



ATTITUDE AND ACCEPTANCE OF ARTIFICIAL INTELLIGENCE TECHNOLOGIES IN THE SOUTH AFRICAN FINANCIAL SERVICES INDUSTRY

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ABSTRACT

Despite Artificial Intelligence (AI) being topical, the successful adoption of AI technologies within organisations has been slower than expected. Literature and past research highlights the mixed and contradictory views and findings regarding employees' attitude and acceptance of AI technologies, which challenge the successful implementation and use of AI technologies. Further, research on employees' attitude and acceptance of AI technologies in emerging market economies, such as South Africa, and specifically within mandatory settings is limited. The purpose of this research was to investigate and determine factors influencing employees' attitude and acceptance of AI technologies amongst employees within the financial services industry, where the use of AI technologies is mandatory. The Technology Acceptance Model (TAM) and the Technology-Organisation-Environment (TOE) framework were integrated and extended. This quantitative research study used a cross-sectional design. An online survey was distributed to employees within financial services organisations. A total of 410 valid responses were analysed using descriptive statistics, correlation analysis and regression analysis. Textual responses from the open-ended questions were categorised and presented visually in the form of word clouds. The research results indicate that each of the technological, individual, organisational, and environmental factors have a significant positive effect on attitude towards use of AI technologies. Multiple regression and stepwise regression analysis were used to identify the most influential determinants of attitude towards use of AI technologies from all the technological, individual, organisational and environmental factors. The results indicate that employee wellbeing, competitive pressure, perceived usefulness, management support, perceived ease of use, organisational justice and customer pressure are key determinants of attitude towards the use of AI technologies. The attitude-acceptance relationship is confirmed, as attitude towards use of AI technologies positively influences the acceptance of AI technologies. Although employees' job roles do not moderate the relationship between attitude and acceptance of AI technologies, their experience with using AI technologies does. Based on these findings the ITOE model for implementing AI technologies is developed, and can be used to facilitate the successful implementation and use of AI technologies. The implications of this research, as well as recommendations for organisations and future research are also discussed.

Keywords: *Technology Acceptance Model (TAM); Technological, Environmental, Organisational framework (TOE); Perceived ease of use, Perceived usefulness, Relative advantage; Organisational Justice; Employee Wellbeing, Management Support, Training support; Innovative Culture; Social Influence Customer Pressure, Competitive Pressure; Attitude; Acceptance; Experience; Job role.*

DECLARATION

I declare that this thesis is my own unaided work. It is submitted in fulfilment of the requirements for the PhD in Management at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: Ruth Rumbidzai Wotela

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Date: 30 August 2024

DEDICATION

This research is a dedication to my late mother, who, even when not physically present, continues to be my source of courage, motivation, and inspiration.

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I would like to thank God for giving me courage and strength throughout this challenging but also fulfilling process. I would not have been able to do this without you.

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CHAPTER 1: INTRODUCTION

1.1 Research background

The COVID-19 pandemic amplified the need to use digital technologies in many sectors across the world and forced individuals and businesses to rethink new ways of working and conducting businesses (Merhi & Harfouche, 2023; Mhlanga et al., 2022). Various businesses implemented digital technologies such as AI technologies to enable them to continue to carry out their business activities, service customers, as well as gain competitive advantage and survive during the pandemic (Bartolotta & Gritt, 2021; Siderska et al., 2023; Vasiljeva et al., 2021). As such, research on the application of AI technologies continues to grow (Ahn & Chen, 2022; Noreen et al., 2023), as these are being implemented in a variety of industries, processes, and functions (Gu et al., 2022; O'Shaughnessy et al., 2023). Organisations continue to be urged to find effective ways of preparing for, implementing and using AI technologies (Alsheibani et al., 2018; Bhargava et al., 2020; Füller et al., 2022; Strusani & Hounghonon, 2019).

However, the adoption and use of AI technologies within organisations has been slow (Sampene et al., 2022; Weinert et al., 2022). The continued debates, inconsistencies and conflicting views on understanding AI and its impact on businesses, productivity and employment are prevalent (Fast & Horvitz, 2017; Siderska et al., 2023; Tussyadiah & Miller, 2019). AI technologies are expected to provide both opportunities and challenges to individuals, businesses, the economy and society (Mehrotra, 2019; O'Shaughnessy et al., 2023; Strusani & Hounghonon, 2019). However, Floridi et al. (2018) caution against the underuse and/or misuse of AI technologies due to fear, lack of knowledge and misplaced concerns which may result in opportunity costs. Investigating, identifying and managing the drivers and barriers to the successful implementation and use of AI technologies will enable organisations to leverage the potential of AI (Chen et al., 2020; Damerji & Salimi, 2021).

To ensure the successful implementation and use of AI technologies within organisations, understanding employees' attitude and acceptance of the use of AI technologies is vital as the attitude and acceptance of employees towards AI technologies can either facilitate or hinder the successful implementation and use of AI technologies (Cao et al., 2021; Lichtenthaler, 2020; Siderska et al., 2023). The attitude and acceptance of a new technology are noted in literature as key determinants of the successful implementation and use of new technologies (Brown et al., 2002; Cao et al., 2021; Lichtenthaler, 2020; Linders, 2006; Nadal et al., 2019).

Although decisions to implement and use AI technologies in organisations are generally made by certain groups of people in the organisation such as IT professionals, AI experts and/or senior management, consideration should be given to all employees' attitude and acceptance of AI technologies, including employees who are the actual users of AI technologies and are directly impacted by its implementation and use (Jöhnk et al., 2020; Kar & Kushwaha, 2021; Sartori & Bocca, 2022).

Therefore, the purpose of this research is to investigate factors influencing the attitude and acceptance of AI technologies in mandatory settings, within an emerging market economy, from the perspective and experiences of employees across the different levels within organisation. Literature also shows that there is limited research and insight into employees' experience, attitudes and acceptance of AI related technologies and their role in the successful implementation AI technologies within organisations (Chiu et al., 2021; Malik et al., 2021; Siderska et al., 2023; Vasiljeva et al., 2021). This is because as the research on the implementation and use of AI related technologies is still developing and growing, there is a need for continued research to understand experiences, attitudes and acceptance of AI technologies (Haenlein & Kaplan, 2019; Siderska et al., 2023; Vasiljeva et al., 2021). Further, considering that the application and use of AI technologies in the financial services industry continues to grow (Khera et al., 2022; Noreen et al., 2023), and that the financial services industry is generally a significant contributor to the economy (Hanif, 2021; Zhang et al., 2021), this research is conducted within the financial services industry.

Given that AI technologies are complex (Chatterjee et al., 2021; Füller et al., 2022), the literature review indicates that the successful implementation, integration and use of AI technologies within organisations requires a holistic multidimensional approach (Biswas et al., 2020; Holmström, 2022; Nazareno & Schiff, 2021). This research therefore integrates and extends the Technology Acceptance Model (TAM) and the Technology-Organisation-Environment (TOE) framework to examine and determine individual, technological, organisational and environmental factors impacting the attitude and acceptance of AI technologies amongst employees in the financial services industry. This will provide guidance to the successful implementation and use of AI technologies, and enable organisations to leverage the potential of AI technologies.

1.2 Research context

Emerging market economies are developing countries experiencing a fast pace of economic growth and development, that have put in place policies to promote economic, political and social growth and stability (Hoskisson et al., 2000). They are differentiated from developed countries that are more industrialised and have higher per capita incomes (Kelley, 2019, p. 6). Most of the emerging market economies can be found in Asia, Latin America, Africa, the Middle East, and Central and Eastern Europe (Hoskisson et al., 2000)

Although literature provides potential benefits and challenges to implementing and using AI technologies in different contexts, there are also variations between developed and developing countries, as well as within emerging market economies (Arakpogun et al., 2021; Gwagwa et al., 2020; Hoskisson et al., 2000; Kelley, 2019; Kshetri, 2020). Therefore, understanding the specific context under investigation is key (Arakpogun et al., 2021; Gwagwa et al., 2020). In this case, an overview of the South African economy and the financial services industry is presented.

South Africa, one of the leading African emerging market economies has experienced increased technological innovation over the past few years (Gwagwa et al., 2020; Udeagha & Ngepah, 2022). However, as with most emerging market economies, South Africa is characterised by a number of socio-economic challenges such as high levels of inequality, unemployment, educational, training and infrastructural constraints (Ngoro et al., 2020; Rapanyane & Sethole, 2020; Schoeman et al., 2021; Van Rensburg et al., 2019). Implementing new technologies such as AI technologies is often perceived to be a threat to the already high levels of unemployment and inequality (Rapanyane & Sethole, 2020; Van Rensburg et al., 2019). The Quarter 3, Quarterly Labour Force Survey by Statistics South Africa (2023) indicates that although the unemployment rate has decreased over the past year by 1% (Q3:2022 vs Q3:2023), it is still high at 31.9%.

Despite these concerns raised, the use of AI technologies is also conversely seen as having the ability to reverse the current status of the economy and increase productivity in many industries (Magwentshu et al., 2019; Sampene et al., 2022). For example, Magwentshu et al.'s (2019) research on the future of work in South Africa indicate that although fears surrounding job losses in South Africa and globally are evident, a net gain of more than 1 million jobs by 2030 as a result of the use of AI technologies is projected.

