies, specifically expected that Trust has a link to the relationship between readiness and Behavioural Intention. However, they did not explicitly state moderation. Complementing the results, Yin et al. (2023), who did a study in the context of AI in customer engagement behaviours, tested for mediation between

Readiness Motivators and customer engagement behaviour, which is associated with Behavioural Intention, and found that Trust neither mediates the relationship between Readiness Optimism nor Readiness Innovativeness to engagement behaviour, which is associated with Behavioural Intention.

Thus, the results are partially in contrast with the literature (Lin & Hsieh, 2007; Yin et al., 2023) because, in the results, Trust does not moderate all the relationships between Readiness Motivators (Optimism and Innovativeness) and the factors of Adoption. Trust only moderates the relationship between Readiness Motivators (Optimism and Innovativeness) and the Use Specialised Tasks factor of Adoption, which represents the more specialised use cases. Since the results do not fully align with the literature in the broader technology context, it suggests that the significant positive moderation of Trust in the relationship between the Readiness Motivators (Optimism and Innovativeness) with the Use Specialised Tasks factor of Adoption is likely only generalisable to AI technology in an organisation, but further replication studies are required to confirm. The significant positive moderation of Trust in the relationship between Readiness Motivators and Use Specialised Tasks may indicate that trust is essential in specialised tasks, given the risk, which is typically associated with specialised tasks executed with AI tools, e.g. engineering designs. Blut and Wang (2020) and Gillath et al. (2021) noted that the risk versus benefit tradeoff is essential for using technology. However, it is worth highlighting that the sample was biased towards a large percentage of individuals working as specialists, who tend to execute specialised tasks with risk involved. The sample bias could have influenced the statistical result because it was not controlled.

6.3.3. Hypothesis H3

Hypothesis H3 is first discussed without the presence of control variables and then in the presence of control variables.

6.3.3.1. Hypothesis H3

H3 hypothesised that Readiness Inhibitors (Discomfort and Insecurity) negatively influence Adoption. The results did not show a significant negative relationship between the Readiness Inhibitors (Discomfort and Insecurity) and all the factors of Adoption. The factors of Adoption are Behavioural Intention, Use Defined Tasks, Use General Tasks, and Use Specialised Tasks. The correlation does not allow for causality to be concluded but needs to be taken from previous literature (Blut &

Wang, 2020; Flavián et al., 2022; Hwang & Good, 2014; Parasuraman & Colby, 2015). Thus, there is a significant and negative influence of Readiness Inhibitors on the following factors of Adoption: Behavioural Intention and Use Defined Tasks. Thus, since not all the relationships between the factors are significant, Hypothesis H3 is rejected without considering the control variables. The results are further discussed and compared to the literature in the next section in the presence of control variables.

6.3.3.2. Hypothesis H3 with Control Variables

The Readiness Inhibitors (Discomfort and Insecurity) did not significantly explain the variance of all the factors of Adoption, which are Behavioural Intention, Use Defined Tasks, Use General Tasks, and Use Specialised Tasks, in the presence of the control variables Respondent Age, Respondent Gender, Respondent AI Experience and Country Development. Thus, since not all the relationships between the factors are significant, Hypothesis H3 is rejected in the presence of the control variables. However, 5% of the variance of Use Defined Tasks, a factor of Adoption, was explained by the Readiness Inhibitors (Discomfort and Insecurity). Thus, the Readiness Inhibitors (Discomfort and Insecurity) significantly negatively influence Use Defined Tasks even in the presence of the control variables. Therefore, with an increase in the Readiness Inhibitors (Discomfort and Insecurity), the Use Defined Tasks will decrease, even in the presence of the control variables.

It should be noted that in the absence of control variables, there was a significant relationship between the Readiness Inhibitors (Discomfort and Insecurity) and Behavioural Intention; however, in the presence of control variables, there was no significant relationship between the Readiness Inhibitors (Discomfort and Insecurity) and Behavioural Intention. This is due to the influence of the control variables on Use General Tasks. Further highlighting the need for the control variables are Respondent Age, Respondent Gender, Country Development, and Respondent AI Experience.

In contrast to the results, Hwang and Good (2014), who did a study in the context of intelligent sensor-based services, found that the presence of negative information Readiness Discomfort, a factor of the Readiness Inhibitors (Discomfort and Insecurity), negatively and significantly influences shopping intention at a retailer with intelligent sensor-based services, which is associated with Behavioural Intention.

Furthermore, in contrast with the results, Flavián et al. (2022), who did a study in the AI services context, showed that Readiness Inhibitors (Discomfort and Insecurity) negatively influence the intention to use AI, which is associated with Behavioural Intention. Furthermore, in contrast with the results, Blut and Wang (2020), who did a study in the cutting-edge technology context, which can be grouped under Use Defined Tasks, have found that Readiness Inhibitors (Discomfort and Insecurity) do not significantly influence usage behaviour, which is associated with Use and, more specifically, Use Defined Tasks. Furthermore, in contrast to the results, Blut and Wang (2020), who did a study in the context of intelligent sensor-based services, have found that Readiness Inhibitors (Discomfort and Insecurity) significantly and positively influence usage intention, which is associated with Behavioural Intention. The significant positive influence of Readiness inhibitors (Discomfort and Insecurity) on usage intention was unexpected to Blut and Wang (2020), as this relationship was expected to be a negative influence. Thus, the results show a significant and negative influence of the Readiness Inhibitors (Discomfort and Insecurity) on the factor of Adoption, Use Defined Tasks.

However, the literature discussed above does not align with the broader technology context, thus suggesting that the significant and negative influence of the Readiness Inhibitors (Discomfort and Insecurity) on the Use Defined Tasks is likely only generalisable to AI technology in an organisation but further replication studies are required to confirm. The significant and negative influence of the Readiness Inhibitors (Discomfort and Insecurity) on the Use Defined Tasks may indicate well-defined AI tasks, e.g., voice recognition, voice reader, phone assistant, and personal computer assistant. The user perceives that they are in control of the technology and that the technology will be able to complete the task as expected (Parasuraman & Colby, 2015) because the task being executed is well-defined, making these types of AI applications more susceptible to a possible perceived lack of control and inconvenience caused by the AI technology when it fails to execute as expected (Parasuraman & Colby, 2015).

6.3.4. Hypothesis H4

H4 hypothesised that Trust positively moderates the negative influence of Readiness Inhibitors (Discomfort and Insecurity) on Adoption. A pre-condition for moderation is that there should be a significant relationship with which to interact (Hayes, 2018). The only significant relationship in the presence of the control variables was between the Readiness Inhibitors (Discomfort and Insecurity) and Use General Tasks. However, the increase in the explanation of the variance of Use General Tasks due to the interaction terms of Trust is insignificant. Thus, Trust does not moderate the relationship between Readiness Inhibitors (Discomfort and Insecurity) to Adoption or any of its factors. Therefore, since not all the relationships between Readiness Inhibitors, which are Discomfort and Insecurity, and the factors of Adoption are significantly moderated by Trust, Hypothesis H4 is rejected.

In contrast to the results, Kaur and Arora (2021), who did a study in the context of online banking technology, found that Trust positively and significantly moderates the relationship between perceived risk, which is associated with Readiness Inhibitors (Discomfort and Insecurity), and Behavioural Intention. Furthermore, in contrast, Lin and Hsieh (2007), who did a study in the context of self-service technologies, expected that Trust has a link to the relationship between Readiness and Behavioural Intention, although not explicitly stating moderation. Since the results do not align with the literature in the broader technology context, it suggests the result that Trust does not moderate the relationship between Readiness Inhibitors (Discomfort and Insecurity) to Adoption or any of its factors is likely only generalisable to AI technology in an organisation, but further replication studies are required to confirm. Trust does not moderate the relationship between Readiness Inhibitors (Discomfort and Insecurity) and Adoption, which may indicate that Discomfort and Insecurity in the AI technology context are based on the belief in the user's control of the technology and belief in the ability of the equipment (Parasuraman & Colby, 2015) and believe is an antecedent driving Trust (Shamim et al., 2023) rather than Trust driving the believe.

6.3.5. Hypothesis H5

Hypothesis H5 is first discussed without the presence of control variables and then in the presence of control variables.

6.3.5.1. Hypothesis H5

H5 hypothesised that Performance Expectancy positively influences Adoption. The results showed that there was a significant positive relationship between Performance Expectancy and Adoption. The correlation does not allow for causality to be concluded but needs to be taken from previous literature (Blut & Wang, 2020; Venkatesh et al., 2003; Venkatesh et al., 2012). Thus, it was established that

Performance Expectancy has a significant positive influence on Adoption, i.e. when Performance Expectancy increases, Adoption will also increase. Thus, Hypothesis H5 is accepted without considering the control variables. The results are further discussed and compared to the literature in the next section in the presence of control variables.

6.3.5.2. Hypothesis H5 with Control Variables

Performance Expectancy significantly explained the variance in Adoption even in the presence of the control variables Respondent Age, Respondent Gender, Respondent AI Experience and Country Development. More specifically, it explained 37% of Behavioural Intention, 2% of Use Defined Tasks, 12% of Use General Tasks, and 5% of Use Specialised Tasks. Thus, an increase in Performance Expectancy drives an increase in Adoption even in the presence of the control variables Respondent Age, Respondent Gender, Country Development and Respondent AI Experience. Thus, Hypothesis H5 is accepted in the presence of the control variables.

In alignment with the results, Venkatesh and Zhang (2010) did a study in the context of technology systems, and Venkatesh et al. (2003) did a study in the context of information technology systems, showed that Performance Expectancy positively and significantly influenced intention which is associated with Behavioural Intention. Furthermore, in alignment with the results, Venkatesh et al. (2012), who did a study in the context of mobile internet consumers, Budhathoki et al. (2024) did a study in the context of ChatGPT in higher education, and Dwivedi et al. (2019) did a study in the context of information technology systems, showed that Performance Expectancy positively and significantly influences Behavioural Intention. Furthermore, in alignment with the results, Blut and Wang (2020), who did a study in the context of technology in an organisation, showed that usefulness, which is associated with Performance Expectancy, positively and significantly influences usage behaviour, which is associated with Use. Thus, with the results and multiple studies (Blut & Wang, 2020; Budhathoki et al., 2024; Dwivedi et al., 2019; Khan et al., 2023; Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012) in alignment, it suggests that the significant positive influence of Performance Expectancy on Adoption is not only generalisable in the context of AI technology in an organisation but likely generalisable in the broader context of technology. The significant positive influence of Performance Expectancy on Adoption may indicate that the drive for improved performance (Chin et al., 2024) from AI systems is essential to the Adoption of AI technology in organisations by individuals.

6.3.6. Hypothesis H6

H6 hypothesised that Trust positively moderates the influence of Performance Expectancy on Adoption. A pre-condition for moderation is that there should be a significant relationship with which to interact (Hayes, 2018), which is the case even in the presence of the control variables. However, the increase in the explanation of the variance of all the factors of Adoption due to the interaction terms of Performance Expectancy and Trust is insignificant. The factors of Adoption were Behavioural Intention, Use Defined Tasks, Use General Tasks, and Use Specialised Tasks. The factors of Trust were Trust Cognitive Benevolence, Trust Cognitive Competence, Trust Cognitive Integrity, and Trust Emotional. Thus, Trust does not moderate the relationship between Performance Expectancy and Adoption or any of its factors. Thus, since not all the relationships between Performance Expectancy and the factors of Adoption are significantly moderated by Trust, Hypothesis H6 is rejected.

In contrast to the results, Chin et al. (2024), who did a study in the context of AI-powered devices in smart homes, rejected the hypothesis that hypothesised the moderating role of Trust in the relationship between perceived usefulness, which is associated with Performance Expectancy, and intention to use, which is associated with Behavioural Intention, however, it should be noted with the confidence interval specified for this research, the hypothesis by Chin et al. (2024) is accepted. Furthermore, in contrast to the results, even though Kim et al. (2023) did not explicitly suggest moderation, it was stated that Trust is a critical factor associated with Adoption. Kim et al. (2023), who did a study in the context of large language models, further noted that trust is the user’s expectation that the technology should perform, which is associated with Performance Expectancy. The results of this research showed that none of the statements by Kim et al. (2023) can be represented by Trust as a moderator in the relationship between Performance Expectancy and Adoption. Since the results do not align with the literature in the broader technology context, it suggests the result that Trust does not moderate the relationship between Performance Expectancy to Adoption or any of its factors is likely only generalisable to AI technology in an organisation, but further replication studies are required to confirm.

Complementing the results, Shi et al. (2021), who did a study in the context of AI travel recommendations, showed that cognitive Trust significantly mediates the relationship between performance efficacy, which is associated with Performance Expectancy, and intention to adopt, which is associated with Behavioural Intention. Thus, instead of moderation, the relationship may be mediation, as shown by Shi et al. (2021).

6.3.7. Hypothesis H7

Hypothesis H7 is first discussed without the presence of control variables and then in the presence of control variables.

6.3.7.1. Hypothesis H7

H7 hypothesised that Effort Expectancy positively influences Adoption. The results showed that there was a significant positive relationship between Effort Expectancy and Adoption. The correlation does not allow for causality to be concluded but needs to be taken from previous literature (Blut & Wang, 2020; Venkatesh et al., 2003; Venkatesh et al., 2012). Thus, it was established that Effort Expectancy positively and significantly influences Adoption. Thus, Hypothesis H7 is accepted without considering the control variables. The results are further discussed and compared to the literature in the next section in the presence of control variables.

6.3.7.2. Hypothesis H7 with Control Variables

Effort Expectancy did not significantly explain the variance in all the factors of Adoption in the presence of the control variables Respondent Age, Respondent Gender, Respondent AI Experience and Country Development. However, Effort Expectancy significantly explained 14% of Behavioural Intention, 9% of Use General Tasks, and 5% of Use Specialised Tasks. Thus, in the presence of the control variables, an increase in Performance Expectancy drives an increase in some of the factors of Adoption, i.e. Behavioural Intention, Use General Tasks, Use Specialised Tasks, but not in Use Defined Tasks. Thus, since not all the relationships between Effort Expectancy and the factors of Adoption are significant, Hypothesis H7 is rejected in the presence of the control variables. However, Effort Expectancy has a significant positive influence on Behavioural Intention, Use General Tasks, and Use Specialised Tasks in the presence of the control variables.

It should be noted that in the absence of control variables, there was a significant relationship between Effort Expectancy and Use Defined Tasks; however, in the presence of control variables, there was no significant relationship between Effort Expectancy and Use Defined Tasks. This is due to the control variables' influence on Use General Tasks when not controlled. Further highlighting the need for the control variables.

In alignment with the results, Venkatesh et al. (2012) did a study in the context of mobile internet consumers, Budhathoki et al. (2024) did a study in the context of ChatGPT in higher education, and Dwivedi et al. (2019) did a study in the context of information technology systems, showed a significant positive relationship between Effort Expectancy and Behavioural Intention. Furthermore, in alignment with the results, Blut and Wang (2020), who did a study in the context of technology in an organisation, showed a significant positive relationship between ease of use, which is associated with Effort Expectancy, and usage intention, which is associated with Behavioural Intention. Furthermore, Khan et al. (2023) did a study in the context of AI in conservative industries who did a study in the context of technology in an organisation, which showed that effort expectancy positively and significantly influences AI acceptance intention, which is associated with Behavioural Intention, which leads to Adoption.

In partial contrast with the results, Blut and Wang (2020), who did a study in the context of technology in an organisation, showed a significant positive relationship between ease of use, which is associated with Effort Expectancy, and usage behaviour, which is associated with Use. Note that in the results, the significant relationship was only between Effort Expectancy and Use General Tasks and Effort Expectancy and Use Specialised Tasks, not between Effort Expectancy and Use Defined Tasks. In contrast to the results, Venkatesh and Zhang (2010), who did a study in the context of technology systems, and Venkatesh et al. (2003), who did a study in the context of information technology systems, found that the relationship between Effort Expectancy and Behavioural Intention is not significant. Thus, even though this study has shown that Effort Expectancy significantly and positively influences three factors of Adoption, which are Behavioural Intention, Use General Tasks, and Use Specialised Tasks, there is aligned literature (Blut & Wang, 2020; Budhathoki et al., 2024; Dwivedi et al., 2019; Khan et al., 2023; Venkatesh et al.,

2012) and contrasting literature (Blut & Wang, 2020; Venkatesh & Zhang, 2010; Venkatesh et al., 2003). Thus, the results are only generalisable in the context of AI technology in an organisation but not generalisable in the broader context of technology. Interestingly, there is not a significant positive relationship between Effort Expectancy and Use Defined Tasks. It may be because the user already knows that these well-defined tasks are easy, straightforward, and consistent to use, and they will have to exert low effort (Chin et al., 2024). In contrast, for Use General Tasks, e.g., ChatGPT, and Use Specialised Tasks, e.g., engineering AI tool, the user has to exert a higher amount of effort writing a prompt for ChatGPT or setting the constraints in an engineering tool after which they execute the task required.

6.3.8. Hypothesis H8

H8 hypothesised that Trust positively moderates the influence of Effort Expectancy on Adoption. A pre-condition for moderation is that there should be a significant relationship with which to interact (Hayes, 2018). There is a significant relationship in the presence of the control variables between Effort Expectancy and the following factors of Adoption: Behavioural Intention, Use General Tasks, Use Specialised Tasks. However, the increase in the explanation of the variance of all the factors of Adoption due to the interaction terms of Effort Expectancy and Trust is insignificant. The factors of Adoption were Behavioural Intention, Use Defined Tasks, Use General Tasks, and Use Specialised Tasks. The factors of Trust were Trust Cognitive Benevolence, Trust Cognitive Competence, Trust Cognitive Integrity, and Trust Emotional. Thus, since not all the relationships between Effort Expectancy and the factors of Adoption are significantly moderated by Trust, Hypothesis H8 is rejected.

In contrast to the results, Chin et al. (2024), who did a study in the context of AI-powered devices in smart homes, found that Trust significantly and positively moderates the relationship between ease of use, which is associated with Effort Expectancy, and intention to use, which is associated with Behavioural Intention. Since the results do not align with the literature in the broader technology context, it suggests the result that Trust does not moderate the relationship between Effort Expectancy to Adoption or any of its factors is likely only generalisable to AI technology in an organisation, but further replication studies are required to confirm. The results of Chin et al. (2024) have shown that Trust positively moderates the relationship between Effort Expectancy and Behavioural Intention, which may indicate that in the context of a consumer, Trust in AI technology is more critical since private data will be accessible to the AI technology requiring cognitive trust and the AI technology could have a human-like interface which requires emotional trust (Shi et al., 2021). In contrast, within the context of an organisation, trust is contractually established in case of, for example, data breaches, vulnerabilities, technological failures and system failures and is not an essential factor for the individual in the organisation (Chin et al., 2024).