According to Statistics South Africa (2023), the financial services industry is classified to entail financial intermediation, banks, insurance, pension funding, real estate, accounting, auditing and business services. This industry as shown in Table 1.1 continues to be the highest contributor to the country's GDP in South Africa (Statistics South Africa, 2023).

Table 1.1 Industry value added and GDP Q3, 2023

	Agriculture, forestry and fishing	Mining	Manufacturing	Electricity, gas and water	Construction	Trade, catering and accommodation	Transport, storage and communication	Finance, real estate and business services	General government services	Personal services	Total value added at basic prices	Taxes less subsidies	GDP at market prices
	R million												
2016	93 672	220 141	555 880	109 947	155 996	564 281	365 766	938 154	351 165	659 643	4 014 646	435 525	4 450 171
2017	111 545	225 420	554 833	110 275	147 076	556 707	369 580	961 364	356 086	668 356	4 061 243	440 458	4 501 702
2018	112 095	223 613	563 250	111 280	144 861	562 325	380 339	994 663	362 957	672 452	4 127 833	443 950	4 571 783
2019	104 785	222 100	559 322	107 571	139 986	559 935	378 211	1 016 210	367 515	681 249	4 136 884	446 783	4 583 667
2020	123 482	194 863	493 681	101 365	115 076	492 829	320 394	1 025 152	371 405	669 642	3 907 890	402 436	4 310 327
2021	132 672	218 196	526 711	103 295	112 718	523 439	336 408	1 050 933	371 538	705 466	4 081 378	431 666	4 513 044
2022	133 843	202 605	524 771	100 745	108 906	541 821	364 246	1 087 014	371 730	724 014	4 159 695	439 566	4 599 261

Source: Stats SA, 2023

Table 1.2 shows that the financial industry is the third highest contributor of total employment in the country and the second highest contributor to formal employment in South Africa (Statistics South Africa, 2023).

Table 1.2 Employment by industry

	Jul-Sep 2022	Oct-Dec 2022	Jan-Mar 2023	Apr-Jun 2023	Jul-Sep 2023	Qtr-to-qtr change	Year-on-year change	Qtr-to-qtr change	Year-on-year change
	Thousand	Thousand	Thousand	Thousand	Thousand	Thousand	Thousand	Per cent	Per cent
Total employed	15 765	15 934	16 192	16 346	16 745	399	979	2,4	6,2
Formal and informal sector (non-agricultural)	13 805	13 933	14 248	14 358	14 674	315	868	2,2	6,3
Mining	407	436	413	444	409	-35	2	-7,8	0,5
Manufacturing	1 630	1 656	1 654	1 558	1 508	-50	-123	-3,2	-7,5
Utilities	116	124	135	129	113	-16	-3	-12,5	-2,9
Construction	1 223	1 212	1 201	1 304	1 357	53	134	4,1	11,0
Trade	3 245	3 297	3 269	3 361	3 390	29	145	0,9	4,5
Transport	939	982	992	986	966	-20	27	-2,0	2,9
Finance	2 380	2 484	2 667	2 599	2 836	237	456	9,1	19,1
Community and social services	3 849	3 727	3 902	3 965	4 084	119	235	3,0	6,1
Other	15	15	15	12	10	-2	-5	-15,5	-30,3
Formal sector (non-agricultural)	10 835	10 977	11 186	11 329	11 616	287	781	2,5	7,2
Mining	399	427	402	431	404	-27	5	-6,4	1,3
Manufacturing	1 410	1 440	1 423	1 371	1 300	-70	-109	-5,1	-7,7
Utilities	103	120	128	120	108	-12	5	-10,0	4,7
Construction	767	753	747	808	930	122	163	15,1	21,3
Trade	2 078	2 177	2 133	2 204	2 192	-12	114	-0,6	5,5
Transport	623	641	637	675	631	-45	8	-6,6	1,3
Finance	2 108	2 162	2 319	2 290	2 521	230	413	10,1	19,6
Community and social services	3 335	3 245	3 383	3 418	3 519	101	184	3,0	5,5
Other	12	13	13	11	10	0	-2	-2,6	-14,8
Informal sector (non-agricultural)	2 971	2 955	3 062	3 029	3 058	29	87	0,9	2,9
Mining	8	10	11	12	5	-7	-3	-59,1	-38,5
Manufacturing	221	216	231	187	207	20	-13	10,7	-6,1
Utilities	13	4	7	9	5	-4	-8	-45,0	-62,3
Construction	456	458	454	496	427	-69	-29	-13,9	-6,4
Trade	1 167	1 120	1 136	1 157	1 199	42	32	3,6	2,7
Transport	316	341	355	310	335	25	19	8,0	6,0
Finance	273	322	348	309	315	7	43	2,1	15,6
Community and social services	514	482	519	547	565	17	51	3,2	9,9
Other	3	2	3	2					
Agriculture	873	860	888	894	956	61	83	6,8	9,5
Private households	1 088	1 142	1 056	1 093	1 116	22	28	2,0	2,6

For all values of 10 000 or lower, the sample size is too small for reliable estimates.
Due to rounding, numbers do not necessarily add up to totals.

Quarterly Labour Force Survey, Quarter 3: 2023

Source: Stats SA, 2023

As the digitalisation, automation and use of AI technologies is growing in South Africa (Gwagwa et al., 2020; Sampene et al., 2022; Schoeman et al., 2021), the Q3 Quarterly Labour Force Survey by South African Statistics (2023) indicates that the finance, construction and services industries continue to experience positive employment growth as illustrated in Figure 1.1. This aligns with Magwentshu et al.'s (2019) prediction that although digitalisation and the use of AI related technologies is expected to create more jobs in South Africa, this is likely to not be the case for all industries. For example, they predicted that in the manufacturing and retail industries, the jobs lost are likely to outnumber the job created, compared to the construction, finance, community and social services industries (Magwentshu et al., 2019).

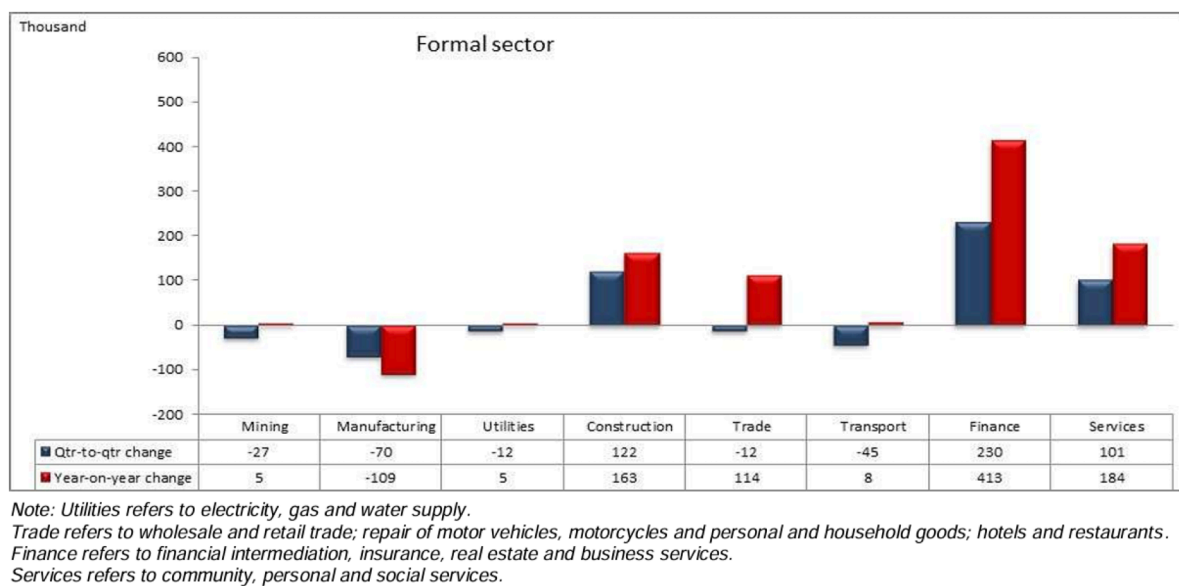


Figure 1.1 Employment changes in the formal sector by industry

Source: Stats SA, 2023

The financial services industry is generally known to adopt new technologies early (Mogaji & Nguyen, 2021), and as such, the use of AI technologies is growing in this industry (Kurshan et al., 2021; Mogaji & Nguyen, 2021). Non-traditional financial services institutions such as Fintech companies and Insurtech companies are using AI technologies to bring innovative business models, applications, products and processes to the market, which are appealing to customers (Flavián et al., 2021; Gupta et al., 2022; Khera et al., 2022; Strusani & Hounghonon, 2019). This, together with the expectations from customers for more convenient products, services and personalisation (Nam et al., 2020; Payne et al., 2018), puts traditional financial services organisations under pressure to adopt the use of AI technologies and be able to

effectively compete in the industry, service customers and keep growing their businesses (Hentzen et al., 2021; Kheira, 2021; Pillai et al., 2021).

1.3 Research problem

While research on attitude and acceptance of AI technologies is growing, the findings have been contradictory and inconclusive (Cao et al., 2021; de Saint Laurent, 2018; Siderska et al., 2023). Pereira et al. (2021) and Kelly et al. (2023) also argue that although research on the implementation and use of AI technologies is growing, it has focused more on specific levels of analysis, disciplines and functions, resulting in inconsistent research, views and experiences of the impact of AI. If the paradoxes, uncertainties, conflict, concerns and complexities surrounding the use and impact of AI technologies are not identified, attended to or managed, they are likely to impact the organisation's ability to successfully implement and use AI technologies, and have an unfavourable impact on employees and the organisation as a whole. As such, there is a need for continued research on the adoption of AI technologies to provide better understanding of the successful implementation and use of AI technologies (Cao et al., 2021; Füller et al., 2022; Ghislieri et al., 2018; Siderska et al., 2023).

The conflicting views towards AI technologies can be summed as follows. The optimistic view postulates that AI will have a positive impact on customer experience, employee experience, job creation, productivity and performance of employees and businesses (Lane & Saint-Martin, 2021; Pereira et al., 2021; Tussyadiah & Miller, 2019). On the other hand, the pessimistic view focuses on concerns of potential job losses as well as the negative impact that AI may have on employees' wellbeing, work relationships, privacy, ethics, and fairness, which causes apprehension towards the use of AI technologies (Lane & Saint-Martin, 2021; Pereira et al., 2021; Tussyadiah & Miller, 2019). However, this view has been criticised by some researchers for overestimating AI's potential to be destructive and negatively impact employment, employee wellbeing and society at large (Wei & Li, 2022).

These differing views are due to number of factors that are contributing to the uncertainty, confusion and complexity towards the implementation, integration, and use of AI technologies. First, there is limited understanding on what AI is (Kelly et al., 2023; Ndoro et al., 2020). Second, there is also uncertainty of what AI can do in practice versus theory (de Saint Laurent, 2018; Dwivedi et al., 2021). Third, as noted by Webster & Ivanov (2020) the opinions of experts, who are meant to be providing understanding and guidance towards AI, its

implementation and use are not consistent. Some of the experts demonstrate fear and uncertainty towards the use of AI, while others view AI to be capable of solving most problems (Webster & Ivanov, 2020). These factors influence the views, expectations, attitude and acceptance of AI technologies and contribute to the divide between those that accept and those that resist the use of AI technologies.

As AI adoption in organisations is growing, management needs to be mindful of employees' attitude and acceptance of AI technologies and not underestimate their impact on the successful implementation and use of AI technologies (Vasiljeva et al., 2021). This is especially important given that some researchers have found that negative attitudes are more common than positive attitude (Lichtenthaler, 2020; Roberts et al., 2021).

Further, technology acceptance theories and models have investigated and measured the success of implementing a new technology based on the usage of the technology (Davis et al., 1989; Hwang et al., 2016). Although this may be valid when the use of technology is voluntary, in mandatory settings, where management makes the decision for employees to use a new technology, measuring usage of a new technology is a tick box exercise and pointless because employees in these settings have no choice but to use the new technology (Brown et al., 2002; Hwang et al., 2016). In such mandatory settings, measuring behavioural aspects that determine the continued, extended and effective use of technology is more valuable (Brown et al., 2002; Po-An Hsieh & Wang, 2017).

Failure to be aware of employees' attitude towards the use of AI technologies, as well as failure to manage and facilitate the acceptance of AI technologies would inhibit employees and organisations from leveraging the potential of AI and result in an opportunity cost (Floridi et al., 2018). Employees' resistance to new technology in mandatory settings is seen to contribute to destructive and counterproductive behaviours impacting negatively on the organisations performance (Hwang et al., 2016).

Unlike other technologies that have been implemented in the past, AI is said to be a complex technology in nature, implementation and use (Chatterjee et al., 2021; Hanif, 2021; O'Shaughnessy et al., 2023). A multidimensional approach that takes a holistic and comprehensive analysis of factors that could impact the successful implementation and use of AI technologies is needed (Freeman et al., 2021; Holmström, 2022; Phuoc, 2022).

Research on the attitude, acceptance, implementation and use of AI technologies has not only been limited but has mostly been conducted in developed than in developing countries (Ahmad et al., 2020; Georgieff & Hyee, 2022). This is because in most developing countries or emerging market economies including South Africa, although the use of AI technologies is growing, it is still in its early stages (Tjebane et al., 2022). Developing countries have often lagged behind developed countries and often replicate what is done in developed countries (Carbonero et al., 2021). Manda and Dhaou (2019) and Arakpogun et al. (2021) argue against a copy and paste approach from developed countries and instead promote a more problem driven approach that is relevant to the contextual situation, problems and needs of developing countries.

In addition, most of the available literature investigating the adoption, attitude and acceptance of AI technologies within organisations has mostly been conducted from the perspective of management, IT senior professionals and/or AI experts, who are the typically AI decision makers (Kar & Kushwaha, 2021). As a result, the views of other groups of employees are limited. The focus on a certain group or limited groups of employees in the organisation when investigating attitude and acceptance of AI technologies creates a biased view of the adoption, attitude, and acceptance of AI technologies.

1.4 Research objectives

The main objective of this research is to investigate and determine factors influencing employees' attitude and acceptance of AI technologies within mandatory environments, and develop a model that can be used to ensure successful implementation and use of AI technologies in organisations. This main objective is broken down into the following five objectives.

1. By integrating and extending the Technology Acceptance Model (TAM) and the Technology-Organisation-Environment (TOE) framework, the first objective is **to analyse the extent to which the individual, technological, organisational, and environmental factors independently influence employees' attitude towards the use of AI technologies in the financial services industry in South Africa**. Factors identified from the literature review as influencing employees' attitude towards AI technologies will be analysed and their effect on employees' attitude towards the use of AI technologies will be investigated within the context of the financial services industry in South Africa.

2. The second objective is **to determine which technological, individual, organisational, and environmental factors are the most influential determinants of employees' attitude towards the use of AI technologies.** This multidimensional approach will enable the analysis and identification of comprehensive and crucial factors contributing to employees' attitude towards the use of AI technologies, which need to be prioritised and addressed to ensure the successful implementation and use of AI technologies. This will also enable management to proactively put in place and apply relevant strategies and processes to effectively manage these factors when implementing and using AI technologies.
3. The third objective is **to investigate the extent to which employees' attitude towards the use of AI technologies influences their acceptance of AI technologies.** Not only has the attitude-acceptance relationship in technology acceptance research been inconsistent (Sun & Zhang, 2006; Venkatesh et al., 2003), the role of employees' attitudes when implementing a new technology in mandatory settings also been contested (Hwang et al., 2016). Employees' attitudes are particularly important within corporate and mandatory environments where although the initial decision to adopt AI technologies is generally made by management and IT experts (Kar & Kushwaha, 2021), the successful implementation, integration and use of the AI technologies depends on employees' attitudes and acceptance of AI technologies (Jöhnk et al., 2020; Lichtenthaler, 2020; Malik et al., 2021). The significance of the attitude construct in technology acceptance research will therefore be investigated.
4. The fourth objective is **to investigate the moderating effect of factors such as employees' job role and employees' experience with using AI technologies on the attitude-acceptance relationship.** Literature notes that although all job roles will be impacted in one way or the other by the use of AI technologies, jobs will be impacted differently, which would influence employees' attitudes and acceptance of AI technologies (Georgieff & Hyee, 2022; Gnambs & Appel, 2019; Lichtenthaler, 2020). This is because in some instances, the use of AI technologies may be considered a threat to employee's role identity and job security (Ivanov et al., 2020; Strich et al., 2021). Experience with using AI technologies has also been shown to influence attitudes and acceptance of AI technologies (Horowitz & Kahn, 2021; Lichtenthaler, 2020; Robb et al., 2020). Therefore, the research set-out to investigate the extent to which these two moderating variables impact the relationship between attitude and acceptance of AI technologies.

5. The fifth objective of this research **is to use the research findings to develop a model that can be used to facilitate the successful implementation and use of AI technologies within organisations.** This is especially relevant in emerging market economies such as South Africa given that the adoption of AI is still limited (Tjebane et al., 2022). This model can provide guidelines to enable organisations to leverage the potential of AI.

1.5 Significance of research

This research is significant in the following ways. First, considering the limited research on attitude and acceptance of AI related technologies in emerging market economies (Ahmad et al., 2020; Georgieff & Hyee, 2022), This research aims to fill the research gap by conducting research within the context of an emerging market economy. In so doing, this research will provide insight on factors impacting attitude towards the use of AI technologies and the acceptance of AI technologies within this context. This will also assist in addressing the inconsistencies and mixed views on the perceptions, expectations, attitude and acceptance of AI technologies, which are causing anxiety and uncertainty regarding the use of AI technologies (Arakpogun et al., 2021; Magwentshu et al., 2019).

Second, research on AI has largely focused on AI techniques, tools, methods, and as well as the technical and theoretical definitions and assessments of fairness, in order to contribute to the accuracy, transparency and robustness of AI algorithms (Freeman et al., 2021; Hanif, 2021; Kurshan et al., 2021). Ndoro et al. (2020) indicate that in South Africa for example, research on the use of AI technologies in the financial services industry focuses more on the application of specific AI technologies or specific algorithms applied to solve a specific financial related problem. This research is not specialised or technical as most previous research have been, and focuses on contributing to research on employees' attitude and acceptance of AI technologies, which is key to the successful implementation and use of AI technologies.