6.3.9. Hypothesis H9

Hypothesis H9 is first discussed without the presence of control variables and then in the presence of control variables.

6.3.9.1. Hypothesis H9

H9 hypothesised that Social Influence positively influences Adoption. The results showed that there was not a significant positive relationship between Social Influence and all the factors of Adoption. However, there were significant positive relationships between Social Influence and the following factors of Adoption: Behavioural Intention, Use Defined Tasks, and Use Specialised Tasks. The correlation does not allow for causality to be concluded but needs to be taken from previous literature (Blut & Wang, 2020; Venkatesh et al., 2003; Venkatesh et al., 2012). Thus, it was established that Social Influence significantly influences the following factors of Adoption: Behavioural Intention, Use Defined Tasks, and Use Specialised Tasks. Thus, Hypothesis H9 is rejected without considering the control variables. The results are further discussed and compared to the literature in the next section in the presence of control variables.

6.3.9.2. Hypothesis H9 with Control Variables

Social Influence did not significantly explain the variance in all the factors of Adoption in the presence of the control variables Respondent Age, Respondent Gender, Respondent AI Experience and Country Development. However, Social Influence significantly explained 6% of Behavioural Intention, 2% of Use General Tasks, and 4% of Use Specialised Tasks. Thus, in the presence of the control variables, an increase in Social Influence drives an increase in some of the factors of Adoption, i.e. Behavioural Intention, Use General Tasks, Use Specialised Tasks, but not in Use Defined Tasks. Thus, since not all the relationships between the factors are significant, Hypothesis H9 is rejected in the presence of the control variables. However, Social Influence has a significant positive influence on Behavioural

Intention, Use General Tasks, and Use Specialised Tasks in the presence of the control variables.

It should be noted that in the absence of control variables, there was no significant relationship between Social Influence and Use General Tasks. However, in the presence of control variables, there was a significant relationship between Social Influence and Use General Tasks. This is due to the control variables masking the influence of Social Influence on Use General Tasks when not controlled. Further highlighting the need for the control variables.

In alignment with the results, Venkatesh et al. (2012) did a study in the context of mobile internet consumers, Budhathoki et al. (2024) did a study in the context of ChatGPT in higher education, and Dwivedi et al. (2019) did a study in the context of information technology systems, showed a significant relationship between Social Influence and Behavioural Intention. In contrast to the results, Venkatesh and Zhang (2010), who did a study in the context of technology systems, and Venkatesh et al. (2003), who did a study in the context of information technology systems, found that the relationship between Social Influence and Behavioural Intention is not significant. In contrast to the results, Chin et al. (2024), who did a study in the context of AI-powered devices in smart homes, found that social identity, associated with Social Influence, has no significant influence on intention to use, which is associated with Behavioural Intention.

Thus, even though this study has shown that Social Influence has a significant positive influence on Behavioural Intention, Use General Tasks, and Use Specialised Tasks, which are some factors of Adoption, there are both aligned (Budhathoki et al., 2024; Dwivedi et al., 2019; Venkatesh et al., 2012) and contrasting (Chin et al., 2024; Venkatesh & Zhang, 2010; Venkatesh et al., 2003) which suggest the results are likely only generalisable to AI technology in an organisation, but further replication studies are required to confirm. It is noteworthy that the only relationship not significantly influenced by Social Influence is Use Defined Tasks. This may be because Use Defined Tasks, e.g., voice recognition, voice reader, phone assistant, and personal computer assistant, now have such a large user base that it has little Social Influence or perceived image (Venkatesh et al., 2003), so their use is considered normal.

6.3.10. Hypothesis H10

H10 hypothesised that Trust positively moderates the influence of Social Influence on Adoption. A pre-condition for moderation is that there should be a significant relationship with which to interact (Hayes, 2018), which is the case in the presence of the control variables for the following factors of Adoption: Behavioural Intention, Use General Tasks, and Use Specialised Tasks. However, the increase in the explanation of the variance of all the factors of Adoption due to the interaction terms of Social Influence and Trust is insignificant. The factors of Adoption were Behavioural Intention, Use Defined Tasks, Use General Tasks, and Use Specialised Tasks. The factors of Trust were Trust Cognitive Benevolence, Trust Cognitive Competence, Trust Cognitive Integrity, and Trust Emotional. Thus, Trust does not moderate the relationship between Social Influence and Adoption or any of its factors. Thus, since not all the relationships between Social Influence and the factors of Adoption are significantly moderated by Trust, Hypothesis H10 is rejected.

In alignment with the results, Chin et al. (2024), who did a study in the context of AI-powered devices in smart homes, wrongly found that Trust significantly moderates the relationship between Social Identity, which is associated with Social Influence, and intention to use, which is associated with Behavioural Intention, this moderation is not valid because Chin et al. (2024) could not significantly show a relationship between social identity and intention to use. Since the results align in the broader technology context, it suggests that the result of Trust does not moderate the relationship between Social Influence and Adoption or that any of its factors are likely generalisable to AI technology in an organisation and possibly to the broader technology context, but further replication studies are required to confirm. Furthermore, it could be generalisable to the broader technology context since we do not have any evidence that contradicts this, but more studies should be done.

As an alternative to how Trust manifests, Shi et al. (2021), who did a study in the context of AI travel recommendations, have shown that emotional trust, a factor of Trust, significantly mediates the relationship between Social Influence and Intention to Adopt, which is associated with Behavioural Intention. Thus, as per the finding by Shi et al. (2021), the relationship between Social Influence and Adoption might be mediated by Trust.

6.3.11. Hypothesis H11

Hypothesis H11 is first discussed without the presence of control variables and then in the presence of control variables.

6.3.11.1. Hypothesis H11

H11 hypothesised that Facilitating Conditions positively influence Adoption. The results showed that there was a significant positive relationship between Facilitating Conditions and all the factors of Adoption: Behavioural Intention, Use Defined Tasks, Use General Tasks, and Use Specialised Tasks. The correlation does not allow for causality to be concluded but needs to be taken from previous literature (Blut & Wang, 2020; Venkatesh et al., 2003; Venkatesh et al., 2012). Thus, it was established that Facilitating Conditions significantly and positively influences Adoption. Thus, Hypothesis H11 is accepted without considering the control variables. The results are further discussed and compared to the literature in the next section in the presence of control variables.

6.3.11.2. Hypothesis H11 with Control Variables

Facilitating Conditions did not significantly explain the variance of all the factors of Adoption in the presence of the control variables Respondent Age, Respondent Gender, Country Development and Respondent AI Experience. However, Facilitating Conditions significantly explained 11% of Behavioural Intention and 2% of Use General Tasks. Thus, in the presence of the control variables, an increase in Facilitating Conditions drives an increase in some of the factors of Adoption, i.e. Behavioural Intention and Use General Tasks, but not in Use Defined Tasks and Use Specialised Tasks. Thus, hypothesis H11 is rejected in the presence of the control variables. However, Facilitating Conditions have a significant positive influence on Behavioural Intention and Use General Tasks.

In partial contrast with the results, Venkatesh et al. (2012) did a study in the context of mobile internet consumers and Dwivedi et al. (2019) did a study in the context of information technology systems, showed a significant positive relationship between Facilitating Conditions and Use, where the results only showed a significant positive influence to the one factor of Use, Use General Tasks. Furthermore, in partial contrast with the results, Venkatesh et al. (2003), who did a study in the context of information technology systems, Venkatesh and Zhang (2010), who did a study in the context of technology systems, and Budhathoki et al. (2024), who did a study in the context of ChatGPT in higher education, found no significant relationship between Facilitating Conditions and usage behaviour, which is associated with Use, where the results showed a significant positive influence to the one factor of Use, Use General Tasks. Furthermore, in contrast with the results, Venkatesh et al. (2003), who did a study in the context of information technology systems, and Venkatesh and Zhang (2010), who did a study in the context of technology systems, found no significant relationship between Facilitating Conditions and intention, which is associated with Behavioural Intention.

Thus, since the results show Facilitating Conditions have a significant positive influence on Behavioural Intention and Use General Tasks, and the literature (Budhathoki et al., 2024; Dwivedi et al., 2019; Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012) from the broader technology context does not align, it suggests that the result of Facilitating Conditions have a significant positive influence on Behavioural Intention and Use General Tasks is likely only generalisable to the context of AI technology in an organisation, but further replication studies are required to confirm. It is noteworthy that Facilitating Conditions only influence Use General Tasks of the factors of Use. It may indicate that in the general use case, e.g., large language model, AI-driven image tool, and AI-driven code assistant, individual users in the organisation need the organisation to support the infrastructure and use of the system (Venkatesh et al., 2003). In contrast, for Use Defined Tasks, the infrastructure and support are usually already integrated, e.g., Office 365. Furthermore, for Used Specialised Tasks, it is expected that the users of, for example, engineering tools also want organisational infrastructure and use support. However, this result could be biased due to the large amount of specialised individuals in the sample.

6.4. Revised Concept Model

The results from this study are used to update the suggested concept model presented in the Research Question Chapter. The revised concept model is shown in Figure 12. The revised concept model captures a holistic view of the results from this study. Solid lines are indicative of relationships which significantly influenced all of the factors of adoption, and dotted lines where there were only some factors which were influenced significantly, both in the presence of the control variables: Respondent Age, Respondent Gender, Respondent AI Experience, and Country Development. The moderator Trust has a dotted line because the results showed that it only moderated one relationship between Readiness Motivators (Innovativeness and Optimism) and one factor of Adoption: Use Specialised Tasks. Readiness Motivators (Innovativeness and Optimism) and Performance expectancy influenced all the factors of Adoption, but that does not mean they are the most important because the factors of Adoption include Behavioural Intention, Use Defined Tasks, Use of General Tasks, and Use of Specialised Tasks. Thus, one needs to know under which use type the technology application falls before deciding on which independent variables to focus one's efforts on to achieve Adoption in the organisation.

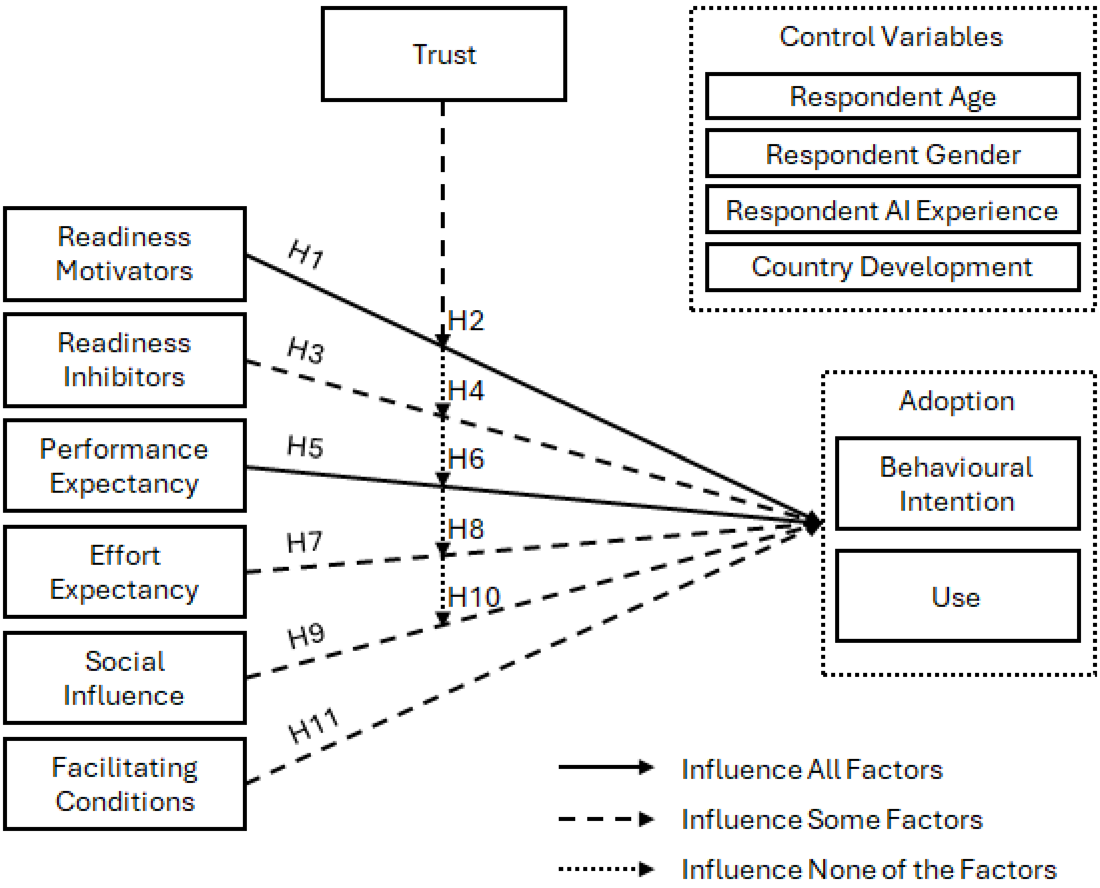


Figure 12: Revised Concept Model

Based on the need to identify the independent variables determined by the use type, or factor of Use, under which the technology application falls, a detailed revised concept model is shown in Figure 13. It is worth noting that every independent variable has a significant influence on Behavioural Intention, which makes sense because in multiple studies (Venkatesh et al., 2012; Venkatesh & Zhang, 2010; Venkatesh, 2022), it was found that Behavioural Intention is a mediator for the relationship between the independent variables, Performance Expectancy, Effort Expectancy, and Social Influence Adoption. Except for the significant relationship between Facilitating Conditions and Behavioural Intention, which is not included as a relationship in most research (Budhathoki et al., 2024; Venkatesh et al., 2012; Venkatesh & Zhang, 2010; Venkatesh, 2022) but was included by Vimalkumar et al. (2021).

Furthermore, other studies (Blut & Wang, 2020; Flavián et al., 2022; Hwang & Good, 2014) found that Readiness Motivators (Innovativeness and Optimism) and Readiness Inhibitors (Discomfort and Insecurity) have a direct influence on Behavioural Intention. Only two independent variables, Readiness Motivators (Innovativeness and Optimism) and Performance Expectancy, have a significant influence on Use Defined Tasks. Five independent variables, Readiness Motivators (Innovativeness and Optimism), Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, significantly influenced the Use General Tasks. Finally, four independent variables, Readiness Motivators (Innovativeness and Optimism), Performance Expectancy, Effort Expectancy, and Social Influence, influenced Use Specialised Tasks, with Trust moderating the relationship between Readiness Motivators (Innovativeness and Optimism) and Use Specialised Tasks. It is worth noting that the research (Blut & Wang, 2020; Chin et al., 2024; Venkatesh & Zhang, 2010; Venkatesh et al., 2012; Venkatesh, 2022) did not divide their use into multiple factors by the type of task: defined, general, and specialised. Since their Use construct was not split into smaller factors, it would suggest that these types of tasks are novel when evaluating Adoption in the context of AI technology in the organisation. The previous research in the technology context narrowed the context to a particular application: Smart homes (Chin et al., 2024), ChatGPT, a large language model (Budhathoki et al., 2024) and voice-based digital assistants (Vimalkumar et al., 2021). Hence, this division of the type of task could not be observed in their analysis.

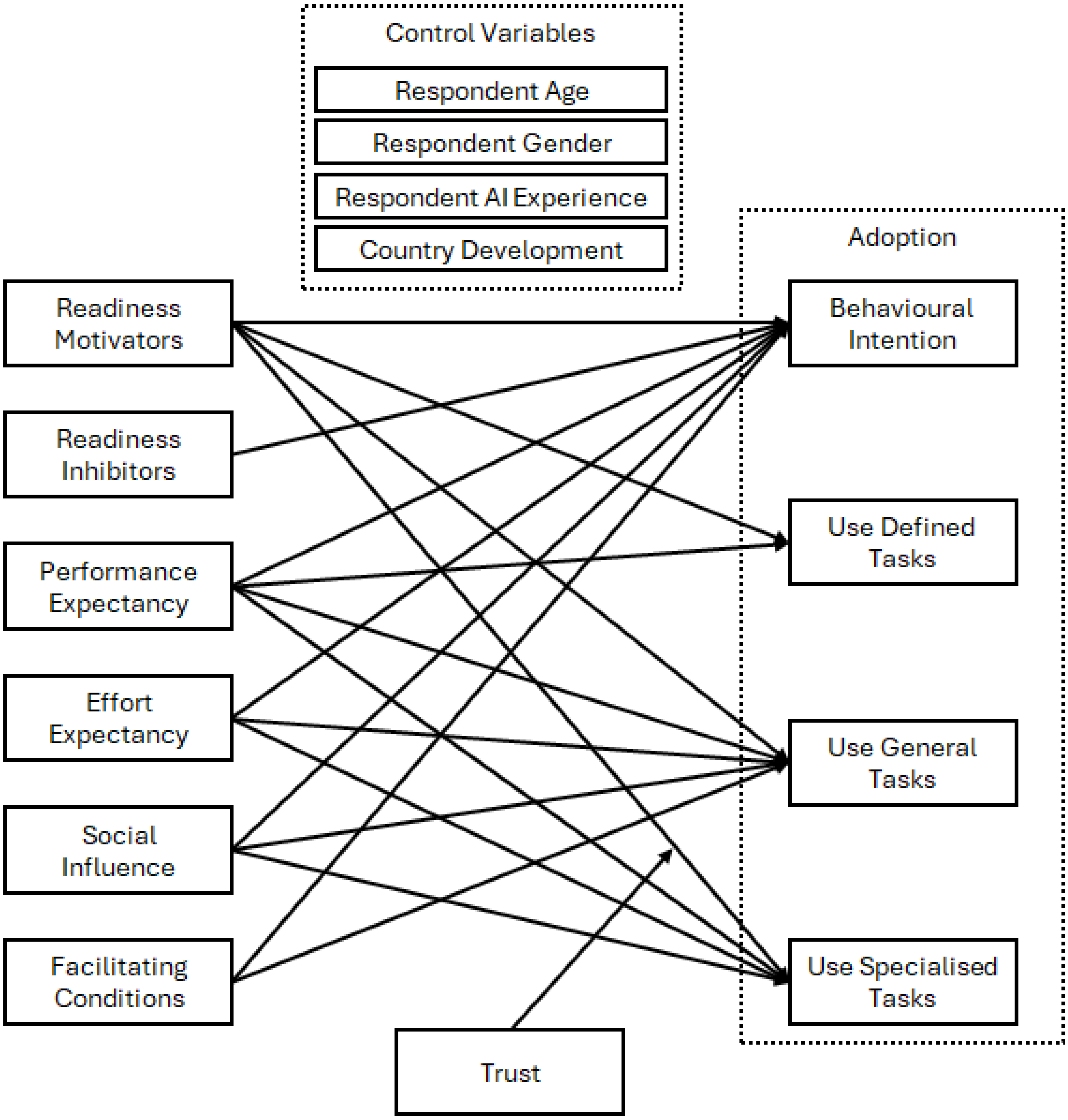


Figure 13: Detailed Revised Concept Model

Notes:

The Detailed Revised Concept Model only shows the relationships between variables that were tested as significant. Furthermore, it only shows where Trust moderates the relationship significantly, i.e. the only relationship being moderated significantly by Trust is between Readiness Motivators to Use Specialised Tasks. None of the non-significant relationships and moderations were drawn in the model.