Third, past research has recommended the need to consider psychological factors such as an individuals' perceptions, emotions and wellbeing when investigating attitudes and acceptance of AI technologies (Flavián et al., 2021; Ghislieri et al., 2018; Na et al., 2022; Nazareno & Schiff, 2021; Wei & Li, 2022). By integrating and expanding the TAM-TOE framework to include factors such as perceptions of organisational justice and employee wellbeing, this research contributes to research on how technology adoption and acceptance models can be

expanded to incorporate perceptions of fairness, wellbeing and psychological factors when investigating the adoption, attitude and acceptance of AI technologies.

Fourth, studies investigating attitude and acceptance of AI technologies tends to focus mostly on views from the general public (Fast & Horvitz, 2017; Kelley, 2019; Roberts et al., 2021), management and IT experts (Bartolotta & Gritt, 2021; Füller et al., 2022; Ndoro et al., 2020) and customers (Belanche et al., 2019; Flavián et al., 2021). Limited research on the views and factors influencing the adoption of AI technologies across different employees in the organisation is evident (Kar & Kushwaha, 2021; Siderska et al., 2023). The views of employees, who are the main users of the AI technologies in corporate and mandatory settings are often limited. This research therefore addresses this shortcoming by extending the research participation on attitude and acceptance of AI technologies to employees across the various job levels and job roles, in corporate and mandatory settings within the South African financial services industry.

Fifth, debates in literature on the significance of the attitude construct in technology acceptance research, have resulted in some researchers excluding the attitude construct in technology acceptance research (Bhattacharjee et al., 2018; Hwang et al., 2016; Sun & Zhang, 2006). This research aims to contribute to this debate by exploring the role and significance of the attitude constructs in technology acceptance research, specifically in mandatory settings.

Sixth, given that most technology adoption and acceptance research focuses on attitude and acceptance of a new technology during the initial usage stage, the behavioural factors influencing the continued, extended and efficient use of AI technologies beyond its standard and routine use is rarely considered (Kim & Crowston, 2011; Po-An Hsieh & Wang, 2017). This is especially important in mandatory settings where employees may initially reluctantly use AI technologies because they have to, resulting in the minimum use of AI and failure to leverage the potential of AI technologies adopted in the organisation. By expanding the definition of acceptance of technology to include behaviours that demonstrates the continued use of the technology beyond its mandated use, this research expands the meaning of technology acceptance especially within mandatory settings.

Lastly, this research is significant because of the context of the research, specifically the fact that the research is conducted within the financial services industry. As discussed earlier, the

financial services industry is one of the primary drivers of South Africa's economy. By providing financial services organisations with a model to use when implementing and using AI technologies, these organisations will be more enabled to leverage the potential of AI and continue to contribute significantly to South Africa's economy.

1.6 Definition of terms

Based on the literature review conducted as well as the objective of the research, the following terms are defined in the context of this research. Specific reference and acknowledgement to these definitions is made in the thesis.

- Artificial Intelligence (AI) - refers to advanced technologies that can sense, comprehend, act, learn and perform tasks normally performed humans in order to enhance individual and organisational performance.
- AI technologies - within the context of financial services industry, refers to advanced technologies used to intelligently automate various business processes; to analyse data and make recommendations and predictions; to gain insights on data; to authentic users; to monitor transactions (e.g., fraud detection) and to engage with customers (e.g., chatbots/virtual assistants)
- Acceptance of AI technologies – the extent to which employees express openness, willingness and commitment to integrate and embrace AI technologies in their way of working, and continue to use and learn more about AI technologies
- Attitude towards use of AI technologies – the extent to which employees are positive or negative towards the use of AI technologies
- Customer pressure – the extent to which employees perceive that the pressure to implement and use AI technologies within the organisation comes from customers
- Competitive pressure - the extent to which employees perceive that the pressure to implement and use AI technologies within the organisation comes from competitors
- Employee wellbeing – the extent to which employees think or feel that using AI technologies will contribute more to their job satisfaction, career development, engagement with others and autonomy, and less to their work-related stress, anxiety and feelings of job insecurity
- Experience – employees' exposure and practical experience with using AI related technologies in doing their work
- Financial services organisations – includes banks, insurance companies, asset management companies, wealth management companies, financial advisory companies

and organisations involved in regulation, compliance and risk management within the financial services industry

- Innovative culture – the extent to which employees feel that their organisation’s culture is innovative and promotes collaboration, openness, agility, flexibility and is capable of effectively implementing AI technologies in their way of working
- Job role – the functions or roles fulfilled by employees in the organisation
- Management support – the extent to which employees feel that management provides sufficient guidelines on the use of AI technologies, access to training, resources and software as well opportunities for employees to provide feedback on the use of AI technologies
- Mandatory settings – environments where AI experts and management/decision makers make the decision to implement AI technologies within the organisations, and employees within the organisations are mandated to use the AI technologies implemented
- Organisational justice – the extent to which employees perceive fairness in the procedures, processes, communication, and treatment they receive, throughout the implementation and use of AI technologies
- Perceived ease of use - the extent to which employees perceive AI technologies to be user friendly and easy to use
- Perceived usefulness – the extent to which employees feel that the AI technologies are useful in improving their performance
- Relative advantage –the extent to which using AI technologies is perceived to provide additional benefits over its alternative as well as current and/or previous technologies used.
- Social influence –the extent to which others' positive beliefs about the use of AI technologies influences employees’ attitude towards the use of AI technologies.
- Training support – the extent to which employees feel that there is sufficient training provided to help them understand AI, be more comfortable and confident when using AI technologies as well as be more receptive towards the use of AI technologies
- Voluntary setting - environments where users of a new technology have a choice to accept to reject the new technology implemented

1.7 Structure of the research report

Chapter 1 introduced the research topic, while highlighting some of the debates, inconsistencies and research gaps in literature that warrant this research on attitude and acceptance of AI technologies. The context for this research, as well as the objectives of this research were ascertained.

Chapter 2 provides a literature review of artificial intelligence and technology acceptance theories and models used to investigate the adoption, attitude and acceptance of new technologies such as AI. The AI paradoxes that exist for both businesses and employees when using AI technologies are highlighted. A conceptual framework is developed by integrating and extending the TAM and TOE framework with factors identified to be impacting the attitude and acceptance of AI technologies from the literature review. Hypotheses to be tested are formulated. The research questions and research model are presented.

Chapter 3 details the research methodology applied in carrying out the research. An overview of the research instrument for the survey conducted is presented. Ethical considerations and measures considered and taken to ensure research and data quality are discussed. The analysis of data collected is described and limitations with this research are noted.

Chapter 4 is a presentation of the research results. The research results from the descriptive and inferential analysis of the data collected are presented. Data collected is used to analyse each factor included in this research, and the results from testing each hypothesis are presented. A discussion of these research results is provided in Chapter 5, and each research question is addressed. In addition, based on the research findings, a model that provides guidelines to the successful implementation, integration, and use of AI technologies is presented. Chapter 6 concludes by summarising the research findings, discussing the theoretical implications and practical contributions of the research and making recommendations for future research.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This chapter provides a literature review of attitude and acceptance of artificial intelligence (AI) and technology adoption and acceptance theories that will inform the development of a conceptual framework used to address the research questions identified from the gaps and/or inconsistencies in literature. To begin with, an overview of AI, and its application in the financial services industry and emerging market economies is presented. This is followed by a discussion of the AI paradoxes for both businesses and employees, highlighting opportunities and challenges of using AI technologies. Important to note is that this chapter is not intended to provide an all-encompassing review of AI technologies. It however highlights the main applications of AI in financial services, as well as debates on the use of AI technologies that influence attitude and acceptance of AI technologies.

The chapter then provides a review of the technology adoption and acceptance models and theories. Given that this research is conducted within corporate organisations where the use of new technologies is mandated, a discussion on the mandated use of technology in organisations is provided. Based on the literature review, a conceptual framework is presented, which includes factors expected to influence attitude and acceptance of AI technologies. Hypotheses to be tested are formulated. The chapter then concludes with a research model depicting the proposed relationship between these factors as well as the linkage between the research questions and the hypotheses.

2.2 Artificial Intelligence technologies

Artificial intelligence (AI) technologies have been described as one of the most distinguishable features of the 4th and 5th Industrial Revolution (Ali et al., 2022). Industrial revolutions refer to the fundamental changes in production processes, technological innovation of how work is done, the replacement of manual labour with automated tools, as well as the changes in how humans live and work (Ali et al., 2022). Despite debates on the number of revolutions and the period of when they started or ended, Table 2.1 below is a summary of the most notable characteristics and timelines of the different industrial revolutions constructed from Ali et al. (2022), Mourtzis (2021), Sarfraz et al. (2021) and Wisskirchen et al. (2017). While Ali et al. (2022) note the anticipation and uncertainty of when and what the fifth revolution entails, Sarfraz et al. (2021) have asserted that some countries are already at the verge of the fifth

industrial revolution as they started experiencing some of the key characteristics of this industrial revolution since the COVID-19 pandemic in 2020.

It should be noted that most of the features experienced with recent industrial revolutions to date as noted below are more notable in developed countries where there has been continued advancements made in terms of automation and digitalisation compared to emerging market economies that are lagging behind as they not that do not have sufficient access to these advancements and innovations (Ali et al., 2022; Sarfraz et al., 2021; Wisskirchen et al., 2017). The technology inequality and digital divide between developed countries and developing countries, as well as within these countries is still prevalent (Ali et al., 2022; Ghaleb et al., 2021). Gwagwa et al. (2020) for example, note the gender digital divide that is persistent in African countries as women have less internet access compared to men.

Table 2.1 Industrial revolutions

	REVOLUTION	EMERGENCE	CHARACTERISTICS
<i>Industry 1.0 Mechanical production</i>	1 st Industrial Revolution	1780	• Mechanisation of production • Transition from an agricultural and handicraft economy to machine manufacturing • Water and steam power • Economies of scale
<i>Industry 2.0 Mass production</i>	2 nd Industrial Revolution	1870	• Use of new materials, and energy sources such as coal, steam engine, petroleum, and electricity. • Growth of management programs and scientific principles such as division of labour; mass production of good utilizing assembly line and quick and lean production principles in order to increase performance, efficiency and output
<i>Industry 3.0 Automated production</i>	3 rd Industrial Revolution	1970	• Advancement of electronic and mechanical analog devices to the digital technology, e.g. personal computers, the Internet, and information and communication technology • Global access to information • Computerisation of repetitive and routine tasks
<i>Industry 4.0 Digital transformation</i>	4 th Industrial Revolution	2011	• Technologies merging the physical, digital, biological worlds. • Prominent tools include, nanotechnology, robots, artificial intelligence, internet of things, self-driving cars, mobile phones, bitcoins and blockchain, smart clothes, implantable technologies • Power sources – electrical, renewable, fossil-based fuels • Renewable power sources
<i>Industry 5.0 Smart society</i>	5 th Industrial Revolution	2020	• High dependency on data, digital devices, artificial intelligence and the virtual space • Limited barriers between the natural and virtual worlds • Advanced technologies that are faster and more scalable • Collaboration between machines and humans • Automation, and efficiency, with a personal human touch • Increased generation of value added goods/products • Mass customization and personalisation for humans • Power sources – electrical and renewable power sources

Table constructed from Ali et al. (2022), Mourtzis (2021), Sarfraz et al. (2021) and Wisskirchen et al. (2017)

The concept of AI was established by John McCarthy and colleagues in 1955 (Kaplan & Haenlein, 2019; Payne et al., 2018). AI has not been clearly defined and there is no consensus on the definition yet (Fast & Horvitz, 2017; Freeman et al., 2021; Kelley, 2019), resulting in the use of various definitions being used to define AI. AI encompasses many different technologies which may be the reason why it is defined differently (Wang & Siau, 2019). In addition, Vasiljeva et al. (2021) state that variations in the definition of AI are sometimes based on the perceived objective or expectation of AI, for example, whether the objective is to define machine's ability to find solutions to complex problems or whether the objective is to provide a comparison with human performance. Table 2.2 provides some of the definitions of Artificial Intelligence in literature.

Table 2.2 Definitions of AI

Author	Definition
Wisskirchen et al. (2017, p.10)	Work processes of machines that would require intelligence if performed by humans
Dwivedi et al. (2019, p. 2)	The ability of machines to perform specific roles and tasks currently performed by humans within the workplace and society in general
Kaplan and Haenlein (2019, p. 17)	A system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation
Organisation for Economic Co-operation and Development (OECD) (2019, p. 1)	A machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments
Webb (2019, p. 2)	Artificial intelligence, or machine learning, refers to algorithms that learn to complete tasks by identifying statistical patterns in data, rather than following instructions provided by humans
Kaur et al. (2020, p. 578)	AI is simulation of human intelligence in machines...which helps to build smarter machines capable of doing human work in a smart way
Ryan (2020, p. 2751)	Intelligence that is differentiated from natural intelligence as it is artificial or machine intelligence. Refers to systems that can facilitate complex tasks, and can process information in a similar way to humans
Hanif (2021, p.3)	AI enables machines to learn from human experience, adjust to new inputs, and perform human-like tasks
Nazareno and Schiff (2021, p. 7)	In the context of human work, it refers to its potential to simulate or computerize human tasks and capacities (including cognitive and social-emotional ones) previously thought unique to humans
Schoeman et al. (2021, p. 5)	Comprises of different technologies that can be combined in different ways to sense, comprehend, act, and learn
Georgieff and Hyee (2022, p.2)	AI refers to computer software that relies on highly sophisticated algorithmic techniques to find patterns in data and make predictions about the future

Considering these definitions, AI technologies have been differentiated from traditional information technologies or automation solutions (Damerji & Salimi, 2021; Neumann et al., 2022). For the purposes of this study, AI is used to refer to advanced technologies that can sense, comprehend, act, learn and perform tasks normally performed humans in order to enhance individual and organisational performance. The following is an overview of the different types of AI technologies.

2.2.1 Types of AI technologies

AI has been classified in different ways. AI researchers distinguish between strong and weak AI (Mpu & Adu, 2019; Wisskirchen et al., 2017). Weak AI is referred to as the development of algorithms where computers simulate human intelligence through replicating observed behaviour (Mpu & Adu, 2019; Wisskirchen et al., 2017). Strong AI on the other hand is described as machines having the ability to exceed human intelligence, self-learn, and optimise their own behaviour (Mpu & Adu, 2019; Wisskirchen et al., 2017).

Kaplan and Haenlein (2019) and Ryan (2020) discuss another classification of AI in terms of artificial narrow intelligence (AI systems that can only perform a specific, defined and limited tasks using human-like capabilities but are unable to solve problems autonomously in other areas); artificial general intelligence (AI technologies that can learn, reason, understand, and function like a human being and can solve problems autonomously in other areas) and artificial super intelligence (AI systems with greater memory, faster data processing and analysis, problem solving and decision-making capabilities compared to humans in all areas).

Figure 2.1 below was constructed based on literature on the developments, application and types of AI technologies, which includes machine learning (Ahn & Chen, 2022; Kaplan & Haenlein, 2019), natural language processing (Ahn & Chen, 2022; Boyd & Holton, 2018), computer vision, robotic/intelligent process automation (Hofmann et al., 2020; Siderska et al., 2023), speech recognition (Ahn & Chen, 2022; Boyd & Holton, 2018), expert systems (Kaplan & Haenlein, 2019; Rzepka & Berger, 2018), virtual agents (Hofmann et al., 2020; Siderska et al., 2023), robotics (Boyd & Holton, 2018; Robb et al., 2020) and autonomous systems (Ahn & Chen, 2022; Rzepka & Berger, 2018).

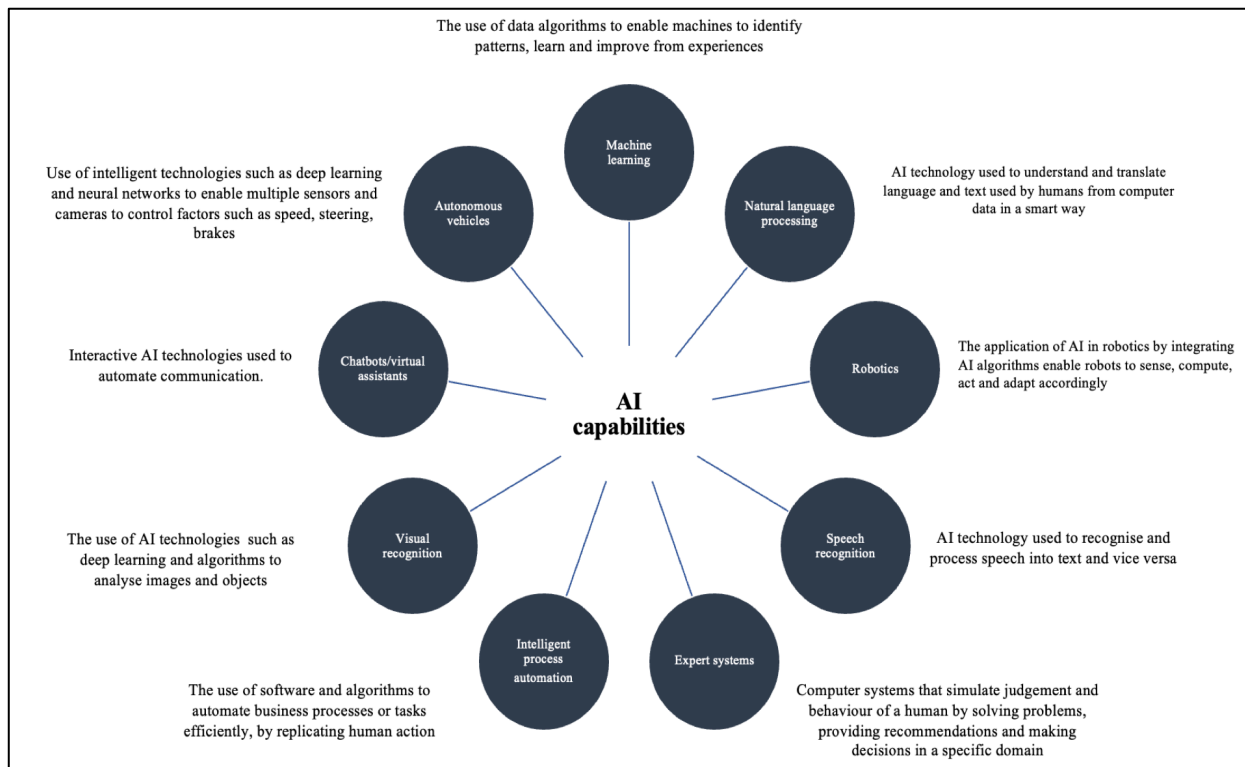


Figure 2.1 Types of AI technologies

2.2.2 AI in Emerging market economies

The growth in interest and use of AI technologies is evident not only in developed countries, but also in developing or emerging market economies (Arakpogun et al., 2021; Sampene et al., 2022). As a result, research on AI in emerging market economies is growing, even though it is still limited compared to developed countries (Ahmad et al., 2020; Carbonero et al., 2021; Georgieff & Hyee, 2022). Specific research that is practical and relatable to emerging market economies is therefore encouraged.