6.5. Model for Effectively Targeting Resources in an Organisation.

Even though previous research (Blut & Wang, 2020; Shamim et al., 2023) suggested that Trust is essential in driving Adoption, the study has shown that for employees working in an organisation, Trust will only significantly and positively moderate the relationship between Readiness and Use Specialised Tasks. Thus, more Trust will assist in the drive of Adoption when the task that needs to be completed is a specialised task that requires, e.g., a video creation tool, a graphics design tool, or an engineering design tool. This aligns well with the case of the engineering design tool, where the risk versus benefit tradeoff is essential for using the technology (Blut & Wang, 2020; Gillath et al., 2021). The contrary is also true that if the Adoption drive inside the organisation forms part of the Use Defined Tasks or Use General Tasks, little resources should be spent on building Trust and would be more effectively used on other factors.

The findings summarised in Figure 12 and Figure 13 can practically be leveraged. Understanding which factors are most important to achieving the adoption of either of the three use factors: Use Defined Tasks, Use General Tasks, and Use Specialised Tasks. The independent variables to choose from according to the significance that was established were Readiness Motivators (Innovativeness and Optimism), Readiness Inhibitors (Discomfort and Insecurity), Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions. As an example, if the need is to drive Use Specialised Tasks, the resources and efforts applied should align to increase the following factors: Readiness Motivators (Innovativeness and Optimism), Performance Expectancy, Effort Expectancy, Social Influence, and Trust. Even though Readiness Inhibitors (Discomfort and Insecurity) and Facilitating Conditions will contribute through Behavioural Intention (Blut & Wang, 2020), they will be less effective than the direct effects. Thus, the detailed revised model in Figure 13 was simplified into a model to facilitate the identification of factors driving Adoption. The resources should be focussed on the factors identified from the model to use resources effectively. The model for targeting resources effectively is shown in Table 31. A task type is selected on the left, and then the tick marks are checked for which factors resources should be focussed on. It is important to note that this model should only be used for AI technology Adoption by individuals working for organisations in a Developing Country due to the limited context generisability.

Table 31: Model for Effectively Targeting Resources in an Organisation

Model for Targetting Resources Effectively							
Use Task Type of Technology	Factors to Focus on to Drive Technology Adoption						
	Readiness Motivators	Readiness Inhibitors	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions	Trust
Use Defined Tasks	✓	⊗	✓	⊗	⊗	⊗	⊗
Use General Tasks	✓	⊗	✓	✓	✓	✓	⊗
Use Specialised Tasks	✓	⊗	✓	✓	✓	⊗	✓

6.6. Chapter Conclusion

The study aimed to determine if Trust moderates the relationship between Readiness and Adoption in organisations by individuals. In this chapter, progress was made towards this goal by discussing the demographic data. Discuss each of the hypotheses and link them to previous literature, highlighting where they aligned, extended, contrasted the findings, and made findings in terms of generalisability. Finally, the chapter ended with a simplified concept model, which was transformed into a practical table that can be used to determine where to focus resources effectively depending on the type of AI technology that needs to be adopted in the organisation.

7. Conclusions and Recommendations

In this chapter, an overview of the study is given, followed by the principal findings. A discussion of the contribution to theory that was made by the research and the implications the results have for management. The limitations encountered in the study are discussed, and recommendations for future research are made.

7.1. Overview of the Study

With the background of AI technology becoming more powerful and more widely used (Yang et al., 2022), this study helps to understand the moderating role of Trust on the influence of AI Readiness on Adoption, which could assist organisations to realise more value by increasing Adoption and taking advantage of the added performance enabled by AI technology (Navarro et al., 2022).

The study aimed to determine if Trust moderates the relationship between Readiness and Adoption of technology by individuals in organisations. The study is based on a model based on TRI 2.0 (Parasuraman & Colby, 2015) and UTAUT (Venkatesh et al., 2003). The relationships considered were between which were tested for the significance of the relationship and the significance of the moderation of trust in the relationship were Readiness Motivators (Optimism and Innovativeness) and Adoption, Readiness Inhibitors (Discomfort and Insecurity) and Adoption, Performance Expectancy and Adoption, Effort Expectancy and Adoption, and Social Influence and Adoption. The relationship between Facilitating Conditions and Adoption was only tested for significance. The relationships were tested in the presence of the control variables Respondent Age, Respondent Gender, Respondent AI Experience and Country Development. The relationships investigated are grounded in previous literature (Blut & Wang, 2020; Budhathoki et al., 2024; Chin et al., 2024; Flavián et al., 2022; Hwang & Good, 2014; Parasuraman & Colby, 2015; Shamim et al., 2023; Shi et al., 2021; Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012; Yin et al., 2023).

The variable names were introduced above. Even though against convention, to facilitate reading, the variable names are written with each word starting with a capital letter. This should facilitate the identification of the variable names for the Conclusion and Recommendations Chapter.

7.1.1. Research Context and Significance

The context of the research was in the organisational setting, considering the Adoption by only individuals working for organisations and how the role of Trust influences the relationships between Readiness and Adoption. The context aligns with the need to understand the moderating role of Trust in the relationship between Readiness and Adoption, which could unlock the added performance enabled by AI technology (Navarro et al., 2022) in a world where AI technology is becoming more powerful and widely used (Yang et al., 2022).

7.1.2. Summary of Existing Knowledge

A summary of what is known and not known is discussed subsequently. The relationships between Performance Expectancy and Adoption, Effort Expectancy and Adoption, Social Influence and Adoption, and Facilitating Conditions and Adoption are well-researched in the technology context (Blut & Wang, 2020; Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012) and the AI technology context (Chin et al., 2024; Shi et al., 2021; Venkatesh, 2022). The relationships between Readiness (Motivators and Inhibitors) and Adoption have also been explored (Flavián et al., 2022; Hwang & Good, 2014). Trust has been researched as a moderator in the relationships between Performance Expectancy and Adoption, Effort Expectancy and Adoption, as well as Social Influence and Adoption (Chin et al., 2024). In contrast, a need was identified to research the moderators in the relationship between Readiness and Adoption (Blut & Wang, 2020). Since Trust was indicated to be an important determinant in Adoption (Blut & Wang, 2020; Venkatesh et al., 2012; Yin et al., 2023), it was chosen as the moderator to be explored for the relationships to Adoption. Thus, Trust is proposed as a moderator in the relationship between Readiness (Motivators and Inhibitors) and Adoption. These relationships are discussed in more detail in the principal findings section.

7.1.3. Research Question

The main research question for this study was: “Does trust moderate the influence of AI readiness on AI technology adoption in organisations?” The research question was broken down into 11 hypotheses. The relationships in the hypotheses tested were Readiness Motivators (Innovativeness and Optimism) and Adoption, Readiness Inhibitors (Discomfort and Insecurity) and Adoption, Performance Expectancy and Adoption, Effort Expectancy and Adoption, Social Influence and

Adoption, as well as Facilitating Conditions and Adoption. The relationships were also tested in the presence of the following control variables: Respondent Age, Respondent Gender, Respondent AI Experience and Country Development. For each relationship, the moderating effect of Trust in the relationship was tested, except for the relationship between Facilitating Conditions and Adoption, which was not supported by literature (Chin et al., 2024).

7.1.4. Methodological Approach

The research design of the study was quantitative because it was based on well-established constructs which could be measured by adopting and adapting existing questionnaires (Parasuraman & Colby, 2015; Shi et al., 2021; Venkatesh & Zhang, 2010). The data was collected using self-administered surveys, which were distributed using convenience sampling and snowball sampling, initiated with the researcher's personal and professional network. The total usable sample size was 213 respondents. An exploratory factor analysis was executed, which showed that Use should be split into Use Defined Tasks, Use General Tasks, and Use Specialised Tasks. The definitions of the factors of Use are given again in the principal findings section. Next, validity and reliability were checked, and both passed the typical minimum set criteria (Hair et al., 2010).

The data was checked for normality; although it was non-normal, it was chosen to continue based on Maxwell and Delaney (2004) stating that tests requiring normality would still perform well with non-normal data. The linearity of the variables was graphically established based on the method described by Hair et al. (2019). Multiple variables were found not to be homoscedastic, which could negatively influence the confidence intervals of the regression coefficients (Hayes, 2018). The independent and dependent variables were centred to avoid possible multicollinearity caused by the interaction terms (Kutner et al., 2005). Due to non-normality, Spreaman's rank correlation coefficient was used (Kothari, 2004; Kutner et al., 2005) to evaluate the following relationships between the independent variables, Readiness Motivators (Innovativeness and Optimism), Readiness Inhibitors (Discomfort and Insecurity), Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, and Adoption represented by the dependent variables, Behavioural Intention, Use Defined Tasks, Use General Tasks, and Use Specialised Tasks.

Then, the influence of the control variables on the dependent variables was evaluated using hierarchical multiple regression (Bernerth et al., 2018; Hayes, 2018). The control variables were Respondent Age, Respondent Gender, Respondent AI Experience and Country Development. Finally, the moderating effect of Trust in the relationships between the independent and dependent variables was evaluated using hierarchical multiple regression (Hayes, 2018). Quality for the study was ensured through passing reliability and validity. Furthermore, the time it took to complete the surveys was checked to filter for respondents who just randomly answered without paying attention (Parasuraman & Colby, 2015). The methodology suffered from limitations, which are discussed in the subsequent Limitations Section. For further details on methodology, please refer to the Research Methodology Chapter.

7.2. Principal Findings

The principal findings will focus on answering the main research question by first highlighting the key outcomes of the hypotheses tested and the unexpected findings. The structure of the Principal Findings Section aligns with the Results Chapter and Discussion of Results Chapter.

It is worth reminding the reader of the definitions of the three factors of Use, which, together with Behavioural Intention, form Adoption, since they are an integral part of the conclusion. First, Use Defined Tasks are highly defined tasks executed by AI, e.g., voice recognition, voice reader, phone assistant, and personal computer assistant. Second, Use General Tasks are broader and more general tasks executed by AI, e.g., large language model, AI-driven image tool, and AI-driven code assistant. Third, Use Specialised Tasks, which are more specialised tasks, such as AI-driven video tools, AI-driven graphics design tools, AI-driven engineering design tools, and AI-driven data analytics tools.

In terms of context, this study focussed on the Adoption of AI technology by individuals working in organisations. However, not enough previous work was found within this specific context. Hence, previous work from a broader context was included to enable comparison to more previous research, even if the context is not well aligned. To overcome the shortcomings of the misalignment of context, the context of each previous author was noted in the Discussion of Results Chapter when referenced.

7.2.1. Hypothesis H1

H1 hypothesised that Readiness Motivators (Optimism and Innovativeness) positively influence Adoption. The results showed that Readiness Motivators (Optimism and Innovativeness) positively and significantly influenced all the factors of Adoption while controlling for the Respondent Age, Respondent Gender, Respondent AI Experience, and Country Development. Thus, Hypothesis H1 was accepted in the presence of the control variables.

These results are in alignment with some previous findings (Blut & Wan, 2020; Flavián et al., 2022; Hwang & Good, 2014), however, in contrast with other findings (Blut & Wan, 2020). Thus, since the results showed that Readiness Motivators (Optimism and Innovativeness) significantly and positively influence Adoption, but the literature discussed above from the broader technology context does not all align, it suggests that the significant positive influence of Readiness Motivators (Optimism and Innovativeness) on Adoption is likely only generalisable to AI technology in an organisation, but further replication studies are required to confirm.

7.2.2. Hypothesis H2

H2 hypothesised that Trust positively moderates the influence of Readiness Motivators, which are Optimism and Innovativeness, on Adoption. The results showed that Trust only significantly moderates the relationship between Readiness Motivators (Innovativeness and Optimism) and Use Specialised Tasks. Thus, Hypothesis H2 was rejected.

Since the results do not fully align with the literature (Lin & Hsieh, 2007; Yin et al., 2023) in the broader technology context, it suggests that the significant positive moderation of Trust in the relationship between the Readiness Motivators (Optimism and Innovativeness) with the Use Specialised Tasks factor of Adoption is likely only generalisable to the context of AI technology in an organisation, but further replication studies are required to confirm. However, it is worth highlighting that the sample was biased towards a large percentage of individuals working as specialists, who tend to execute specialised tasks. The sample bias could have influenced the statistical result because it was not controlled.

7.2.3. Hypothesis H3

H3 hypothesised that Readiness Inhibitors (Discomfort and Insecurity) negatively influence Adoption. The results showed that Readiness Inhibitors (Discomfort and Insecurity) negatively and significantly influenced only one factor of Adoption, Use Defined Tasks, while controlling for Respondent Age, Respondent Gender, Respondent AI Experience, and Country Development. Thus, hypothesis H3 is rejected in the presence of the control variables.

Not supporting the results, Flavián et al. (2022), Hwang and Good (2014), and Blut and Wang (2020). Thus, since the results show a significant and negative influence of the Readiness Inhibitors (Discomfort and Insecurity) on the factor of Adoption, Use Defined Tasks, but there is literature in contrast from the broader technology context, it suggests that the significant and negative influence of the Readiness Inhibitors (Discomfort and Insecurity) on the Use Defined Tasks is likely only generalisable to AI technology in an organisation, but further replication studies are required to confirm.

7.2.4. Hypothesis H4

H4 hypothesised that Trust positively moderates the negative Influence of Readiness Inhibitors (Discomfort and Insecurity) on Adoption. The results showed that Trust moderates none of the relationships between Readiness Inhibitors and Adoption. Thus, Hypothesis H4 is rejected.

The results are not supported by Kaur and Arora (2021) and neither by Lin and Hsieh (2007). Thus, since the results do not align with the literature in the broader technology context, it suggests the result that Trust does not moderate the relationship between Readiness Inhibitors (Discomfort and Insecurity) to Adoption or any of its factors is likely only generalisable to AI technology in an organisation but further replication studies are required to confirm.

7.2.5. Hypothesis H5

H5 hypothesised that Performance Expectancy positively influences Adoption. The results showed that Performance Expectancy positively and significantly influenced all the factors of Adoption while controlling for the Respondent Age, Respondent Gender, Respondent AI Experience, and Country Development. Thus, hypothesis H5 is accepted in the presence of the control variables.

The results and multiple studies (Blut & Wang, 2020; Budhathoki et al., 2024; Dwivedi et al., 2019; Khan et al., 2023; Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012) are aligned, suggesting that the significant positive influence of Performance Expectancy on Adoption is not only generalisable in the context of AI technology in an organisation but likely generalisable in the broader context of technology, but further replication studies are required to confirm.

7.2.6. Hypothesis H6

H6 hypothesised that Trust positively moderates the influence of Performance Expectancy on adoption. The results showed that Trust moderates none of the relationships between Performance Expectancy and Adoption. Thus, Hypothesis H6 is rejected.

The results are not supported by Chin et al. (2024) and Kim et al. (2023). Since the results do not align with the literature in the broader technology context, it suggests the result that Trust does not moderate the relationship between Performance Expectancy to Adoption or any of its factors is likely only generalisable to AI technology in an organisation, but further replication studies are required to confirm.

7.2.7. Hypothesis H7

H7 hypothesised that Effort Expectancy positively influences Adoption. The results showed that Effort Expectancy only positively and significantly influenced three factors of Adoption: Behavioural Intention, Use General Tasks, and Use Specialised Tasks, while controlling for Respondent Age, Respondent Gender, Respondent AI Experience, and Country Development. The factor Use Defined Tasks is not significantly influenced by Effort Expectancy. Thus, hypothesis H7 is rejected in the presence of the control variables. However, Effort Expectancy has a significant positive influence on Behavioural Intention, Use General Tasks, and Use Specialised Tasks in the presence of the control variables.

Even though this study has shown that Effort Expectancy significantly and positively influences three factors of Adoption, which are Behavioural Intention, Use General Tasks, and Use Specialised Tasks, there is aligned literature (Blut & Wang, 2020; Budhathoki et al., 2024; Dwivedi et al., 2019; Khan et al., 2023; Venkatesh et al., 2012) and contrasting literature (Blut & Wang, 2020; Venkatesh & Zhang, 2010;

Venkatesh et al., 2003). Thus, the results are only generalisable in the context of AI technology in an organisation but not generalisable in the broader context of technology. Furthermore, Effort Expectancy is essential for driving the adoption of AI Technology General Tasks or Specialised Tasks, but not Defined Tasks in an organisation.

7.2.8. Hypothesis H8

H8 hypothesised that Trust positively moderates the influence of Effort Expectancy on Adoption. The results showed that Trust moderates none of the relationships between Effort Expectancy and Adoption. Thus, Hypothesis H8 is rejected.

The findings are not supported by Chin et al. (2024). Since the results do not align with the literature in the broader technology context, it suggests the result that Trust does not moderate the relationship between Effort Expectancy to Adoption or any of its factors is likely only generalisable to AI technology in an organisation, but further replication studies are required to confirm.

7.2.9. Hypothesis H9

H9 hypothesised that Social Influence positively influences Adoption. The results showed that Social Influence only positively and significantly influenced three factors of Adoption, Behavioural Intention, Use General Tasks, and Use Specialised Tasks, while controlling for Respondent Age, Respondent Gender, Respondent AI Experience, and Country Development. Thus, hypothesis H9 is rejected in the presence of control variables. However, Social Influence has a significant positive influence on Behavioural Intention, Use General Tasks, and Use Specialised Tasks in the presence of the control variables.

Thus, even though this study has shown that Social Influence has a significant positive influence on Behavioural Intention, Use General Tasks, and Use Specialised Tasks, which are some factors of Adoption, there is both aligned literature (Budhathoki et al., 2024; Dwivedi et al., 2019; Venkatesh et al., 2012) and contrasting literature (Chin et al., 2024; Venkatesh & Zhang, 2010; Venkatesh et al., 2003) which suggest the results are likely only generalisable to AI technology in an organisation, but further replication studies are required to confirm.

7.2.10. Hypothesis H10

H10 hypothesised that Trust positively moderates the influence of Social Influence on Adoption. The results showed that Trust moderates none of the relationships between Facilitating Conditions and Adoption. Thus, Hypothesis H10 is rejected.

The findings are supported by Chin et al. (2024). Since the results align in the broader technology context, a user and not an individual working for an organisation suggests that the result of Trust does not moderate the relationship between Social Influence and Adoption or any of its factors is likely generalisable to AI technology in an organisation, but further replication studies are required to confirm. Furthermore, it could be generalisable to the broader technology context since we do not have any evidence that contradicts this, but more studies should be done.