In emerging market economies such as South Africa, AI is expected to have the potential of improving productivity, efficiency, employment, quality of lives, financial inclusion, while providing broader services and solutions to diverse communities (Arakpogun et al., 2021; Khera et al., 2022; Strusani & Hounghonon, 2019). Arakpogun et al. (2021) and Sampene et al. (2022) also note the growth of research, implementation and use of AI in various industries that is emerging in Africa through the establishment of AI research hubs and AI technology start-up companies.

Inconsistencies in the research on attitudes and acceptance of AI in emerging market economies are apparent. Research by Kolbjørnsrud et al. (2017) and by Kelley et al. (2019) on perceptions,

attitudes and acceptance towards AI technologies indicates excitement, optimism, and receptiveness towards AI from respondents in developing countries, compared to those from developed countries. Kolbjørnsrud et al. (2017) note that this could be because of the need and pressure from those in emerging market economies to catch up with global trends and be competitive. In contrast Mogaji and Nguyen (2021) find that participants from developed countries are more confident and optimistic towards AI whereas those from developing countries were more pessimistic towards AI technologies. Given the limited understanding and misconception of AI that is highlighted in research within developing countries, for example, by Mogaji and Nguyen (2021) as well as previous studies by Ndoro (2020), the research findings on attitude towards use of AI technologies in emerging market economies should be interpreted with caution.

Past research identified and discussed factors contributing to the resistance and the slow uptake of AI in emerging market economies (Arakpogun et al., 2021; Sampene et al., 2022). These include concerns regarding the limited availability of AI skills, inadequate infrastructure, concerns of data quality, privacy and security, fear and lack of trust of AI, possible job losses, and limited transparency, accountability and regulation regarding of the use of AI (Arakpogun et al., 2021; Gwagwa et al., 2020; Sampene et al., 2022; Strusani & Hounbonon, 2019). Dwivedi et al. (2021) note that developed countries are likely to benefit from the use of AI technologies and experience job creation compared to emerging market economies where the use of AI technologies is likely to displace millions of jobs. In addition, due to the limited regulation when using AI technologies, concerns around data privacy and cybersecurity issues are also a concern (Sampene et al., 2022; Strusani & Hounbonon, 2019). However, the extent to which these factors and concerns impact attitude and acceptance of AI technologies, and the successful implementation and use of AI technologies in emerging market economies is still unclear.

Overall, despite some inconsistencies in research, as well as concerns regarding the use and impact of AI in emerging market economies, AI is seen to be capable of positively driving digital transformation in the emerging markets' economic, political and social landscape (Sampene et al., 2022; Strusani & Hounbonon, 2019). As such, Arakpogun et al. (2021), Gwagwa et al. (2020) and Manda and Dhaou (2019) note that emerging market economies need to focus on developing models and strategies relevant to their context that will enable them to leverage the potential of AI and avoid continuing to lag behind developed countries. Further,

Gupta et al. (2022) emphasise the need for developing countries to adopt AI technologies in order for them to be able to meet modern standards and keep up with technological advances in developed countries.

2.2.3 Application of AI in the financial services industry

Over the past decade, the use of AI has gained significant interest in the financial services industry as the need to digitise and intelligently automate process and leverage the potential of AI continues to grow (Adeleye et al., 2019; Kruse et al., 2019; Kurshan et al., 2021). Financial services organisations have a lot of valuable customer and transactional data constantly being collected and processed (Fernández, 2019; Kruse et al., 2019; Manser Payne et al., 2021; Thowfeek et al., 2020). AI technologies makes it possible to process and generate insights from this large amount of data, as well as develop algorithms that can be used to make decisions and predictions (Biswas et al., 2020; Hanif, 2021; Kruse et al., 2019).

In the financial services industry, AI related technologies have been implemented in core business processes throughout the front office, middle office and back office in various functions such as product development, investment management, trading, marketing, customer engagement, credit services and risk management (Fernández, 2019; Kaur et al., 2020; Kurshan et al., 2021; Lui & Lamb, 2018; Ndoro et al., 2020). Gupta et al. (2022) and Noreen et al. (2023) state that as businesses recover from the COVID-19 pandemic and rearrange their processes and ways of working, while focusing on reducing costs and broadening the services they offer their customers, the use of AI in financial services organisations continues to grow especially in the insurance and banking sector respectively.

The use of AI technologies in the financial services industry is anticipated to improve the overall performance of business by increasing operational efficiency and revenue, facilitating proactive and effective decision making, enhancing the customer experience as well as reducing operational costs (Biswas et al., 2020; Lui & Lamb, 2018; Mehrotra, 2019; Parker & Appel, 2021; Waliszewski & Warchlewska, 2020). AI technologies are expected to replicate and exceed the human performance in collecting and analysing data to identify the patterns and making more accurate predictions for the future that will enhance efficiency (Fernández, 2019; Füller et al., 2022; Hubbard & Rogers, 2019; Mehrotra, 2019). Overall, the use of AI

technologies is expected to enable businesses to gain competitive advantage (Parker & Appel, 2021; Payne et al., 2018; Zhang et al., 2021).

Based on the literature review, Table 2.3 is constructed to indicate areas in which AI technologies are being applied in the financial services industry which include process automation (Davenport & Ronanki, 2018; Hofmann et al., 2020), document analysis (Anderson et al., 2018), data analytics (Gupta et al., 2022; Møller et al., 2018), decision making (Anderson et al., 2018; Gupta et al., 2022), biometrics and authentication solutions (Anderson et al., 2018; Kurshan et al., 2021; Møller et al., 2018), risk and fraud monitoring (Gupta et al., 2022; Noreen et al., 2023), credit check and scoring (Møller et al., 2018; Noreen et al., 2023), customer engagement (Davenport & Ronanki, 2018; Noreen et al., 2023; Sartori & Bocca, 2022) and creating an audit trail for regulation and compliance (Lui & Lamb, 2018; Malik et al., 2021; Møller et al., 2018).

Table 2.3 Application of AI technologies in financial services

Application	Value proposition	Examples of AI technology used
<i>Process Automation</i>	- Automation of manual, repetitive and time-consuming tasks and processes using - Frees human labor to perform other tasks - Increases efficiency and performance in operational and processes - Enables scalability and reduction in costs	- Robotic process automation - Intelligent automation - Machine learning - Natural language processing
<i>Document analysis and processing</i>	- Fast and efficient analysis and processing of documentation - Facilitates the review and verification of documents collated when, for example, opening a new account, processing insurance claims documentation, etc.,	- Machine - Natural language processing
<i>Fraud and risk assessment and monitoring</i>	- Monitoring of transactions detect anomalies - Proactive identification of fraudulent activities - Risk and cybersecurity monitoring	- Natural language processing - Machine learning
<i>Credit checks and scoring</i>	- Conducting due diligence credit vetting and scoring - Credit evaluation and loan/insurance underwriting - Collation and analysis of information to provide input into lending and insurance decisions	- Machine learning - Natural language processing
<i>Analytics and decision making</i>	- Use of AI algorithms to detect patterns in large amounts of data - Ability to make predictions, provide recommendations or make decisions about customers, employees, financial data, and markets	- Machine learning - Deep learning - Natural language processing - Expert systems
<i>Engaging with customers and employees</i>	- Use of interactive robots and virtual assistants, e.g. chatbots to enables 24/7 engagement and communication with customers - Creates opportunities for a convenient and digital experience	- Machine learning - Natural language processing - Robotics - Speech recognition
<i>Identity authentication</i>	- Ability to authenticate users to ensure appropriate access and protection of personal data, personal and restricted information, and personal accounts. - Convenience and security in making use of digital payment methods and authorizing transactions	- Biometrics - Machine vision - Neural networks - Deep learning
<i>Regulation and compliance reporting</i>	Management of risk and reporting obligations by facilitating accounting, auditability, security, and compliance.	- Machine learning - Natural language processing

Despite, the potential of AI to enhance business performance and customer experience, there are concerns raised that appear to undermine the effective implementation and use of AI technologies within the financial services industry. Reliance on outdated and legacy systems (Jang et al., 2021; Kruse et al., 2019; Ndoro et al., 2020), as well as the lack of internal AI expertise (Kruse et al., 2019; Ndoro et al., 2020) are some of the reasons for the slow implementation of AI. Anderson et al. (2018) and Lui and Lamb (2018) also discuss concerns that threaten trust and confidence in the use of AI technologies as algorithms used are sometimes seen to cause and perpetuate bias and discrimination based on race and gender. Research by Anderson et al. (2018) on the use of AI technologies and how it will impact people highlighted concerns raised by a number of respondents with regards to algorithm bias which may continue to disadvantage certain groups of people, given some of the biases that may already exist in data. Lui and Lamb (2018) cite examples of bias in online job advertisements of men receiving higher paying job advertisements than women¹, as well as an example in 2016 of a chatbot which was created to imitate certain language patterns and ended up tweeting racist and sexist². AI technologies have also been referred to as “a black box” due to lack of transparency in how decisions are made (Anderson et al., 2018; Fernández, 2019; Holmström, 2022; Kurshan et al., 2021).

2.2.4 The AI paradox

Current research on the attitude, implementation and use of AI technologies has often been contradictory or left open ended, contributing to the divide between those that fear AI and those that embrace AI. There is an optimistic view highlighting the excitement, opportunities and positive impact and experience for businesses, employees and the overall society (Dwivedi et al., 2021; Lane & Saint-Martin, 2021; Pereira et al., 2021; Tussyadiah & Miller, 2019). On the other hand, there is resistance towards the implementation and use of AI, as AI is feared to negatively disrupt and create more challenges for businesses, employees and society (Dwivedi et al., 2021; Lane & Saint-Martin, 2021; Pereira et al., 2021; Tussyadiah & Miller, 2019). While the use of AI technologies may disrupt industries, opportunities to boost productivity, income and economic growth are also expected (Dwivedi et al., 2021; Magwentshu et al., 2019; Mourtzis, 2021; Wong et al., 2020). The use of AI technologies therefore creates paradoxes for employers and employees which inevitably impacts the attitudes and acceptance of AI

¹ A. Datta, M. Tschanta and A. Dutta, ‘Automated Experiments on Ad Privacy Settings: A Tale of Opacity, Choice, and Discrimination’ (2015) *Proceedings on Privacy Enhancing Technologies* (1), 92

² A. Karanasiou and D. Pinotsis, ‘A study into the layers of automated decision-making: emergent normative and legal aspects of deep learning’ (2017) *International Review of Law, Computers & Technology* 31(2), 170

technologies. The following provides a discussion of the main paradoxes highlighted in literature.

2.2.4.1 The paradox for employers

AI technologies can be applied to most core business processes in various industries and functions within business (Gu et al., 2022; Lane & Saint-Martin, 2021; Strich et al., 2021; Vasiljeva et al., 2021). Siderska et al. (2023) also state that the benefits of using AI technologies is that AI technologies can be applied to businesses of all sizes. In the financial services industry, AI technologies can be used to collect and analyse data, make decisions, enhance efficiencies, detect fraud, enable financial inclusion, reduce costs and facilitate regulatory compliance (Fernández, 2019; Kar & Kushwaha, 2021; Mehrotra, 2019; Payne et al., 2018).

Given the potential benefits of AI presented in literature, and evidence from some of the case studies by Davenport and Ronanki (2018) and Parker and Appel (2021) on the application of AI related technologies in the financial services industry, it is apparent that AI has the ability to improve processes, efficiencies, prediction of risk, productivity and revenue while decreasing human error, inefficiencies and costs. As such, AI technologies have been argued to perform better, faster, and more accurately than humans in most areas of business processes and activities (Fernandez, 2019;Füller et al., 2022; Hubbard & Rogers, 2019; Mehrotra, 2019).

AI technologies such as machine learning for example, have become popular as they can identify patterns, learn from existing data and create intelligent algorithms that enable the improvement of processes and performance of specific tasks, and make predictions (Hanif, 2021; Lane & Saint-Martin, 2021; Siderska et al., 2023; Webb, 2019). With technologies such as robotic process automation, AI is being used to increase efficiency, intelligently automate business processes and decisions and take over manual and repetitive tasks typically performed by employees (Bartolotta & Gritt, 2021; Davenport & Ronanki, 2018; Füller et al., 2022).

The use of chatbots or virtual assistants to engage, communicate and provide recommendations to customers 24/7 makes it possible for businesses to provide cheaper and convenient assistance to customers (Jang et al., 2021; Lui & Lamb, 2018; Ndoro et al., 2020). This also enables employees to attend to customers' queries quicker and provide personalised services that

enhances the individuals' autonomy and the customer experience (Dwivedi et al., 2021; Ngoro et al., 2020; Rufus, 2020).

AI technologies can also be used throughout all phases of the employee lifecycle to facilitate analysis of data and decision making in the recruitment and selection process (Nosratabadi et al., 2022; Strusani & Hounghonon, 2019; Wamba-Taguimdje et al., 2020), promotion process and decisions (Nosratabadi et al., 2022; Robert et al., 2020), reward and compensation decisions (Agrawal et al., 2019), learning and development (Nosratabadi et al., 2022), performance evaluation and management (Nosratabadi et al., 2022; Robert et al., 2020).

Despite the motivation for businesses to use AI technologies, there are many concerns and challenges that have been raised which make the implementation and use of AI technologies complex (Adeleye et al., 2019; Chatterjee et al., 2021; Pumplun et al., 2019). This could explain why although there has been a notable interest in the use of AI technologies, a slow uptake with regards to the implementation and use of AI technologies has been evident (Parker & Appel, 2021; Thowfeek et al., 2020; Weinert et al., 2022).

Researchers including van Ark (2016), Lane and Saint-Martin (2021) and Nazareno and Schiff (2021) have weighed in on the productivity paradox, which highlights that although there has been cases of a productivity boost in certain industries and geographies due to the use of digital technologies such as AI, the increase in productivity and economic growth may have been overstated. They cite research indicating that in the bigger scheme of things, there has not been major evidence to support significant increases in revenue and profits (Lane & Saint-Martin, 2021; van Ark, 2016). This is despite researchers predicting the use of AI technologies to have a significant positive impact on productivity within organisations and overall economic growth (Davenport & Ronanki, 2018; Plastino & Purdy, 2018; Schoeman et al., 2021; Wei & Li, 2022). Factors such as the slow implementation of AI, mismeasurement of productivity, issues with the deployment of the wrong type of AI, lack of adequate AI skills and anti-competitive practices have been identified as contributing to the productivity paradox (Lane & Saint-Martin, 2021; van Ark, 2016).

AI technologies such as machine learning are capable of effectively analysing and making sense of data, making decisions as well as making predictions from existing data (Agrawal et

al., 2019; Ahn & Chen, 2022). However, these technologies have been criticised for being a “black box” due to the lack of transparency and explainability with regards to how decisions are made (Anderson et al., 2018; Hanif, 2021; Kurshan et al., 2021; O’Shaughnessy et al., 2023; Strich et al., 2021). It seems that it is not always clear, even to the developers of AI, how certain variables are combined and how algorithms are created to make decisions and predictions (Hanif, 2021; Kruse et al., 2019; Pumplun et al., 2019). Further, Sako (2020) asserts that machine learning, unlike expert systems, do not necessarily replicate the thinking and processes followed by humans, but are capable of using available data to create their own rules. This contributes to the discomfort, mistrust and concern towards decisions made by AI (Anderson et al., 2018; Hanif, 2021).

As previously indicated, there is evidence of AI decisions contributing to bias and discrimination which raises questions regarding the ethical and fair use of AI (Gupta et al., 2022; Raisch & Krakowski, 2021). These concerns are challenging, specifically in the highly regulated sectors, where a clear audit trail of actions taken, and decisions made to ensure compliance and good governance is required (Dwivedi et al., 2021; Kruse et al., 2019). The fact that there is no official industry regulations and standards regarding the use of AI technologies is also a concern (Anderson et al., 2018; Malik et al., 2021; Mehrotra, 2019; Rahman et al., 2021).

Machines using AI technologies are said to perform routine and repetitive tasks quicker and better than humans (Agrawal et al., 2019; Füller et al., 2022; Georgieff & Hyee, 2022). However, unlike humans, AI technologies can only do what they are programmed to do and do not possess the emotional and social skills that is often required to solve certain problems (Georgieff & Hyee, 2022; Mehrotra, 2019; Raisch & Krakowski, 2021). AI technologies are ineffective in uncertain and complex tasks requiring intuition, human judgement, creativity, persuasion and social or emotional intelligence (Mehrotra, 2019; Raisch & Krakowski, 2021; Vishwanath et al., 2019). As such, the use of AI technologies should be positioned as the use of technologies to assist and complement human performance instead of having a narrow focus on merely automating tasks to cut costs and replace human labour (de Saint Laurent, 2018; Mehrotra, 2019; Noponen, 2019; Vishwanath et al., 2019). A mindset that encourages augmented intelligence by enabling collaboration and integration between AI technologies and

human skills is therefore encouraged (Lui & Lamb, 2018; Nazareno & Schiff, 2021; Raisch & Krakowski, 2021; Wang et al., 2019).

Dwivedi et al. (2021) note that the use of interactive, 24/7 AI technologies such as chatbots to engage with customers and provide a personalised service and experience to customers has been growing. However, it has been argued that customer personalisation infringes on customers' autonomy by hiding and restricting information shared with customers (Rufus, 2020). The security and privacy of customer information when businesses use and integrate AI technologies has also been questioned (Dwivedi et al., 2021; Neumann et al., 2022)

2.2.4.2 The paradox for employees

Ivanov et al. (2020) states that the use of AI technologies, when not used to replace human employees, has the ability to improve their performance and productivity. Using AI technologies can assist and make work easier for employees, by automating mundane tasks for them, assisting with the analysing and reporting of large amounts of information, providing insights to facilitate the decision making process, facilitating personalised learning and development, as well as assisting with customer engagement (Bartolotta & Gritt, 2021; Bhargava et al., 2020; Nosratabadi et al., 2022).