7.2.11. Hypothesis H11

H11 hypothesised that Facilitating Conditions positively influence Adoption. The results showed that Facilitating Conditions only positively and significantly influenced two factors of Adoption, Behavioural Intention and Use General Tasks, while controlling for Respondent Age, Respondent Gender, Respondent AI Experience, and Country Development. Thus, hypothesis H11 is rejected. However, Facilitating Conditions have a significant positive influence on Behavioural Intention and Use General Tasks in the presence of control variables.

Thus, the results show that Facilitating Conditions have a significant positive influence on Behavioural Intention and Use General Tasks and are not supported by the literature (Budhathoki et al., 2024; Dwivedi et al., 2019; Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012) from the broader technology context. It suggests that the significant positive influence of Facilitating Conditions on Behavioural Intention and Use General Tasks is likely generalisable only to AI technology in an organisation, but further replication studies are required to confirm.

7.2.12. Research Question Answered

The main research question for this study was: “Does trust moderate the influence of AI readiness on AI technology adoption in organisations?” The short answer is no: Trust does not significantly moderate the relationship between the complete constructs of Readiness and Adoption, which was shown by working through each of the Hypotheses checking for moderation. However, it was determined that Trust does moderate one of the relationships between factors: Trust has a positive and significant moderating effect in the relationship between the Readiness Motivators, Readiness Optimism and Readiness Innovativeness, and the factor of Adoption, Use Specialised Tasks. The moderation of the relationship is supported given the risk, which is typically associated with specialised tasks executed with AI tools, e.g. engineering designs.

Blut and Wang (2020) and Gillath et al. (2021) noted that the risk versus benefit tradeoff is essential for using technology. In terms of the relationship between the Readiness Inhibitors (Discomfort and Insecurity), which Trust did not moderate, the results further showed that Trust moderates none of the relationships between the Readiness Inhibitors (Discomfort and Insecurity) and the factors of Adoption. The results are not supported by Kaur and Arora (2021), who did a study in the context of online banking technology and neither by Lin and Hsieh (2007), who did a study in the context of self-service technologies, which suggests that the results are likely restricted to the tested context AI technology Adoption by individuals working in an organisation.

7.3. Contribution to Theory

The study made some theoretical contributions planned for, and some were discovered during the research process. The first two discussed were planned for, followed by those that were discovered during the research process.

The First contribution to theory is that Trust does not significantly moderate the relationship between the complete constructs of Readiness and Adoption in the context of individuals working in an organisation. However, it was determined that Trust does moderate one of the relationships between factors: Trust significantly and positively moderates the relationship between the Readiness Motivators (Optimism and Readiness) and the factor of Adoption, Use Specialised Tasks.

The Second was that multiple studies (Blut & Wang, 2020; Chin et al., 2024; Flavián et al., 2022; Hwang & Good, 2014; Kim et al., 2023; Parasuraman & Colby, 2015; Shamim et al., 2023; Shi et al., 2021; Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012; Yin et al., 2023) does not consider the effect of the four control variables proposed for this study: Respondent Age, Respondent Gender, Respondent AI Experience and Country Development. In this study, it was shown that multiple relationships became non-significant when they were tested in the presence of the control variable, while they were tested as significant before without the presence of the control variables. The relationships were Technology Inhibitors (Discomfort and Insecurity) and Behavioural Intention, Effort Expectancy and Use Defined Tasks, Social Influence and Use Defined Tasks, Facilitating Conditions and Use Defined Tasks, and Facilitating Conditions and Use Specialised Tasks. Furthermore, there was also a relationship that was not significant when tested without the control variables, while it became significant after considering the control variables. The relationship was Social Influence and Use General Tasks. Thus, it is suggested that future research check if the significance of the relationships holds in the presence of the control variables: Respondent Age, Respondent Gender, Respondent AI Experience and Country Development.

The Third was the outcome of the exploratory factor analysis, which divided the dependent variable Use into three factors: First, Use Defined Tasks are highly defined tasks executed by AI, e.g., voice recognition, voice reader, phone assistant, and personal computer assistant. Second, Use General Tasks are broader and more general tasks executed by AI, e.g., large language model, AI-driven image tool, and AI-driven code assistant. Third, Use Specialised Tasks are more specialised tasks, such as AI-driven video tools, AI-driven graphics design tools, AI-driven engineering design tools, and AI-driven data analytics tools. The use of AI for specialised tasks as a factor of Use was not considered in the previous research (Chin et al., 2024; Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012), which highlights a factor of Use to explore further.

The fourth was using the revised model shown in Figure 12 and the detailed revised model in Figure 13. One could understand which factors are most important to achieve the adoption of AI technology in either of the three Use factors: Use Defined Tasks, Use General Tasks or Use Specialised Tasks. The independent variables to choose from according to the significance that was established were Readiness Motivators (Innovativeness and Optimism), Readiness Inhibitors (Discomfort and Insecurity), Performance Expectancy, Effort Expectancy, Social Conditions, and Facilitating Conditions. Furthermore, to know if Trust is essential for the Adoption of the technology, e.g. for Use Specialised Tasks.

7.4. Implication for Management

There were multiple outcomes from this study, which will have practical implications for managers and can assist with efficiency by focusing on what is essential to achieving Adoption. Management can practically leverage the findings through the model that was developed and subsequently explained. The manager can understand which factors are most important to achieving the adoption of either of the three Use factors: Use Defined Tasks, Use General Tasks and Use Specialised Tasks. The independent variables to choose from according to the significance that was established were Readiness Motivators (Innovativeness and Optimism), Readiness Inhibitors (Discomfort and Insecurity), Performance Expectancy, Effort Expectancy, Social Conditions, and Facilitating Conditions. A model was established to facilitate the selection process for effectively targeting resources in an organisation, as shown in Table 32. How to use the table is further explained below the table.

Table 32: Model for Effectively Targeting Resources in an Organisation

Model for Targetting Resources Effectively							
	Factors to Focus on to Drive Technology Adoption						
Use Task Type of Technology	Readiness Motivators	Readiness Inhibitors	Performance Expectancy	Effort Expectancy	Social Influence	Facilitating Conditions	Trust
Use Defined Tasks	✓	⊗	✓	⊗	⊗	⊗	⊗
Use General Tasks	✓	⊗	✓	✓	✓	✓	⊗
Use Specialised Tasks	✓	⊗	✓	✓	✓	⊗	✓

From Table 32, first, the manager should select the use task type on the left. Second, the manager should find all the columns with a check mark. Third, the manager should note the headings of the columns corresponding to the check marks in the second step. These headings are the factors to focus on to drive technology adoption effectively according to the use task type selected. As an example, if the manager wants to drive Use Specialised Tasks, their chosen efforts should align to increase the following factors: Readiness Motivators (Innovativeness and Optimism), Performance Expectancy, Effort Expectancy, Social Influence, and Trust. Even though Readiness Inhibitors (Discomfort and Insecurity) and Facilitating conditions will contribute through Behavioural Intention (Blut & Wang, 2020), they will be less effective than the direct effects. The resources should be focussed on the factors identified from the model to ensure resources are used effectively. It is important to note that this model should only be used for AI technology adoption by individuals working for organisations in a developing country due to the limited context generisability.

7.5. Limitations

There were multiple limitations in the study, which the researcher attempted to mitigate, and some which were not mitigated. These limitations have consequences on the conclusions, such as limited generisability. Thus, it is essential to discuss these limitations and what was done to mitigate the consequences and risks, thus enabling an objective and contextualised presentation of the conclusions.

A limitation of the study was the limited previous research, which was done in the same context as Adoption by individuals in organisations. It was shown that the significance of some relationships changes when the context changes, which is a clear indication that the results and conclusions should be considered non-generalisable and should be used only in the context of AI technology adoption by individuals in organisations.

The sampling introduced sampling bias (Mercer et al., 2017), which caused some categories of the population to be over or under-represented. The sampling bias led to the results not being representative of the population, limiting the generisability of the conclusions (Mercer et al., 2017). The chosen sampling methods led to selection bias, a type of sampling bias (Mercer et al., 2017). The sampling methods used were convenience sampling and snowball sampling, which favoured the individuals who were close to the researcher, excluding specific demographics to some extent. The sampling was initiated with the researcher's personal and professional network. However, it was planned that the snowball sampling should alleviate the sampling bias as it exceeds the convenience sampling. It is clear from the demographic results that there is an extreme bias towards white males working in South Africa, which does not correspond to the demographics of South Africa (Statistics South Africa, 2024), which is much more diversified with males and females balanced. Furthermore, there was also a strong bias towards individuals with postgraduate degrees who were employed as specialists or managers, which is also not representative of South Africa's working population. The control variables did control for gender but not for race, education or seniority level in the organisation, which might influence the conclusions with such strong bias.

The survey was self-executed online. Although online surveys are widely adopted in literature (Vimalkumar et al., 2021), the respondent is likely to have experience using technology in the form of a personal computer or a mobile phone, which introduces bias because of the prior technology use experience of the respondents. Although AI Experience was being controlled, individuals without technology or online experience were excluded from the study (Evans & Mathur, 2018). Thus, the bias was not mitigated.

Previous research (Parasuraman & Colby, 2015) randomised the questions to minimise the effect of the questions' order. In contrast, other research (Wu et al., 2023; Shi et al., 2021; Venkatesh & Zhang, 2010) did not. The questions in every survey were presented to the respondents in the same order. Thus, there could be some bias due to the order of the questions.

Common method bias is likely when a single measurement instrument is used to measure both the dependent and independent variables, especially when it is self-reported by the respondent (Podsakoff et al., 2003). Only a survey was used for this study, which the respondent completed. Thus, common method bias could influence the validity of the statistical tests (Podsakoff et al., 2003). Even though the anonymity of the respondent was guaranteed to alleviate the risk (Podsakoff et al., 2003), no other mitigations were implemented against common method bias. Another factor driving common method bias is respondents not being honest despite the guarantee of anonymity (Damerji & Salimi, 2021). Thus, the statistical results might be overstated or understated due to the common method bias.

The TRI 2.0 framework has limitations related to Discomfort and Insecurity, both inhibitor dimensions, that are not representable as homogeneous attributes

(Parasuraman & Colby, 2015). As mitigation, they were determined as factors in the exploratory factor analysis and passed the reliability and validity tests.

The survey was only circulated at one point in time due to the period of the research project. It was not able to measure the change over time, as was done by Venkatesh et al. (2012). Thus, the results might be biased towards effects at a certain point in time and do not capture any long-term effects.

A limitation of the anonymous online survey was that it is not possible to know if someone completed the survey once, which could not be mitigated while keeping anonymity. Thus, it is possible that a respondent completed the survey more than once.

The study focused on the variables being measured quantitatively by the models and may miss other factors not included in the models (Budhathoki et al., 2024). Although this approach aligned well with the positivist nature of the study, it is not without its shortcomings, overemphasising quantitive data, which makes it hard to capture a holistic view of respondents and the fact that reality cannot always be accurately defined by definite law-like generalisations (Saunders et al., 2016). To partially mitigate the difficulty of achieving law-like generalisations, control variables were introduced, a larger sample size (Saunders et al., 2016) was obtained, and generalisations were made noting the selected significance level (Saunders et al., 2016). Furthermore, the shortcoming of only relying on quantitative data from a mono-method survey, which did not allow the capturing of the underlying reasons for the choices that were made (Saunders et al., 2016), was not mitigated.

Not all the assumptions required for the statistical tests were statistically checked and achieved. The distributions were non-normal, but it was suggested that even when extremely non-normal distributions are used, tests that assume normality can still perform well with large sample sizes (Maxwell & Delaney, 2004). The linearity of variable pairs was graphically checked (Hair et al., 2019) using scatterplots. Although not all the variables were homoscedastic, it was chosen to continue with the study because as long as the researcher is cognisant that when the assumption of homoscedasticity does not hold, it could negatively influence the accuracy of the confidence intervals for regression coefficients (Hayes, 2018).

7.6. Recommendations for Future Research

The findings and limitations of the study are a strong foundation for proposing future research. These will include recommendations related to all aspects of the research where the researcher found that more work needs to be done or the work could be done better.

More research needs to be done in the context of Adoption by an individual working in an organisation with a focus on AI technology. After it was determined that the results changed with the context, the author struggled to make like-for-like comparisons due to the literature shortage in the chosen context.

Future research should attempt to avoid sampling bias by choosing sampling methods which introduce less bias in the selection of samples (Mercer et al., 2017). The convenient sampling method used to seed the data collection of this study should be avoided, and a sampling method that selects the respondents more at random should be selected. This will result in less biased results and more representative of the target population.

Since some literature proposes that the order of questions could influence the results (Parasuraman & Colby, 2015), it is suggested that the questions should remain grouped per construct. However, the order of the constructs should be randomised to lessen the effect of the possible question order bias.

Standard method bias should be reduced by using more than one measurement instrument, which can be used to triangulate the results to reduce the bias (Podsakoff et al., 2003). Thus, a suggestion would be to complement the self-reported survey with scenario-based tasks to measure the same constructs (Podsakoff et al., 2003).

The survey was only circulated at one point in time, a cross-sectional study; this could be improved to measure at least two points in time, a longitudinal study, in line with what was done by Venkatesh et al. (2012). Thus reducing the bias due to effects at a certain point in time.

The study was done only using quantitative measures, which likely do not capture a holistic view of the respondents (Budhathoki et al., 2024) because reality cannot always be defined by definite law-like generalisations (Saunders et al., 2016). Thus, it is recommended that future research be complemented with qualitative structured interviews to capture more of reality, especially the factors that are hard to measure quantitively.

All of the tests for Trust as a moderator in the relationships in the study were not significant, except one, which was the relationship between technology readiness and Use Specialised Tasks, a factor of Adoption. However, Shi et al. (2021) found that cognitive trust significantly mediates the relationship between Performance Expectancy and Adoption. Furthermore, Shi et al. (2021) found that emotional trust significantly mediates the relationship between Social Influence and intention to adopt, which is associated with Behavioural Intention. Thus, a future study should focus on testing the relationships evaluated in this study again, but for mediation rather than moderation.

The use of AI for specialised tasks as a factor of Use was not considered in the previous research (Chin et al., 2024; Venkatesh & Zhang, 2010; Venkatesh et al., 2003; Venkatesh et al., 2012), which highlights a factor of Use to explore further.

7.7. Final Remarks

The Conclusions and Recommendations Chapter has answered the main research question, given managers some practical implementable suggestions, listed the limitations faced during the study and offered recommendations to future scholars on the work that still needs to be done.

In conclusion, although there was some support from the literature (Kaur & Arora, 2021; Lin & Hsieh, 2007) for Trust as a moderator in the relationship between Readiness and Adoption, the study only found a significant positive relationship between Readiness Motivators (Innovativeness and Optimism) and the use of AI in specialised tasks, a factor of Adoption. The research delivered a model that managers can use to facilitate the effective adoption of AI technology by individuals in their organisations. A need was identified to do more research, especially on the adoption of AI technology by individuals in an organisation. The research project was indeed a test of resilience and a worthwhile learning journey.

8. References

Aguinis, H., Gottfredson, R. K., & Joo, H. (2013). Best-practice recommendations for defining, identifying, and handling outliers. *Organizational Research Methods*, *16*(2), 270-301. https://doi.org/10.1177/1094428112470848

Balakrishnan, J., Abed, S. S., & Jones, P. (2022). The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services? *Technological Forecasting and Social Change*, *180*, 121692. https://doi.org/10.1016/j.techfore.2022.121692

Beavers, A. S., Lounsbury, J. W., Richards, J. K., Huck, S. W., Skolits, G. J., & Esquivel, S. L. (2013). Practical considerations for using exploratory factor analysis in educational research. *Practical Assessment, Research, and Evaluation*, *18*, Article 6. https://doi.org/10.7275/qv2q-rk76

Belanche, D., Casaló, L. V., Flavián, C., & Schepers, J. (2020). Service robot implementation: A theoretical framework and research agenda. *The Service Industries Journal*, *40*(3-4), 203-225. https://doi.org/10.1080/02642069.2019.1672666

Berg, A., Buffie, E. F., & Zanna, L. F. (2018). Should we fear the robot revolution? (The correct answer is yes). *Journal of Monetary Economics*, *97*, 117-148. https://doi.org/10.1016/j.jmoneco.2018.05.014

Bernerth, J. B., Cole, M. S., Taylor, E. C., & Walker, H. J. (2018). Control variables in leadership research: A qualitative and quantitative review. *Journal of Management*, *44*(1), 131-160. https://doi.org/10.1177/0149206317690586

Blut, M., & Wang, C. (2020). Technology readiness: A meta-analysis of conceptualizations of the construct and its impact on technology usage. *Journal of the Academy of Marketing Science*, *48*, 649-669. https://doi.org/10.1007/s11747-019-00680-8

Budhathoki, T., Zirar, A., Njoya, E. T., & Timsina, A. (2024). ChatGPT adoption and anxiety: A cross-country analysis utilising the unified theory of acceptance and use of technology (UTAUT). *Studies in Higher Education*, 1-16. https://doi.org/10.1080/03075079.2024.2333937

Chin, C. H., Wong, W. P. M., Cham, T. H., Thong, J. Z., & Ling, J. P. W. (2024). Exploring the usage intention of AI-powered devices in smart homes among millennials and zillennials: The moderating role of trust. *Young Consumers*, *25*(1), 1-27. https://doi.org/10.1108/YC-05-2023-1752

Damerji, H., & Salimi, A. (2021). Mediating effect of use perceptions on technology readiness and adoption of artificial intelligence in accounting. *Accounting Education*, *30*(2), 107-130. https://doi.org/10.1080/09639284.2021.1872035

Davenport, T. H., & Ronanki, R. (2018, January-February). Artificial intelligence for the real world. *Harvard Business Review*, *96*(1), 108-116.

Davis, F. D. (1985). *A technology acceptance model for empirically testing new end-user information systems: Theory and results* [Doctoral dissertation, Massachusetts Institute of Technology]. https://dspace.mit.edu/handle/1721.1/15192

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340. https://doi.org/10.2307/249008

Dhiman, N., Jamwal, M., & Kumar, A. (2023). Enhancing value in the customer journey by considering the (ad)option of artificial intelligence tools. *Journal of Business Research*, *167*, 114142. https://doi.org/10.1016/j.jbusres.2023.114142

Diamantopoulos, A., & Winklhofer, H. M. (2001). Index construction with formative indicators: An alternative to scale development. *Journal of Marketing Research*, *38*(2), 269-277. https://doi.org/10.1509/jmkr.38.2.269.18845

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. *Information Systems Frontiers*, *21*(3), 719-734. https://doi.org/10.1007/s10796-017-9774-y

Evans, J. R., & Mathur, A. (2018). The value of online surveys: A look back and a look ahead. *Internet Research*, *28*(4), 854-887. https://doi.org/10.1108/IntR-03-2018-0089

Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2022). Intention to use analytical artificial intelligence (AI) in services–the effect of technology readiness and awareness. *Journal of Service Management*, *33*(2), 293-320. https://doi.org/10.1108/JOSM-10-2020-0378

Friedrich, R. J. (1982). In defense of multiplicative terms in multiple regression equations. *American Journal of Political Science*, *26*(4), 797-833. https://doi.org/10.2307/2110973

Gillath, O., Ai, T., Branicky, M. S., Keshmiri, S., Davison, R. B., & Spaulding, R. (2021). Attachment and trust in artificial intelligence. *Computers in Human Behavior, 115*, 106607. https://doi.org/10.1016/j.chb.2020.106607

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis* (7th ed.). Pearson Prentice Hall.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning EMEA.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2-24. http://dx.doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., Jr., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook*. Springer Nature. https://doi.org/10.1007/978-3-030-80519-7

Hayes, A. F. (2018). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (2nd ed.). The Guilford Press.

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155-172. https://doi.org/10.1177/1094670517752459

Hwang, J., & Good, L. (2014). Intelligent sensor-based services success: The role of consumer characteristics and information. *European Journal of Marketing*, *48*(3/4), 406-431. http://dx.doi.org/10.1108/EJM-11-2011-0689

International Monetary Fund. (2023). *Groups and aggregates information*. https://www.imf.org/en/Publications/WEO/weo-database/2023/April/groups-and-aggregates

Kaur, S., & Arora, S. (2021). Role of perceived risk in online banking and its impact on behavioral intention: Trust as a moderator. *Journal of Asia Business Studies*, *15*(1), 1-30. http://dx.doi.org/10.1108/JABS-08-2019-0252

Kaushik, M. K., & Agrawal, D. (2021). Influence of technology readiness in adoption of e-learning. *International Journal of Educational Management*, *35*(2), 483-495. https://doi.org/10.1108/IJEM-04-2020-0216

Khan, A. N., Jabeen, F., Mehmood, K., Soomro, M. A., & Bresciani, S. (2023). Paving the way for technological innovation through adoption of artificial intelligence in conservative industries. *Journal of Business Research*, *165*, 114019. https://doi.org/10.1016/j.jbusres.2023.114019

Kim, J. H., Kim, J., Park, J., Kim, C., Jhang, J., & King, B. (2023). When ChatGPT gives incorrect answers: The impact of inaccurate information by generative AI on tourism decision-making. *Journal of Travel Research*, Advance online publication. https://doi.org/10.1177/00472875231212996

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). The Guilford Press.

Kothari, C. R. (2004). *Research methodology: Methods and techniques* (2nd ed.). New Age International Publishers.

Kutner, M. H., Nachtsheim, C. J., Neter, J., & Li, W. (2005). *Applied linear statistical models* (5th ed.). McGraw-Hill.

Li, J. J., Bonn, M. A., & Ye, B. H. (2019). Hotel employee's artificial intelligence and robotics awareness and its impact on turnover intention: The moderating roles of perceived organizational support and competitive psychological climate. *Tourism Management*, *73*, 172-181. https://doi.org/10.1016/j.tourman.2019.02.006

Lin, J. S. C., & Hsieh, P. L. (2007). The influence of technology readiness on satisfaction and behavioral intentions toward self-service technologies. *Computers in Human Behavior*, *23*(3), 1597-1615. https://doi.org/10.1016/j.chb.2005.07.006

Lewis, J. D., & Weigert, A. (1985). Trust as a social reality. *Social Forces*, *63*(4), 967-985. https://doi.org/10.1093/sf/63.4.967

Lu, C. H. (2021). The impact of artificial intelligence on economic growth and welfare. *Journal of Macroeconomics*, *69*, 103342. https://doi.org/10.1016/j.jmacro.2021.103342

Maxwell, S. E., & Delaney, H. D. (2004). *Designing experiments and analyzing data: A model comparison perspective* (2nd ed.). Psychology Press.

Mcknight, D. H., Carter, M., Thatcher, J. B., & Clay, P. F. (2011). Trust in a specific technology: An investigation of its components and measures. *ACM Transactions on Management Information Systems*, *2*(2), Article 12. https://doi.org/10.1145/1985347.1985353

Mende, M., Scott, M. L., Van Doorn, J., Grewal, D., & Shanks, I. (2019). Service robots rising: How humanoid robots influence service experiences and elicit compensatory consumer responses. *Journal of Marketing Research*, *56*(4), 535-556. https://doi.org/10.1177/0022243718822827

Mercer, A. W., Kreuter, F., Keeter, S., & Stuart, E. A. (2017). Theory and practice in nonprobability surveys: Parallels between causal inference and survey inference. *Public Opinion Quarterly*, *81*(S1), 250-271. https://doi.org/10.1093/poq/nfw060

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, *57*(2), 103169. https://doi.org/10.1016/j.im.2019.05.004

Mishra, A., Shukla, A., & Sharma, S. K. (2022). Psychological determinants of users' adoption and word-of-mouth recommendations of smart voice assistants. *International Journal of Information Management*, *67*, 102413. https://doi.org/10.1016/j.ijinfomgt.2021.102413

Navarro, J., Heuveline, L., Avril, E., & Cegarra, J. (2018). Influence of human-machine interactions and task demand on automation selection and use. Ergonomics, 61(12), 1601-1612. https://doi.org/10.1080/00140139.2018.1501517

Navarro, J., Osiurak, F., Ha, S., Communay, G., Ferrier-Barbut, E., Coatrine, A., & Hancock, P. A. (2022). Development of the Smart Tools Proneness Questionnaire (STP-Q): An instrument to assess the individual propensity to use smart tools. *Ergonomics*, *65*(12), 1639-1658. https://doi.org/10.1080/00140139.2022.2048895

Orlikowski, W. J., & Baroudi, J. J. (1991). Studying information technology in organizations: Research approaches and assumptions. *Information Systems Research*, *2*(1), 1-28. https://doi.org/10.1287/isre.2.1.1

Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research*, *2*(4), 307–320. https://doi.org/10.1177/109467050024001

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. *Journal of Service Research*, *18*(1), 59–74. https://doi.org/10.1177/1094670514539730

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879-903. https://doi.org/10.1037/0021-9010.88.5.879

Qasem, Z. (2021). The effect of positive TRI traits on centennials adoption of try-on technology in the context of e-fashion retailing. *International Journal of Information Management*, *56*, 102254. https://doi.org/10.1016/j.ijinfomgt.2020.102254

Rafdinal, W., & Senalasari, W. (2021). Predicting the adoption of mobile payment applications during the COVID-19 pandemic. *International Journal of Bank Marketing*, *39*(6), 984-1002. https://doi.org/10.1108/IJBM-10-2020-0532

Ransbotham, S., Khodabandeh, S., Fehling, R., LaFountain, B., & Kiron, D. (2019). Winning with AI. *MIT Sloan Management Review*. https://sloanreview.mit.edu/projects/winning-with-ai/

Reio, T. G., Jr., & Shuck, B. (2015). Exploratory factor analysis: Implications for theory, research, and practice. *Advances in Developing Human Resources*, *17*(1), 12-25. https://doi.org/10.1177/1523422314559804

Basic Conditions of Employment Act 75 of 1997. (1997). *Government Gazette* No. 18491. Republic of South Africa. https://www.gov.za/sites/default/files/gcis_document/201409/a75-97.pdf

Saunders, M., & Lewis, P. (2018). *Doing research in business and management: An essential guide to planning your project* (2nd ed.). Pearson.

Saunders, M., Lewis, P., & Thornhill, A. (2016). *Research methods for business students* (7th ed.). Pearson.

Shamim, S., Yang, Y., Zia, N. U., Khan, Z., & Shariq, S. M. (2023). Mechanisms of cognitive trust development in artificial intelligence among front line employees: An empirical examination from a developing economy. *Journal of Business Research*, *167*, 114168. https://doi.org/10.1016/j.jbusres.2023.114168

Shi, S., Gong, Y., & Gursoy, D. (2021). Antecedents of trust and adoption intention toward artificially intelligent recommendation systems in travel planning: A heuristic–systematic model. *Journal of Travel Research*, *60*(8), 1714-1734. https://doi.org/10.1177/0047287520966395

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551

Statistics South Africa. (2024). *Mid-year population estimates*. (Report No. P0302). https://www.statssa.gov.za/publications/P0302/P03022024.pdf

Straub, D., Boudreau, M. C., & Gefen, D. (2004). Validation guidelines for IS positivist research. *Communications of the Association for Information Systems*, *13*, 380-427. https://doi.org/10.17705/1CAIS.01324

Tussyadiah, I. P., Zach, F. J., & Wang, J. (2020). Do travelers trust intelligent service robots? *Annals of Tourism Research, 81*, 102886. https://doi.org/10.1016/j.annals.2020.102886

Venkatesh, V. (2022). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, *308*(1), 641-652. https://doi.org/10.1007/s10479-020-03918-9

Venkatesh, V., & Zhang, X. (2010). Unified theory of acceptance and use of technology: US vs. China. *Journal of Global Information Technology Management*, *13*(1), 5-27. https://doi.org/10.1080/1097198X.2010.10856507

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157-178. https://doi.org/10.2307/41410412

Vimalkumar, M., Sharma, S. K., Singh, J. B., & Dwivedi, Y. K. (2021). 'Okay Google, what about my privacy?': User's privacy perceptions and acceptance of voice based digital assistants. *Computers in Human Behavior, 120*, 106763. https://doi.org/10.1016/j.chb.2021.106763

Vohra, S., Vasal, A., Roussiere, P., & Guan, L. (2022). *The art of AI maturity: Advancing from practice to performance*. Accenture. https://www.accenture.com/content/dam/system-files/acom/custom-code/ai-maturity/Accenture-Art-of-AI-Maturity-Report-Global-Revised.pdf

Yang, J., Chesbrough, H., & Hurmelinna-Laukkanen, P. (2022). How to appropriate value from general-purpose technology by applying open innovation. *California Management Review, 64*(3), 24-48. https://doi.org/10.1177/00081256211041787

Yin, D., Li, M., & Qiu, H. (2023). Do customers exhibit engagement behaviors in AI environments? The role of psychological benefits and technology readiness. *Tourism Management*, *97*, 104745. https://doi.org/10.1016/j.tourman.2023.104745

Wu, M., Wang, N., & Yuen, K. F. (2023). Can autonomy level and anthropomorphic characteristics affect public acceptance and trust towards shared autonomous vehicles? *Technological Forecasting and Social Change, 189*, 122384. https://doi.org/10.1016/j.techfore.2023.122384

Zikmund, W. G., Babin, B. J., Carr J. C., & Griffin, M. (2013). *Business research methods* (9th ed.). Cengage Learning.

9. Appendix A – Questionnaire

9.1. Cover Page of Questionnaire

Dear Respondent,

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

You are invited to participate in my research project. The title is 'Trust as a Moderator in the Influence of AI Technology Readiness on AI Technology Adoption'. I would like you to complete an anonymous online questionnaire. This may take about 20 minutes. All information will be kept confidential, and no names will be collected on the questionnaire.

The Research Ethics Committee of the Gordon Institute of Business Science has granted written approval for this study. Participation in this study is voluntary, and you can withdraw at any time without penalty. Your participation is anonymous, and only aggregated data will be reported. Completing this survey indicates that you voluntarily participate in this research.

If you have any concerns, please feel free to contact my supervisor or me.

Prof. Manoj Chiba (chibam@gibs.co.za)
Hendrik van Niekerk (28314761@mygibs.co.za)

9.2. Questions

9.2.1. Demographic and Control Questions

Please answer the following questions on your background.

9.2.1.1. Respondent Age

The following are adapted from Kaur and Arora (2021).

How old are you?

- 18 to 24 (code 1)
- 25 to 34 (code 2)
- 35 to 44 (code 3)
- 45 to 54 (code 4)
- 55 to 64 (code 5)

- 65 and older (code 6)

9.2.1.2. Respondent Gender

The following are adapted from Kaur and Arora (2021).

Gender identity:

- Male (code 0)
- Female (code 1)
- Non-binary (code 2)
- Transgender (code 2)
- Prefer not to reply (code 2)
- Other, please specify: [___________] (code 2)

9.2.1.3. Respondent Race

The following are adapted from Hwang and Good (2014).

Race:

- Black
- Coloured
- Indian
- White
- Other, please specify: [___________]

9.2.1.4. Country

The following are adapted from Venkatesh and Zhang (2010).

In which country do you live?

- South Africa
- Other, please specify: [__________]

Countries will be regrouped and coded according to developed and developing.

9.2.1.5. Country Development

Country Development was deducted from the Country.

- Developing & Emerging (Code 0)
- Developed (Code 1)

9.2.1.6. Respondent Education

The following are adapted from Hwang and Good (2014).

What is your highest level of education?

- Matric
- Diploma
- Undergraduate degree
- Postgraduate degree (up to Master's level)

- Doctoral degree
- Other, please specify: [_________]

9.2.1.7. Respondent Department in Organisation

The following are adapted from Hwang and Good (2014).

Which department do you currently work in?

- Not employed
- Finance
- Human Resources
- Information Technology
- Marketing
- Operations / Production
- Projects
- Research and Development
- Sales
- General Management
- Other, please specify: [_________]

The following are adapted from Mikalef et al. (2020).

In which industry is your organisation?

- Agriculture
- Arts, culture, fashion, entertainment
- Automotive
- Construction
- Education
- Fast-moving consumer goods
- Financial services
- Healthcare
- Hospitality and tourism
- Manufacturing
- Mining
- Professional services
- Retail
- Security
- Technology
- Other, please specify: [_________]

9.2.1.8. Respondent Employment Status

The following are adapted from Kaur and Arora (2021).

What is your current role within the organisation?

- Staff

- Specialist
- Supervisor
- Middle manager
- Senior manager
- Executive
- Other, please specify: [________]

9.2.1.9. Respondent AI Experience

The following are adapted from Yin et al. (2023).

AIXP1. How familiar are you with AI tools (e.g., ChatGPT)?

- Extremely (code 5)
- Very (code 4)
- Moderately (code 3)
- Slightly (code 2)
- Not at all (code 1)

The following are adapted from Kaur and Arora (2021).

AIXP2. How much experience do you have using AI tools (e.g., ChatGPT)?

- Ten years or more (code 6)
- Five years to less than ten years (code 5)
- One year to less than five years (code 4)
- One month to less than one year (code 3)
- Once to less than one month (code 2)
- Never used AI tools (code 1)

9.2.1.10. Human Trust Propensity

The default answer set for each question in this section unless specified otherwise:

Please indicate your level of agreement with each of the following statements. Choose one response on the scale between 'strongly agree' and 'strongly disagree':

- Strongly agree (code 7)
- Agree (code 6)
- Somewhat agree (code 5)
- Neither agree nor disagree (code 4)
- Somewhat disagree (code 3)
- Disagree (code 2)
- Strongly disagree (code 1)

The following are adapted from Wu et al. (2023).

HTP1. Unless there is a reason not to, I usually trust AI technology tools (e.g., ChatGPT)

HTP2. In general, I would take the help of AI technology tools (e.g., ChatGPT).

HTP3. I strongly tend to trust AI technology tools (e.g., ChatGPT).

HTP4. I can easily put my faith in AI technology tools (e.g., ChatGPT) to do tasks.

HTP5. Even if I have limited knowledge about AI technology tools (e.g., ChatGPT), I will likely trust it.

9.2.2. Technology Readiness Motivators Questions

The default answer set for each question in this section unless specified otherwise:

Please indicate your level of agreement with each of the following statements. Choose one response on the scale between 'strongly agree' and 'strongly disagree':

- Strongly agree (code 7)
- Agree (code 6)
- Somewhat agree (code 5)
- Neither agree nor disagree (code 4)
- Somewhat disagree (code 3)
- Disagree (code 2)
- Strongly disagree (code 1)

9.2.2.1. Technology Readiness Optimism

The following are adopted from Parasuraman and Colby (2015).

TRO1. New technologies contribute to a better quality of life.

TRO2. Technology gives me more freedom of mobility.

TRO3. Technology gives people more control over their daily lives.

TRO4. Technology makes me more productive in my personal life.

9.2.2.2. Technology Readiness Innovativeness

The following are adopted from Parasuraman and Colby (2015).

TRIV1. Other people come to me for advice on new technologies.

TRIV2. Generally, I am among the first in my circle of friends to acquire new technology when it appears.

TRIV3. I can usually figure out new high-tech products and services without help from others.

TRIV4. I keep up with the latest technological developments in my areas of interest.

9.2.2.3. Technology Readiness Inhibitors

The default answer set for each question in this section unless specified otherwise:

Please indicate your level of agreement with each of the following statements. Choose one response on the scale between 'strongly agree' and 'strongly disagree':

- Strongly agree (code 7)
- Agree (code 6)
- Somewhat agree (code 5)
- Neither agree nor disagree (code 4)
- Somewhat disagree (code 3)
- Disagree (code 2)
- Strongly disagree (code 1)

9.2.2.4. Technology Readiness Discomfort

The following are adopted from Parasuraman and Colby (2015).

TRD1. When I get technical support from a high-tech product or service provider, I sometimes feel as if I am being taken advantage of by someone who knows more than I do.

TRD2. Technical support lines are not helpful because they do not explain things in terms I understand.

TRD3. Sometimes, I think that technology systems are not designed for use by ordinary people.

TRD4. There is no such thing as a manual for a high-tech product or service that’s written in plain language.

9.2.2.5. Technology Readiness Insecurity

The following are adopted from Parasuraman and Colby (2015).

TRIS1. People are too dependent on technology to do things for them.

TRIS2. Too much technology distracts people to a point that is harmful.

TRIS3. Technology lowers the quality of relationships by reducing personal interaction.

TRIS4. I do not feel confident doing business with a place that can only be reached online.

9.2.3. UTAUT Questions

9.2.3.1. Performance Expectancy

Please indicate your level of agreement with each of the following statements. Choose one response on the scale between 'strongly agree' and 'strongly disagree':

- Strongly agree (code 7)
- Agree (code 6)

- Somewhat agree (code 5)
- Neither agree nor disagree (code 4)
- Somewhat disagree (code 3)
- Disagree (code 2)
- Strongly disagree (code 1)

The following are adapted from Venkatesh (2012).

UTPE1. I find AI technology tools (e.g., ChatGPT) useful in my daily life.

UTPE2. Using AI technology tools (e.g., ChatGPT) increases my chances of achieving things that are important to me.

UTPE3. Using AI technology tools (e.g., ChatGPT) helps me accomplish things more quickly.

UTPE4. Using AI technology tools (e.g., ChatGPT) increases my productivity.

9.2.3.2. Effort Expectancy

Please indicate your level of agreement with each of the following statements. Choose one response on the scale between 'strongly agree' and 'strongly disagree':

- Strongly agree (code 7)
- Agree (code 6)
- Somewhat agree (code 5)
- Neither agree nor disagree (code 4)
- Somewhat disagree (code 3)
- Disagree (code 2)
- Strongly disagree (code 1)

The following are adapted from Venkatesh (2012).

UTEE1. Learning to use AI technology tools (e.g., ChatGPT) is easy for me.

UTEE2. My interactions with AI technology tools (e.g., ChatGPT) are clear and understandable.

UTEE3. I find AI technology tools (e.g., ChatGPT) easy to use.

UTEE4. I easily become skilful at using AI technology tools (e.g., ChatGPT).

9.2.3.3. Social Influence

Please indicate your level of agreement with each of the following statements. Choose one response on the scale between 'strongly agree' and 'strongly disagree':

- Strongly agree (code 7)
- Agree (code 6)
- Somewhat agree (code 5)
- Neither agree nor disagree (code 4)
- Somewhat disagree (code 3)
- Disagree (code 2)

- Strongly disagree (code 1)

The following are adapted from Venkatesh (2012).

UTSI1. People who are important to me think I should use AI technology tools (e.g., ChatGPT).

UTSI2. People who influence my behaviour think I should use AI technology tools (e.g., ChatGPT).

UTSI3. People whose opinions I value prefer that I use AI technology tools (e.g., ChatGPT).

9.2.3.4. Facilitating Conditions

Please indicate your level of agreement with each of the following statements. Choose one response on the scale between 'strongly agree' and 'strongly disagree':

- Strongly agree (code 7)
- Agree (code 6)
- Somewhat agree (code 5)
- Neither agree nor disagree (code 4)
- Somewhat disagree (code 3)
- Disagree (code 2)
- Strongly disagree (code 1)

The following are adapted from Venkatesh (2012).

UTFC1. I have the resources necessary to use AI technology tools (e.g., ChatGPT).

UTFC2. I have the knowledge necessary to use AI technology tools (e.g., ChatGPT).

UTFC3. AI technology tools (e.g., ChatGPT) are compatible with other technologies I use.

UTFC4. I can get help from others when I have difficulties using AI technology tools (e.g., ChatGPT).

9.2.4. Adoption Questions

9.2.4.1. Behavioural Intention

Please indicate your level of agreement with each of the following statements. Choose one response on the scale between 'strongly agree' and 'strongly disagree':

- Strongly agree (code 7)
- Agree (code 6)
- Somewhat agree (code 5)
- Neither agree nor disagree (code 4)
- Somewhat disagree (code 3)

- Disagree (code 2)
- Strongly disagree (code 1)

The following are adapted from Venkatesh (2012).

ADBI1. I intend to continue using AI technology tools (e.g., ChatGPT) in the future.

ADBI2. I will always try to use AI technology tools (e.g., ChatGPT) in my daily life.

ADBI3. I plan to continue using AI technology tools (e.g., ChatGPT) frequently.

9.2.4.2. Use

The default answer set for each question in this section unless specified otherwise: Please choose your usage frequency for each of the following. Select one response on the scale between 'Several times a day' and 'Never':

- Several times a day (code 7)
- Daily (code 6)
- Several times a week (code 5)
- Weekly (code 4)
- Monthly (code 3)
- Less than monthly (code 2)
- Never (code 1)

The following are adapted from Venkatesh (2012).

ADU1. Spelling and grammar checker, e.g., Grammarly.

ADU2. Voice recognition, e.g., Dictate in Microsoft Word.

ADU3. Voice reader, e.g., Read Aloud in Microsoft Word.

ADU4. Assistant on your phone, e.g., Siri on Apple.

ADU5. Assistant on your PC, e.g., ClickUp.

ADU6. Large language model, e.g., ChatGPT.

ADU7. AI-driven picture/image tool, e.g., DALL.E.

ADU8. AI-driven video tool, e.g., SORA.

ADU9. AI-driven graphics design tool, e.g., Adobe Firefly.

ADU10. AI-driven engineering design tool, e.g., Design Assistant in SOLIDWORKS.

ADU11. AI-driven data analysis tool, e.g., Google Cloud Smart Analytics.

ADU12. AI-driven code assistant, e.g., Copilot.

ADU13. Other AI-driven tools not listed above.

Please specify other AI-driven tools corresponding to the previous question.

[________]

9.2.4.3. Purchase License

Please select all the AI tools for which you or your organisation(work) purchased a license in the past 12 months. (More than one selection is allowed for this question).

The following are adapted from Venkatesh (2012).

- ☐ Spelling and grammar checker, e.g., Grammerly.
- ☐ Voice recognition, e.g., Dictate in Microsoft Word.
- ☐ Voice reader, e.g., Read Aloud in Microsoft Word.
- ☐ Assistant on your phone, e.g., Siri on Apple.
- ☐ Assistant on your PC, e.g., ClickUp.
- ☐ Large language model, e.g., ChatGPT.
- ☐ AI-driven picture/image tool, e.g., DALL.E.
- ☐ AI-driven video tool, e.g., SORA
- ☐ AI-driven graphics design tool, e.g., Adobe Firefly.
- ☐ AI-driven engineering design tool, e.g., Design Assistant in SOLIDWORKS.
- ☐ AI-driven data analysis tool, e.g., Google Cloud Smart Analytics.
- ☐ AI-driven code assistant, e.g., Copilot.
- ☐ Other, please specify: [__________]

9.2.5. Trust Questions

The default answer set for each question in this section unless specified otherwise:

Please indicate your level of agreement with each of the following statements. Choose one response on the scale between 'strongly agree' and 'strongly disagree':

- o Strongly agree (code 7)
- o Agree (code 6)
- o Somewhat agree (code 5)
- o Neither agree nor disagree (code 4)
- o Somewhat disagree (code 3)
- o Disagree (code 2)
- o Strongly disagree (code 1)

9.2.5.1. Trust Cognitive Benevolence

The following are adapted from Shi et al. (2021).

TCB1. The AI technology tool (e.g., ChatGPT) would execute its task to my best benefit.

TCB2. If I required a task to be done, the AI technology tool (e.g., ChatGPT) would do its best to execute it for me.

TCB3. The AI technology tool (e.g., ChatGPT) is interested in my benefits, not just its own.

9.2.5.2. Trust Cognitive Competence

The following are adapted from Shi et al. (2021).

TCC1. The AI technology tool (e.g., ChatGPT) is competent and effective in its tasks.

TCC2. The AI technology tool (e.g., ChatGPT) performs its role very well during tasks.

TCC3. The AI technology tool (e.g., ChatGPT) is capable and proficient in its tasks.

TCC4. Generally, the AI technology tool (e.g., ChatGPT) is very knowledgeable in its field of expertise.

9.2.5.3. Trust Cognitive Integrity

The following are adapted from Shi et al. (2021).

TCI1. The AI technology tool (e.g., ChatGPT) is truthful in dealing with me.

TCI2. I would characterise the AI technology tool (e.g., ChatGPT) as being honest.

TCI3. The AI technology tool (e.g., ChatGPT) would keep its commitments.

TCI4. The AI technology tool (e.g., ChatGPT) is sincere and genuine.

9.2.5.4. Trust Emotional

The following are adapted from Shi et al. (2021).

TE1. I feel secure about relying on the AI technology tool (e.g., ChatGPT) to execute tasks.

TE2. I feel comfortable relying on the AI technology tool (e.g., ChatGPT) to execute tasks.

TE3. I feel content about relying on the AI technology tool (e.g., ChatGPT) to execute tasks.

9.2.6. Survey Sharing Questions

Please share the survey link with as many of your contacts as possible. Your help in distributing the survey will greatly contribute to our data collection efforts. Thank you!

Please indicate the number of people with whom you are willing to share the survey.

- More than 20 people
- 10-19 people
- 5-9 people
- 2-4 people
- 1 person
- No one

Could you please follow up with the people to whom you shared the survey link within two days?

- Yes
- No

Could you please confirm to the person who shared the survey that you have completed it?

- Yes
- No

10. Appendix B – Ethical Clearance

Gordon Institute of Business Science
University of Pretoria

Ethical Clearance Approved

Dear Hendrik van Niekerk,

Please be advised that your application for Ethical Clearance has been approved.
You are therefore allowed to continue collecting your data.
We wish you everything of the best for the rest of the project.

Ethical Clearance Form

Kind Regards

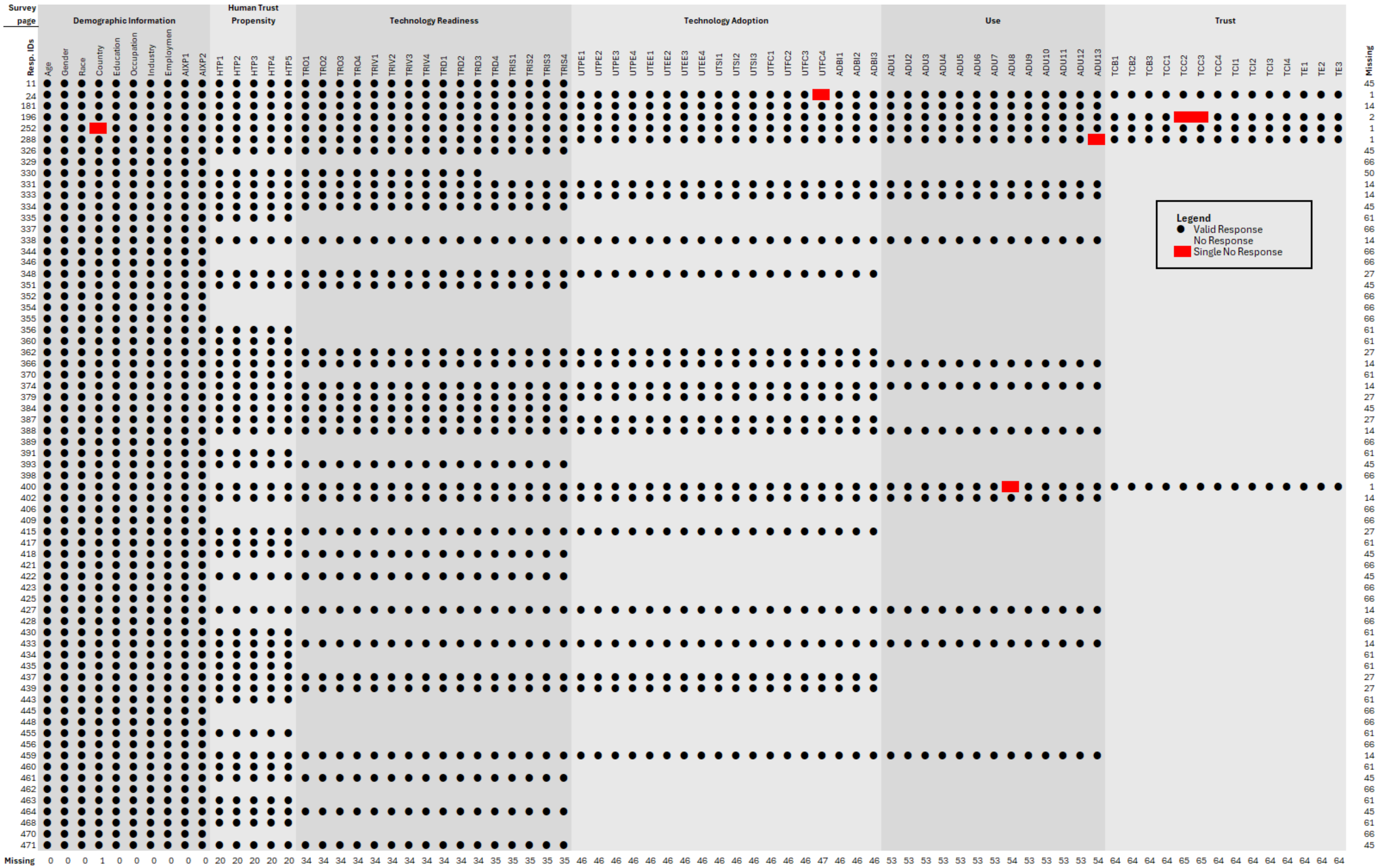
This email has been sent from an unmonitored email account. If you have any comments or concerns, please contact the GIBS Research Admin team.

11. Appendix C – Response Deletion Summary

Response Deletion Summury				
Discription	**Total**	**%**	**Action**	**Response IDs**
Total responses	476	100%	-	1-476
Surveys not started. Reason for deletion: known reason for missing data.	-46	10%	Deleted	266, 283, 316, 340, 345, 347, 349, 350, 353, 357, 359, 363, 364, 367, 368, 371, 375, 376, 378, 383, 390, 395, 396, 399, 401, 404, 424, 429, 436, 438, 441, 442, 444, 446, 447, 449, 450, 451, 453, 454, 457, 458, 467, 469, 472, 476
Respondents that are not part of the population: Not employed	-55	12%	Deleted	4, 13, 33, 47, 59, 67, 75, 78, 79, 83, 85, 86, 87, 88, 90, 93, 94, 95, 96, 104, 109, 114, 123, 130, 142, 164, 179, 194, 198, 212, 214, 222, 249, 289, 293, 303, 311, 314, 317, 321, 325, 332, 342, 343, 358, 361, 365, 369, 386, 410, 411, 412, 426, 452, 466
Missing data due to respondents not going to the next page of the survey. Known reason for missing data, thus deleted.	-64	13%	Deleted	24, 181, 326, 329, 330, 331, 333, 334, 335, 337, 338, 344, 346, 348, 351, 352, 354, 355, 356, 360, 362, 366, 370, 374, 379, 384, 387, 388, 389, 391, 393, 398, 402, 406, 409, 415, 417, 418, 421, 422, 423, 425, 427, 428, 430, 433, 434, 435, 437, 439, 443, 445, 448, 455, 456, 459, 460, 461, 462, 463, 464, 468, 470, 471
Missing data skipping individual questions. Reason for deletion: Very low percentage of possible non-random missing data.	-5	1%	Deleted	11, 196, 252, 288, 400
Fully Completed valid responses	306	64%		
Outliers of variates: (>1,5 x IQR)				
HTP				16, 36, 154, 254, 290
TRO				46, 101, 108, 125, 177, 202, 207, 224, 270, 295, 297, 298, 382, 392, 407, 414
TRIV				53, 102, 112, 126, 145, 233
TRD				-
TRIS				18, 89, 119, 235
UTPE				5, 31, 36, 40, 98, 183, 262, 270, 298, 313, 318
UTEE				5, 36, 73, 103, 133, 189, 265, 302, 308, 313, 336
UTSI				6, 20, 64, 66, 128, 131, 143, 146, 190, 210, 211, 223, 228, 241, 254, 270, 281
UTFC				5, 40, 57, 158, 175, 272, 273, 302, 323, 328, 416
TCB				5, 36, 40, 301, 432
TCC				36, 189, 234, 240, 298, 301
TCI				254, 269, 270, 287, 297, 298
TE				57, 178, 206, 298, 301, 313, 465
ADBI				5, 36, 57, 61, 71, 200, 247, 270, 313, 420
ADU				23, 35, 144, 152, 178, 186, 215, 229, 231, 296
Total Outliers:	-93	20%	Deleted	
Total usable responses:	213	45%		

12. Appendix D – Missing Data Analysis

Table 33: Missing Data Analysis



13. Appendix E – Code Book

Table 34: Code Book

Code Book		
Items	**Options**	**Code**
AGE	18 to 24	1
	25 to 34	2
	35 to 44	3
	45 to 54	4
	55 to 64	5
	65 and older	6
GEN	Male	0
	Female	1
CD	Developping	0
	Developpped	1
AIXP1	Extremely	5
	Very	4
	Moderately	3
	Slightly	2
	Not at all	1
AIXP2	Ten years or more	6
	Five years to less than ten years	5
	One year to less than five years	4
	One month to less than one year	3
	Once to less than one month	2
	Never used AI tools	1
TRO1-4, TRIV1-4, TRD1-4, TRIS1-4, UTPE1-4, UTEE1-4, UTSI1-3, UTFC1-4, ADBI1-3, TCB1-3, TCC1-4, TCI1-4, TE1-3	Strongly agree	7
	Agree	6
	Somewhat agree	5
	Neither agree nor disagree	4
	Somewhat disagree	3
	Disagree	2
	Strongly disagree	1
ADU1-13	Several times a day	7
	Daily	6
	Several times a week	5
	Weekly	4
	Monthly	3
	Less than monthly	2
	Never	1

14. Appendix F – Regression Results for Control Variables

Table 35: Regression with Control Variables for Hypothesis H1, Betas

Regression of ADBI									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,98	n/a	n/a	0,25		0,00	0,00
	AGE	0,07	0,17	0,95	1,05				
	GEN	0,05	0,68	0,96	1,04				
	CD	-0,13	0,47	0,98	1,02				
	AIXP	0,47	0,00	0,92	1,09				
2	Constant	0,00	0,98	n/a	n/a	0,38	0,13	0,00	0,00
	AGE	0,08	0,09	0,95	1,05				
	GEN	0,10	0,35	0,90	1,11				
	CD	-0,09	0,58	0,98	1,02				
	AIXP	0,41	0,00	0,81	1,24				
	TRO	0,45	0,00	0,89	1,12				
	TRIV	0,00	0,97	0,74	1,34				

Regression of ADUD									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,99	n/a	n/a	0,05		0,04	0,04
	AGE	-0,04	0,62	0,95	1,05				
	GEN	-0,36	0,04	0,96	1,04				
	CD	0,18	0,50	0,98	1,02				
	AIXP	0,14	0,09	0,92	1,09				
2	Constant	0,00	0,99	n/a	n/a	0,08	0,03	0,03	0,01
	AGE	-0,03	0,66	0,95	1,05				
	GEN	-0,29	0,09	0,90	1,11				
	CD	0,21	0,42	0,98	1,02				
	AIXP	0,08	0,34	0,81	1,24				
	TRO	0,24	0,03	0,89	1,12				
	TRIV	0,06	0,44	0,74	1,34				

Regression of ADUG									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,99	n/a	n/a	0,24		0,00	0,00
	AGE	-0,07	0,35	0,95	1,05				
	GEN	-0,10	0,60	0,96	1,04				
	CD	0,01	0,96	0,98	1,02				
	AIXP	0,66	0,00	0,92	1,09				
2	Constant	0,00	1,00	n/a	n/a	0,29	0,05	0,00	0,00
	AGE	-0,07	0,36	0,95	1,05				
	GEN	0,07	0,69	0,90	1,11				
	CD	0,08	0,76	0,98	1,02				
	AIXP	0,53	0,00	0,81	1,24				
	TRO	0,19	0,10	0,89	1,12				
	TRIV	0,27	0,00	0,74	1,34				

Regression of ADUS									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,97	n/a	n/a	0,01		0,70	0,70
	AGE	-0,03	0,63	0,95	1,05				
	GEN	-0,05	0,73	0,96	1,04				
	CD	0,05	0,80	0,98	1,02				
	AIXP	0,08	0,25	0,92	1,09				
2	Constant	0,00	0,98	n/a	n/a	0,07	0,06	0,00	0,01
	AGE	-0,03	0,64	0,95	1,05				
	GEN	0,08	0,57	0,90	1,11				
	CD	0,10	0,62	0,98	1,02				
	AIXP	-0,02	0,83	0,81	1,24				
	TRO	0,11	0,22	0,89	1,12				
	TRIV	0,20	0,00	0,74	1,34				

Table 36: Regression Betas with Control Variables for Hypothesis H3, Betas

Regression of ADBI									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-1,80	0,00			0,25		0,00	0,00
	AGE	0,07	0,17	0,95	1,05				
	GEN	0,05	0,68	0,96	1,04				
	CD	-0,13	0,47	0,98	1,02				
	AIXP	0,24	0,00	0,92	1,09				
2	Constant	-1,64	0,00			0,26	0,01	0,16	0,00
	AGE	0,06	0,28	0,93	1,08				
	GEN	0,03	0,80	0,95	1,05				
	CD	-0,14	0,46	0,98	1,02				
	AIXP	0,22	0,00	0,86	1,17				
	TRD	-0,05	0,35	0,88	1,13				
	TRIS	-0,07	0,18	0,85	1,18				

Regression of ADUD									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-0,27	0,52			0,05		0,04	0,04
	AGE	-0,04	0,62	0,95	1,05				
	GEN	-0,36	0,04	0,96	1,04				
	CD	0,18	0,51	0,98	1,02				
	AIXP	0,07	0,09	0,92	1,09				
2	Constant	0,11	0,79			0,10	0,05	0,01	0,00
	AGE	-0,07	0,31	0,93	1,08				
	GEN	-0,41	0,02	0,95	1,05				
	CD	0,17	0,52	0,98	1,02				
	AIXP	0,03	0,42	0,86	1,17				
	TRD	-0,05	0,47	0,88	1,13				
	TRIS	-0,21	0,01	0,85	1,18				

Regression of ADUG									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-1,98	0,00			0,24		0,00	0,00
	AGE	-0,07	0,35	0,95	1,05				
	GEN	-0,10	0,60	0,96	1,04				
	CD	0,01	0,96	0,98	1,02				
	AIXP	0,33	0,00	0,92	1,09				
2	Constant	-1,84	0,00			0,25	0,01	0,37	0,00
	AGE	-0,09	0,25	0,93	1,08				
	GEN	-0,11	0,54	0,95	1,05				
	CD	0,01	0,97	0,98	1,02				
	AIXP	0,32	0,00	0,86	1,17				
	TRD	0,03	0,64	0,88	1,13				
	TRIS	-0,11	0,16	0,85	1,18				

Regression of ADUS									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-0,16	0,63			0,01		0,70	0,70
	AGE	-0,03	0,63	0,95	1,05				
	GEN	-0,05	0,73	0,96	1,04				
	CD	0,05	0,80	0,98	1,02				
	AIXP	0,04	0,25	0,92	1,09				
2	Constant	-0,23	0,50			0,01	0,00	0,76	0,84
	AGE	-0,02	0,72	0,93	1,08				
	GEN	-0,04	0,78	0,95	1,05				
	CD	0,05	0,80	0,98	1,02				
	AIXP	0,05	0,20	0,86	1,17				
	TRD	0,01	0,86	0,88	1,13				
	TRIS	0,04	0,53	0,85	1,18				

Table 37: Regression Results with Control Variables for Hypothesis H5, Betas

Regression of ADBI									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-1,80	0,00			0,25		0,00	0,00
	AGE	0,07	0,17	0,95	1,05				
	GEN	0,05	0,68	0,96	1,04				
	CD	-0,13	0,47	0,98	1,02				
	AIXP	0,24	0,00	0,92	1,09				
2	Constant	-0,91	0,00			0,63	0,37	0,00	0,00
	AGE	0,06	0,07	0,95	1,05				
	GEN	0,15	0,08	0,95	1,05				
	CD	-0,02	0,86	0,98	1,02				
	AIXP	0,10	0,00	0,76	1,32				
	UTPE	0,66	0,00	0,79	1,26				

Regression of ADUD									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-0,27	0,52			0,05		0,04	0,04
	AGE	-0,04	0,62	0,95	1,05				
	GEN	-0,36	0,04	0,96	1,04				
	CD	0,18	0,51	0,98	1,02				
	AIXP	0,07	0,09	0,92	1,09				
2	Constant	0,02	0,96			0,07	0,02	0,02	0,01
	AGE	-0,04	0,60	0,95	1,05				
	GEN	-0,33	0,06	0,95	1,05				
	CD	0,21	0,42	0,98	1,02				
	AIXP	0,03	0,56	0,76	1,32				
	UTPE	0,21	0,02	0,79	1,26				

Regression of ADUG									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-1,98	0,00			0,24		0,00	0,00
	AGE	-0,07	0,35	0,95	1,05				
	GEN	-0,10	0,60	0,96	1,04				
	CD	0,01	0,96	0,98	1,02				
	AIXP	0,33	0,00	0,92	1,09				
2	Constant	-1,20	0,01			0,36	0,12	0,00	0,00
	AGE	-0,08	0,28	0,95	1,05				
	GEN	-0,01	0,97	0,95	1,05				
	CD	0,11	0,68	0,98	1,02				
	AIXP	0,21	0,00	0,76	1,32				
	UTPE	0,57	0,00	0,79	1,26				

Regression of ADUS									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-0,16	0,63			0,01		0,70	0,70
	AGE	-0,03	0,63	0,95	1,05				
	GEN	-0,05	0,73	0,96	1,04				
	CD	0,05	0,80	0,98	1,02				
	AIXP	0,04	0,25	0,92	1,09				
2	Constant	0,16	0,64			0,06	0,05	0,00	0,03
	AGE	-0,03	0,60	0,95	1,05				
	GEN	-0,01	0,94	0,95	1,05				
	CD	0,09	0,66	0,98	1,02				
	AIXP	-0,01	0,76	0,76	1,32				
	UTPE	0,24	0,00	0,79	1,26				

Table 38: Regression Results with Control Variables for Hypothesis H7, Betas

Regression of ADBI									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-1,80	0,00			0,25		0,00	0,00
	AGE	0,07	0,17	0,95	1,05				
	GEN	0,05	0,68	0,96	1,04				
	CD	-0,13	0,47	0,98	1,02				
	AIXP	0,24	0,00	0,92	1,09				
2	Constant	-1,09	0,00			0,39	0,14	0,00	0,00
	AGE	0,10	0,03	0,94	1,06				
	GEN	0,04	0,71	0,96	1,04				
	CD	-0,01	0,94	0,97	1,03				
	AIXP	0,11	0,00	0,64	1,57				
	UTEE	0,53	0,00	0,65	1,55				

Regression of ADUD									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-0,27	0,52			0,05		0,04	0,04
	AGE	-0,04	0,62	0,95	1,05				
	GEN	-0,36	0,04	0,96	1,04				
	CD	0,18	0,51	0,98	1,02				
	AIXP	0,07	0,09	0,92	1,09				
2	Constant	-0,18	0,68			0,05	0,00	0,61	0,07
	AGE	-0,03	0,66	0,94	1,06				
	GEN	-0,36	0,04	0,96	1,04				
	CD	0,19	0,48	0,97	1,03				
	AIXP	0,06	0,27	0,64	1,57				
	UTEE	0,06	0,61	0,65	1,55				

Regression of ADUG									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-1,98	0,00			0,24		0,00	0,00
	AGE	-0,07	0,35	0,95	1,05				
	GEN	-0,10	0,60	0,96	1,04				
	CD	0,01	0,96	0,98	1,02				
	AIXP	0,33	0,00	0,92	1,09				
2	Constant	-1,10	0,01			0,33	0,09	0,00	0,00
	AGE	-0,03	0,67	0,94	1,06				
	GEN	-0,11	0,54	0,96	1,04				
	CD	0,16	0,55	0,97	1,03				
	AIXP	0,18	0,00	0,64	1,57				
	UTEE	0,66	0,00	0,65	1,55				

Regression of ADUS									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-0,16	0,63			0,01		0,70	0,70
	AGE	-0,03	0,63	0,95	1,05				
	GEN	-0,05	0,73	0,96	1,04				
	CD	0,05	0,80	0,98	1,02				
	AIXP	0,04	0,25	0,92	1,09				
2	Constant	0,24	0,49			0,06	0,05	0,00	0,04
	AGE	-0,01	0,88	0,94	1,06				
	GEN	-0,05	0,70	0,96	1,04				
	CD	0,12	0,57	0,97	1,03				
	AIXP	-0,03	0,44	0,64	1,57				
	UTEE	0,30	0,00	0,65	1,55				

Table 39: Regression Results with Control Variables for Hypothesis H9, Betas

Regression of ADBI									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-1,80	0,00			0,25		0,00	0,00
	AGE	0,07	0,17	0,95	1,05				
	GEN	0,05	0,68	0,96	1,04				
	CD	-0,13	0,47	0,98	1,02				
	AIXP	0,24	0,00	0,92	1,09				
2	Constant	-1,77	0,00			0,31	0,06	0,00	0,00
	AGE	0,07	0,16	0,95	1,05				
	GEN	0,07	0,54	0,96	1,05				
	CD	-0,13	0,48	0,98	1,02				
	AIXP	0,23	0,00	0,92	1,09				
	UTSI	0,21	0,00	1,00	1,00				

Regression of ADUD									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-0,27	0,52			0,05		0,04	0,04
	AGE	-0,04	0,62	0,95	1,05				
	GEN	-0,36	0,04	0,96	1,04				
	CD	0,18	0,51	0,98	1,02				
	AIXP	0,07	0,09	0,92	1,09				
2	Constant	-0,25	0,54			0,06	0,02	0,07	0,02
	AGE	-0,04	0,61	0,95	1,05				
	GEN	-0,35	0,04	0,96	1,05				
	CD	0,18	0,49	0,98	1,02				
	AIXP	0,07	0,10	0,92	1,09				
	UTSI	0,14	0,07	1,00	1,00				

Regression of ADUG									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-1,98	0,00			0,24		0,00	0,00
	AGE	-0,07	0,35	0,95	1,05				
	GEN	-0,10	0,60	0,96	1,04				
	CD	0,01	0,96	0,98	1,02				
	AIXP	0,33	0,00	0,92	1,09				
2	Constant	-1,96	0,00			0,26	0,02	0,03	0,00
	AGE	-0,07	0,34	0,95	1,05				
	GEN	-0,08	0,67	0,96	1,05				
	CD	0,02	0,95	0,98	1,02				
	AIXP	0,33	0,00	0,92	1,09				
	UTSI	0,18	0,03	1,00	1,00				

Regression of ADUS									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-0,16	0,63			0,01		0,70	0,70
	AGE	-0,03	0,63	0,95	1,05				
	GEN	-0,05	0,73	0,96	1,04				
	CD	0,05	0,80	0,98	1,02				
	AIXP	0,04	0,25	0,92	1,09				
2	Constant	-0,14	0,66			0,05	0,04	0,00	0,04
	AGE	-0,03	0,61	0,95	1,05				
	GEN	-0,03	0,83	0,96	1,05				
	CD	0,06	0,78	0,98	1,02				
	AIXP	0,04	0,29	0,92	1,09				
	UTSI	0,18	0,00	1,00	1,00				

Table 40: Regression Results with Control Variables for Hypothesis H11, Betas

Regression of ADBI									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-1,80	0,00			0,25		0,00	0,00
	AGE	0,07	0,17	0,95	1,05				
	GEN	0,05	0,68	0,96	1,04				
	CD	-0,13	0,47	0,98	1,02				
	AIXP	0,24	0,00	0,92	1,09				
2	Constant	-1,39	0,00			0,36	0,11	0,00	0,00
	AGE	0,08	0,10	0,95	1,05				
	GEN	0,05	0,68	0,96	1,04				
	CD	-0,01	0,95	0,97	1,04				
	AIXP	0,17	0,00	0,78	1,28				
	UTFC	0,44	0,00	0,82	1,22				

Regression of ADUD									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-0,27	0,52			0,05		0,04	0,00
	AGE	-0,04	0,62	0,95	1,05				
	GEN	-0,36	0,04	0,96	1,04				
	CD	0,18	0,51	0,98	1,02				
	AIXP	0,07	0,09	0,92	1,09				
2	Constant	-0,23	0,59			0,05	0,00	0,76	0,07
	AGE	-0,04	0,63	0,95	1,05				
	GEN	-0,36	0,04	0,96	1,04				
	CD	0,19	0,49	0,97	1,04				
	AIXP	0,07	0,15	0,78	1,28				
	UTFC	0,04	0,76	0,82	1,22				

Regression of ADUG									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-1,98	0,00			0,24		0,00	0,00
	AGE	-0,07	0,35	0,95	1,05				
	GEN	-0,10	0,60	0,96	1,04				
	CD	0,01	0,96	0,98	1,02				
	AIXP	0,33	0,00	0,92	1,09				
2	Constant	-1,73	0,00			0,26	0,02	0,03	0,00
	AGE	-0,07	0,38	0,95	1,05				
	GEN	-0,10	0,60	0,96	1,04				
	CD	0,09	0,76	0,97	1,04				
	AIXP	0,29	0,00	0,78	1,28				
	UTFC	0,27	0,03	0,82	1,22				

Regression of ADUS									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	-0,16	0,63			0,01		0,70	0,70
	AGE	-0,03	0,63	0,95	1,05				
	GEN	-0,05	0,73	0,96	1,04				
	CD	0,05	0,80	0,98	1,02				
	AIXP	0,04	0,25	0,92	1,09				
2	Constant	0,01	0,99			0,03	0,02	0,06	0,32
	AGE	-0,03	0,67	0,95	1,05				
	GEN	-0,05	0,72	0,96	1,04				
	CD	0,10	0,63	0,97	1,04				
	AIXP	0,01	0,75	0,78	1,28				
	UTFC	0,18	0,06	0,82	1,22				

15. Appendix G – Regression Results for Moderation

Table 41: Regression Results for Hypothesis H2, Betas

Regression of ADBI									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
	Constant	0,00	0,95	n/a	n/a				
	TCB	0,18	0,02	0,50	2,01				
	TCC	0,31	0,00	0,39	2,56				
1	TCI	-0,21	0,00	0,48	2,10	0,44		0,00	0,00
	TE	0,24	0,00	0,41	2,42				
	TRO	0,24	0,00	0,75	1,33				
	TRIV	0,09	0,06	0,88	1,14				
	Constant	0,01	0,90	n/a	n/a				
	TCB	0,15	0,06	0,44	2,29				
	TCC	0,31	0,00	0,38	2,67				
	TCI	-0,21	0,01	0,42	2,40				
	TE	0,25	0,00	0,38	2,62				
	TRO	0,23	0,00	0,70	1,42				
	TRIV	0,09	0,05	0,84	1,19				
2	TROxTCB	-0,04	0,73	0,31	3,20	0,45	0,01	0,75	0,00
	TROxTCC	-0,01	0,93	0,26	3,92				
	TROxTCI	0,16	0,17	0,28	3,56				
	TROxTE	-0,08	0,52	0,19	5,14				
	TRIVxTCB	-0,05	0,46	0,50	2,02				
	TRIVxTCC	0,06	0,51	0,37	2,73				
	TRIVxTCI	-0,11	0,14	0,39	2,60				
	TRIVxTE	0,10	0,14	0,37	2,74				

Regression of ADUD									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
	Constant	0,00	1,00	n/a	n/a				
	TCB	-0,01	0,96	0,50	2,01				
	TCC	0,06	0,71	0,39	2,56				
1	TCI	0,04	0,74	0,48	2,10	0,06		0,04	0,04
	TE	0,05	0,69	0,41	2,42				
	TRO	0,19	0,11	0,75	1,33				
	TRIV	0,12	0,11	0,88	1,14				
	Constant	-0,01	0,94	n/a	n/a				
	TCB	-0,05	0,71	0,44	2,29				
	TCC	0,04	0,80	0,38	2,67				
	TCI	0,04	0,75	0,42	2,40				
	TE	0,05	0,69	0,38	2,62				
	TRO	0,20	0,11	0,70	1,42				
	TRIV	0,16	0,04	0,84	1,19				
2	TROxTCB	0,30	0,14	0,31	3,20	0,13	0,06	0,08	0,02
	TROxTCC	-0,13	0,54	0,26	3,92				
	TROxTCI	-0,14	0,46	0,28	3,56				
	TROxTE	-0,11	0,59	0,19	5,14				
	TRIVxTCB	-0,07	0,54	0,50	2,02				
	TRIVxTCC	-0,18	0,18	0,37	2,73				
	TRIVxTCI	0,26	0,03	0,39	2,60				
	TRIVxTE	0,19	0,08	0,37	2,74				

Table 41 (Continue): Regression Results for Hypothesis H2, Betas

Regression of ADUG									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
	Constant	0,00	1,00	n/a	n/a				
	TCB	0,40	0,00	0,50	2,01				
	TCC	0,29	0,07	0,39	2,56				
1	TCI	-0,34	0,01	0,48	2,10	0,25		0,00	0,00
	TE	0,09	0,47	0,41	2,42				
	TRO	0,06	0,66	0,75	1,33				
	TRIV	0,40	0,00	0,88	1,14				
	Constant	0,01	0,89	n/a	n/a				
	TCB	0,41	0,01	0,44	2,29				
	TCC	0,27	0,09	0,38	2,67				
	TCI	-0,25	0,07	0,42	2,40				
	TE	0,01	0,95	0,38	2,62				
	TRO	0,04	0,74	0,70	1,42				
	TRIV	0,42	0,00	0,84	1,19				
2	TROxTCB	-0,07	0,76	0,31	3,20	0,30	0,05	0,12	0,00
	TROxTCC	-0,04	0,86	0,26	3,92				
	TROxTCI	-0,35	0,08	0,28	3,56				
	TROxTE	0,17	0,46	0,19	5,14				
	TRIVxTCB	0,11	0,38	0,50	2,02				
	TRIVxTCC	-0,11	0,46	0,37	2,73				
	TRIVxTCI	-0,01	0,94	0,39	2,60				
	TRIVxTE	0,16	0,16	0,37	2,74				

Regression of ADUS									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
	Constant	0,00	0,98	n/a	n/a				
	TCB	0,13	0,20	0,50	2,01				
	TCC	-0,06	0,60	0,39	2,56				
1	TCI	0,12	0,20	0,48	2,10	0,10		0,00	0,00
	TE	-0,01	0,88	0,41	2,42				
	TRO	0,05	0,57	0,75	1,33				
	TRIV	0,17	0,00	0,88	1,14				
	Constant	-0,02	0,80	n/a	n/a				
	TCB	0,14	0,19	0,44	2,29				
	TCC	-0,12	0,30	0,38	2,67				
	TCI	0,16	0,10	0,42	2,40				
	TE	-0,04	0,66	0,38	2,62				
	TRO	0,04	0,68	0,70	1,42				
	TRIV	0,20	0,00	0,84	1,19				
2	TROxTCB	0,11	0,47	0,31	3,20	0,17	0,07	0,04	0,00
	TROxTCC	-0,19	0,26	0,26	3,92				
	TROxTCI	0,00	0,99	0,28	3,56				
	TROxTE	0,00	0,98	0,19	5,14				
	TRIVxTCB	0,11	0,18	0,50	2,02				
	TRIVxTCC	-0,16	0,14	0,37	2,73				
	TRIVxTCI	0,01	0,89	0,39	2,60				
	TRIVxTE	0,19	0,02	0,37	2,74				

Table 42: Regression Results for Hypothesis H4, Betas

Regression of ADBI									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,95	n/a	n/a	0,40		0,00	0,00
	TCB	0,21	0,01	0,51	1,98				
	TCC	0,35	0,00	0,40	2,49				
	TCI	-0,20	0,01	0,46	2,19				
	TE	0,24	0,00	0,41	2,46				
	TRD	-0,03	0,45	0,86	1,16				
	TRIS	-0,08	0,07	0,87	1,15				
2	Constant	-0,01	0,86	n/a	n/a	0,41	0,02	0,74	0,00
	TCB	0,19	0,02	0,44	2,26				
	TCC	0,36	0,00	0,38	2,63				
	TCI	-0,18	0,03	0,43	2,32				
	TE	0,24	0,00	0,38	2,64				
	TRD	-0,04	0,39	0,79	1,28				
	TRIS	-0,09	0,06	0,81	1,24				
	TRDxTCB	0,01	0,90	0,41	2,45				
	TRDxTCC	-0,15	0,09	0,31	3,23				
	TRDxTCI	0,04	0,49	0,41	2,45				
	TRDxTE	0,09	0,18	0,31	3,24				
	TRISxTCB	0,03	0,73	0,39	2,59				
	TRISxTCC	0,09	0,32	0,25	3,94				
	TRISxTCI	0,00	0,97	0,43	2,33				
	TRISxTE	-0,09	0,17	0,33	3,05				

Regression of ADUD									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,99	n/a	n/a	0,07		0,01	0,01
	TCB	0,03	0,81	0,51	1,98				
	TCC	0,09	0,54	0,40	2,49				
	TCI	0,08	0,50	0,46	2,19				
	TE	0,02	0,89	0,41	2,46				
	TRD	-0,06	0,43	0,86	1,16				
	TRIS	-0,19	0,01	0,87	1,15				
2	Constant	0,01	0,91	n/a	n/a	0,11	0,04	0,40	0,05
	TCB	0,06	0,64	0,44	2,26				
	TCC	0,15	0,32	0,38	2,63				
	TCI	0,09	0,46	0,43	2,32				
	TE	-0,04	0,74	0,38	2,64				
	TRD	-0,04	0,61	0,79	1,28				
	TRIS	-0,22	0,00	0,81	1,24				
	TRDxTCB	0,09	0,47	0,41	2,45				
	TRDxTCC	0,07	0,63	0,31	3,23				
	TRDxTCI	0,02	0,88	0,41	2,45				
	TRDxTE	-0,15	0,16	0,31	3,24				
	TRISxTCB	-0,03	0,79	0,39	2,59				
	TRISxTCC	0,21	0,15	0,25	3,94				
	TRISxTCI	0,00	1,00	0,43	2,33				
	TRISxTE	-0,01	0,93	0,33	3,05				

Table 42 (Continue): Regression Results for Hypothesis H4, Betas

Regression of ADUG									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,99	n/a	n/a	0,17		0,00	0,00
	TCB	0,51	0,00	0,51	1,98				
	TCC	0,30	0,07	0,40	2,49				
	TCI	-0,33	0,02	0,46	2,19				
	TE	0,09	0,52	0,41	2,46				
	TRD	0,04	0,62	0,86	1,16				
	TRIS	-0,15	0,06	0,87	1,15				
2	Constant	-0,02	0,83	n/a	n/a	0,24	0,07	0,02	0,00
	TCB	0,47	0,00	0,44	2,26				
	TCC	0,29	0,08	0,38	2,63				
	TCI	-0,28	0,04	0,43	2,32				
	TE	0,08	0,57	0,38	2,64				
	TRD	-0,04	0,63	0,79	1,28				
	TRIS	-0,09	0,27	0,81	1,24				
	TRDxTCB	0,08	0,52	0,41	2,45				
	TRDxTCC	-0,10	0,48	0,31	3,23				
	TRDxTCI	0,10	0,39	0,41	2,45				
	TRDxTE	0,23	0,06	0,31	3,24				
	TRISxTCB	-0,14	0,25	0,39	2,59				
	TRISxTCC	0,01	0,97	0,25	3,94				
	TRISxTCI	0,07	0,49	0,43	2,33				
	TRISxTE	-0,16	0,16	0,33	3,05				

Regression of ADUS									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,97	n/a	n/a	0,06		0,07	0,07
	TCB	0,17	0,09	0,51	1,98				
	TCC	-0,06	0,63	0,40	2,49				
	TCI	0,11	0,24	0,46	2,19				
	TE	0,02	0,85	0,41	2,46				
	TRD	0,00	0,98	0,86	1,16				
	TRIS	0,04	0,46	0,87	1,15				
2	Constant	-0,03	0,69	n/a	n/a	0,07	0,02	0,88	0,36
	TCB	0,17	0,12	0,44	2,26				
	TCC	-0,07	0,56	0,38	2,63				
	TCI	0,15	0,15	0,43	2,32				
	TE	0,01	0,92	0,38	2,64				
	TRD	0,01	0,91	0,79	1,28				
	TRIS	0,04	0,51	0,81	1,24				
	TRDxTCB	-0,03	0,72	0,41	2,45				
	TRDxTCC	-0,09	0,38	0,31	3,23				
	TRDxTCI	0,12	0,14	0,41	2,45				
	TRDxTE	0,00	1,00	0,31	3,24				
	TRISxTCB	0,01	0,90	0,39	2,59				
	TRISxTCC	-0,03	0,80	0,25	3,94				
	TRISxTCI	0,05	0,50	0,43	2,33				
	TRISxTE	-0,04	0,60	0,33	3,05				

Table 43: Regression Results for Hypothesis H6, Betas

Regression of ADBI									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,97	n/a	n/a	0,64		0,00	0,00
	TCB	0,02	0,75	0,48	2,11				
	TCC	0,21	0,00	0,39	2,55				
	TCI	-0,18	0,00	0,47	2,11				
	TE	0,16	0,01	0,41	2,46				
	UTPE	0,60	0,00	0,65	1,55				
2	Constant	0,01	0,89	n/a	n/a	0,64	0,01	0,62	0,00
	TCB	0,03	0,64	0,45	2,21				
	TCC	0,21	0,00	0,38	2,66				
	TCI	-0,21	0,00	0,41	2,42				
	TE	0,18	0,00	0,38	2,61				
	UTPE	0,60	0,00	0,56	1,79				
	UTPExTCB	-0,05	0,49	0,43	2,33				
	UTPExTCC	0,03	0,72	0,40	2,48				
	UTPExTCI	0,08	0,18	0,41	2,47				
	UTPExTE	-0,05	0,47	0,36	2,78				

Regression of ADUD									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	1,00	n/a	n/a	0,05		0,06	0,06
	TCB	-0,03	0,81	0,48	2,11				
	TCC	0,04	0,78	0,39	2,55				
	TCI	0,05	0,66	0,47	2,11				
	TE	0,04	0,75	0,41	2,46				
	UTPE	0,21	0,04	0,65	1,55				
2	Constant	0,04	0,68	n/a	n/a	0,06	0,01	0,72	0,18
	TCB	-0,03	0,81	0,45	2,21				
	TCC	0,01	0,94	0,38	2,66				
	TCI	0,06	0,63	0,41	2,42				
	TE	0,06	0,65	0,38	2,61				
	UTPE	0,22	0,05	0,56	1,79				
	UTPExTCB	-0,01	0,95	0,43	2,33				
	UTPExTCC	-0,20	0,19	0,40	2,48				
	UTPExTCI	0,05	0,67	0,41	2,47				
	UTPExTE	0,05	0,68	0,36	2,78				

Table 43 (Continue): Regression Results for Hypothesis H6, Betas

Regression of ADUG									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,99	n/a	n/a	0,31		0,00	0,00
	TCB	0,27	0,04	0,48	2,11				
	TCC	0,12	0,43	0,39	2,55				
	TCI	-0,29	0,02	0,47	2,11				
	TE	-0,01	0,93	0,41	2,46				
	UTPE	0,71	0,00	0,65	1,55				
2	Constant	0,02	0,81	n/a	n/a	0,32	0,01	0,63	0,00
	TCB	0,27	0,05	0,45	2,21				
	TCC	0,11	0,46	0,38	2,66				
	TCI	-0,22	0,10	0,41	2,42				
	TE	-0,04	0,75	0,38	2,61				
	UTPE	0,68	0,00	0,56	1,79				
	UTPExTCB	0,01	0,93	0,43	2,33				
	UTPExTCC	-0,09	0,57	0,40	2,48				
	UTPExTCI	-0,15	0,26	0,41	2,47				
	UTPExTE	0,11	0,39	0,36	2,78				

Regression of ADUS									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,98	n/a	n/a	0,08		0,01	0,01
	TCB	0,11	0,28	0,48	2,11				
	TCC	-0,10	0,38	0,39	2,55				
	TCI	0,13	0,16	0,47	2,11				
	TE	-0,03	0,74	0,41	2,46				
	UTPE	0,19	0,02	0,65	1,55				
2	Constant	-0,01	0,87	n/a	n/a	0,09	0,02	0,50	0,02
	TCB	0,08	0,43	0,45	2,21				
	TCC	-0,13	0,25	0,38	2,66				
	TCI	0,16	0,12	0,41	2,42				
	TE	-0,02	0,81	0,38	2,61				
	UTPE	0,22	0,01	0,56	1,79				
	UTPExTCB	0,11	0,30	0,43	2,33				
	UTPExTCC	-0,18	0,11	0,40	2,48				
	UTPExTCI	0,01	0,88	0,41	2,47				
	UTPExTE	0,07	0,49	0,36	2,78				

Table 44: Regression Results for Hypothesis H8, Betas

Regression of ADBI									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,98	n/a	n/a	0,50		0,00	0,00
	TCB	0,09	0,21	0,48	2,09				
	TCC	0,23	0,01	0,39	2,59				
	TCI	-0,18	0,01	0,47	2,12				
	TE	0,26	0,00	0,42	2,39				
	UTEE	0,44	0,00	0,75	1,34				
2	Constant	0,02	0,77	n/a	n/a	0,51	0,02	0,13	0,00
	TCB	0,07	0,36	0,46	2,20				
	TCC	0,29	0,00	0,36	2,80				
	TCI	-0,20	0,01	0,38	2,65				
	TE	0,27	0,00	0,38	2,65				
	UTEE	0,43	0,00	0,67	1,49				
	UTEExTCB	-0,18	0,08	0,44	2,28				
	UTEExTCC	0,26	0,02	0,33	3,06				
	UTEExTCI	-0,03	0,73	0,43	2,32				
	UTEExTE	-0,09	0,34	0,37	2,73				

Regression of ADUD									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	1,00	n/a	n/a	0,03		0,24	0,24
	TCB	0,02	0,87	0,48	2,09				
	TCC	0,08	0,61	0,39	2,59				
	TCI	0,04	0,72	0,47	2,12				
	TE	0,08	0,51	0,42	2,39				
	UTEE	0,06	0,59	0,75	1,34				
2	Constant	0,04	0,65	n/a	n/a	0,04	0,01	0,62	0,41
	TCB	0,06	0,68	0,46	2,20				
	TCC	0,11	0,47	0,36	2,80				
	TCI	-0,03	0,83	0,38	2,65				
	TE	0,09	0,46	0,38	2,65				
	UTEE	0,03	0,79	0,67	1,49				
	UTEExTCB	-0,24	0,20	0,44	2,28				
	UTEExTCC	-0,06	0,77	0,33	3,06				
	UTEExTCI	0,18	0,29	0,43	2,32				
	UTEExTE	0,03	0,84	0,37	2,73				

Table 44 (Continue): Regression Results for Hypothesis H8, Betas

Regression of ADUG									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,98	n/a	n/a	0,32		0,00	0,00
	TCB	0,28	0,04	0,48	2,09				
	TCC	0,07	0,65	0,39	2,59				
	TCI	-0,27	0,03	0,47	2,12				
	TE	0,10	0,38	0,42	2,39				
	UTEE	0,80	0,00	0,75	1,34				
2	Constant	0,00	0,97	n/a	n/a	0,33	0,02	0,34	0,00
	TCB	0,24	0,08	0,46	2,20				
	TCC	0,05	0,77	0,36	2,80				
	TCI	-0,14	0,29	0,38	2,65				
	TE	0,06	0,61	0,38	2,65				
	UTEE	0,78	0,00	0,67	1,49				
	UTEExTCB	0,12	0,53	0,44	2,28				
	UTEExTCC	0,07	0,70	0,33	3,06				
	UTEExTCI	-0,36	0,04	0,43	2,32				
	UTEExTE	0,06	0,73	0,37	2,73				

Regression of ADUS									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,98	n/a	n/a	0,08		0,01	0,01
	TCB	0,11	0,26	0,48	2,09				
	TCC	-0,11	0,34	0,39	2,59				
	TCI	0,14	0,15	0,47	2,12				
	TE	0,00	1,00	0,42	2,39				
	UTEE	0,21	0,02	0,75	1,34				
2	Constant	0,01	0,88	n/a	n/a	0,08	0,01	0,77	0,03
	TCB	0,12	0,26	0,46	2,20				
	TCC	-0,11	0,38	0,36	2,80				
	TCI	0,17	0,11	0,38	2,65				
	TE	-0,03	0,72	0,38	2,65				
	UTEE	0,19	0,04	0,67	1,49				
	UTEExTCB	-0,08	0,55	0,44	2,28				
	UTEExTCC	-0,04	0,77	0,33	3,06				
	UTEExTCI	-0,08	0,56	0,43	2,32				
	UTEExTE	0,15	0,22	0,37	2,73				

Table 45: Regression Results for Hypothesis H10, Betas

Regression of ADBI									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,95	n/a	n/a	0,39		0,00	0,00
	TCB	0,18	0,03	0,47	2,15				
	TCC	0,37	0,00	0,40	2,48				
	TCI	-0,22	0,00	0,48	2,10				
	TE	0,27	0,00	0,42	2,39				
	UTSI	0,08	0,14	0,84	1,19				
2	Constant	0,02	0,71	n/a	n/a	0,40	0,01	0,34	0,00
	TCB	0,20	0,02	0,43	2,30				
	TCC	0,36	0,00	0,36	2,82				
	TCI	-0,23	0,00	0,47	2,11				
	TE	0,27	0,00	0,41	2,44				
	UTSI	0,08	0,14	0,77	1,31				
	UTSIxTCB	0,04	0,64	0,42	2,36				
	UTSIxTCC	-0,05	0,60	0,31	3,20				
	UTSIxTCI	-0,01	0,88	0,44	2,26				
	UTSIxTE	-0,07	0,33	0,36	2,77				

Regression of ADUD									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,99	n/a	n/a	0,04		0,14	0,14
	TCB	-0,01	0,92	0,47	2,15				
	TCC	0,11	0,47	0,40	2,48				
	TCI	0,03	0,78	0,48	2,10				
	TE	0,07	0,52	0,42	2,39				
	UTSI	0,11	0,18	0,84	1,19				
2	Constant	-0,06	0,50	n/a	n/a	0,06	0,02	0,35	0,18
	TCB	0,03	0,83	0,43	2,30				
	TCC	0,01	0,93	0,36	2,82				
	TCI	0,05	0,70	0,47	2,11				
	TE	0,10	0,37	0,41	2,44				
	UTSI	0,08	0,39	0,77	1,31				
	UTSIxTCB	0,16	0,22	0,42	2,36				
	UTSIxTCC	-0,19	0,22	0,31	3,20				
	UTSIxTCI	0,00	0,97	0,44	2,26				
	UTSIxTE	0,13	0,23	0,36	2,77				

Table 45 (Continue): Regression Results for Hypothesis H10, Betas

Regression of ADUG									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,99	n/a	n/a	0,16		0,00	0,00
	TCB	0,49	0,00	0,47	2,15				
	TCC	0,29	0,07	0,40	2,48				
	TCI	-0,34	0,01	0,48	2,10				
	TE	0,12	0,35	0,42	2,39				
	UTSI	0,04	0,69	0,84	1,19				
2	Constant	-0,01	0,92	n/a	n/a	0,16	0,01	0,82	0,00
	TCB	0,52	0,00	0,43	2,30				
	TCC	0,24	0,17	0,36	2,82				
	TCI	-0,34	0,01	0,47	2,11				
	TE	0,14	0,31	0,41	2,44				
	UTSI	0,03	0,79	0,77	1,31				
	UTSIxTCB	0,11	0,48	0,42	2,36				
	UTSIxTCC	-0,12	0,49	0,31	3,20				
	UTSIxTCI	-0,11	0,41	0,44	2,26				
	UTSIxTE	0,08	0,51	0,36	2,77				

Regression of ADUS									
		Standardised Coefficients		Collinearity Statistics		Model Fit Statistics			ANOVA
Step	Variable	Beta	p-value	Tolerance	VIF	R^2	ΔR^2	p-value	p-value
1	Constant	0,00	0,97	n/a	n/a	0,07		0,01	0,01
	TCB	0,11	0,29	0,47	2,15				
	TCC	-0,04	0,72	0,40	2,48				
	TCI	0,11	0,23	0,48	2,10				
	TE	0,00	1,00	0,42	2,39				
	UTSI	0,13	0,04	0,84	1,19				
2	Constant	-0,05	0,47	n/a	n/a	0,10	0,03	0,25	0,01
	TCB	0,15	0,16	0,43	2,30				
	TCC	-0,12	0,31	0,36	2,82				
	TCI	0,12	0,19	0,47	2,11				
	TE	0,03	0,77	0,41	2,44				
	UTSI	0,10	0,13	0,77	1,31				
	UTSIxTCB	0,15	0,14	0,42	2,36				
	UTSIxTCC	-0,17	0,14	0,31	3,20				
	UTSIxTCI	0,01	0,93	0,44	2,26				
	UTSIxTE	0,10	0,21	0,36	2,77				