Østerlund et al. (2021) also cite examples of how employee's roles and tasks are expected to change in the financial services industry, as AI technologies are used to handle repetitive and manual tasks, enabling employees to focus more on human-centred tasks that require judgement based on social and emotional intelligence, as well as background and experience to handle complex situations. A practical example of this would be the use of AI systems to automate the underwriting process, then having credit analysts to review and either accept or override the decision initially provided by the AI system where needed (Østerlund et al., 2021).

The use of AI technologies is also intended to free-up employees from repetitive and mundane tasks and increase employees' exposure to more challenging, value-adding and cognitive tasks that focus more on research, creativity and innovation (Baggio & Omana, 2019; Johnson et al., 2020; Wisskirchen et al., 2017). This is expected to increase employees' job satisfaction, to enhance efficient collaboration with others, to create opportunities for career development and

to enable employees to have more flexibility and autonomy in their work (Johnson et al., 2020; Lane & Saint-Martin, 2021; Magwentshu et al., 2019).

Research by Wei and Li (2022) on the impact of AI on the mental health of manufacturing workers indicates that the use of AI technologies reduces psychological depression and promotes employees' mental health. Research by Parker & Appel (2021) on the impact of implementing a machine-learning robotic process automation solution within a South African financial services organisation also reveals the benefits of using AI technologies with regards to freeing-up employees from repetitive and mundane tasks and enabling employees to focus on services that are more value adding for customers. As such, employees, customers and the overall business benefit from the use of AI technologies.

However, the opportunities created from using AI technologies to free-up employees from mundane and repetitive tasks and have them focus on more value adding tasks which sometimes require different or new skills and changes to the nature of employees' work, has not always been well received. Holmström (2022) and Malik et al. (2021) note that this may introduce a new level of job complexity, dissatisfaction, work stress and job overload for employees. Ivanov et al.'s (2020) research also highlights that many employees may not actually fear being replaced by AI but fear having to take on more complicated tasks and be concerned about having adequate support to perform well in these new and challenging situations and job roles.

Nazareno and Schiff's (2021) research on the impact of automation and AI technologies on workers indicates that employees whose jobs are at risk of automation initially experienced less stress but their health and job satisfaction was negatively impacted over time. They note that the use of AI technologies and automation may be adding stress back into work, through increased work overload, increased surveillance and having to deal with more cognitively challenging work (Nazareno & Schiff, 2021). Similar research findings are reported by Malik et al. (2021) in their study on employees' experiences with using AI technologies, which highlight factors contributing to technostress, stemming from employees' inability to work effectively with technology in a healthy manner.

These research findings also highlight what Bhargava et al. (2020) has referred to as the job satisfaction dilemma. Although employees may be satisfied with the new and challenging

demands in their roles as well as opportunities for better work-life balance, they may be less satisfied with the potential negative impact of AI technologies interfering with their personal and social wellbeing, which blur the boundaries between work and their personal lives (Bhargava et al., 2020). Strich et al. (2021) and Lane and Saint-Martin (2021) acknowledge the potential of AI to compliment and augment human capabilities, but also caution against the potential negative impact on employees' autonomy and wellbeing. Further, fears that AI technologies may threaten or undermine humans are also apparent (Anderson et al., 2018; Moldenhauer & Londt, 2018; Roberts et al., 2021; Wei & Li, 2022).

Anderson et al. (2018) and Dwivedi et al. (2021) highlight the risk of an over-reliance of automation on businesses, which may lead to the erosion of employees' abilities and an increase in automation complacency, given that AI technologies are not always going to be 100% perfect. Research by Strich et al. (2021) highlights a similar concern from employees which indicates that depending on the employees' job role, the use of AI may be viewed as a threat to jobs or lead to deskilling as employees may no longer be able put their skills and experience to use.

Siderska et al. (2023) assert that the automation technologies have enhanced opportunities for workers but also created new challenges for workers. The fear of job losses has been cited as one of the main concerns towards the use of AI technologies (Gwagwa et al., 2020; Ivanov et al., 2020; Lichtenthaler, 2020; Wei & Li, 2022). Wisskirchen et al. (2017) and Baggio and Omana (2019) expect although the use of AI technologies may initially result in short-term job losses, a gradual process of jobs being replaced and created across the different industries will be witnessed. This expectation is based on evidence from previous revolutions that have demonstrated the ability of humans to adapt and create new jobs despite increased automation of tasks (Ali et al., 2022; Wisskirchen et al., 2017). Davenport and Ronanki (2018) and Bhargava et al. (2020) also note from their research and case studies that the use of AI technologies is not intended to eliminate jobs because humans have unique irreplaceable skills that are essential for work to be conducted effectively. However, Roberts et al. (2021) finds that in South Africa, the use of automation is feared to result in human labour being replaced by automation. Dwivedi et al. (2021) also note that emerging market economies are expected to experience massive job losses compared to developed countries.

Debates on which and how jobs will be impacted by the use of AI related technologies are also heightened, with some predicting that lower skilled jobs or jobs with tasks that are fairly standard, repetitive, easily replicated, and automated are at a greater risk of being eliminated (Brougham & Haar, 2018; Pereira et al., 2021; Roberts et al., 2021; Wei & Li, 2022). Highly skilled jobs, requiring specific skills and experience to deal with uncertainty, as well as strong interpersonal skills to solve problems and make decisions, are expected to be at a lower risk of being eliminated (Brougham & Haar, 2018; Lane & Saint-Martin, 2021; Webb, 2019; Wei & Li, 2022). However, what is clear from the literature is that all jobs, in all the different industries will be impacted through the use of AI technologies in some way.

The above reflects the contradictory expectations and research findings regarding the use and impact of AI technologies on employees' wellbeing, way of working, and employment. In addition, concerns regarding limited regulation, privacy, clarity, autonomy and fairness regarding the implementation and use of AI technologies (Kurshan et al., 2021; Lane & Saint-Martin, 2021; Robert et al., 2020; Strich et al., 2021), poses a challenge to the attitude, acceptance, and successful implementation and use of AI technologies. Investigating and identifying context specific factors influencing the attitudes and acceptance of AI technologies, and proactively managing these factors is therefore critical. Given that AI is here to stay, finding collaborative ways for AI and employees to work together is imperative (Lane & Saint-Martin, 2021; Siderska et al., 2023).

2.3 Theories and models investigating attitude and acceptance of new technologies

The previous section provided insight on the contradictory views, expectations and experiences contributing to the AI paradoxes, which may impact the attitude and acceptance of AI technologies. It is therefore important for organisations implementing new technologies such as AI, to investigate and understand factors to be cognisant of and manage in order ensure the successful implementation of use of new technologies such as AI. The following section provides an overview and analysis of some of the prominent theories and models that have been applied when investigating the attitudes, adoption and acceptance of new technologies. By applying technology acceptance models and theories, one is able to predict and explain the acceptance or rejection of a new technology (Alshammari & Rosli, 2020; Attencia & Mattos, 2022; Masimba & Zuva, 2021).

Investigation of the attitude, adoption and acceptance of new technologies has been classified into either individual level or organisational level models and theories (Kasaj, 2016; Kim & Crowston, 2011). The most commonly used individual level theories include the Theory of Reasoned Action (TRA), Theory of Planned Behaviour (TPB), Technology Acceptance Model (TAM), the Technology Acceptance Model 2 (TAM2), Technology Acceptance Model 3 (TAM3), Unified Theory of Acceptance and Use of Technology (UTAUT), the Diffusion of Innovation theory (DOI) and the Social Cognitive Theory (SCT) (Al-Mamary et al., 2016; Kim & Crowston, 2011; Masimba & Zuva, 2021). These theories focus on individual's attitude, acceptance usage and adoption of a new technology (Li, 2020). When researchers want to conduct an organisational level analysis to investigate factors influencing the decision to adopt a new technology within the organisation, they tend to consider the Technology Organisation Environment (TOE) model or the Diffusion of Innovation theory (DOI) (Li, 2020).

Table 2.4 below is constructed based on the literature review conducted to provide an overview of the most widely used technology adoption and acceptance models, the main constructs included in each theory, the moderating variables considered, as well as the level of analysis (individual or organisational). Literature also highlights the strengths and weaknesses of these technology acceptance theories and models, which are important to take note of when deciding which theory or model to use (Al-Mamary et al., 2016; Alshammari & Rosli, 2020; Kim & Crowston, 2011; Masimba & Zuva, 2021).

Table 2.4 Theories/models investigating attitude and acceptance of new technologies

	Description	Constructs	Moderating variable	Level of analysis
Theory of reasoned action (TRA) by Fishbein and Ajzen in 1975 (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975)	Based on social psychology, the theory is used to explain individuals' behavioral intention, which is influenced by attitude towards the behaviour and subjective norms	Attitude towards behaviour; subjective norms; behavioral intention and actual behaviour	N/A	Individual
Theory of Planned Behaviour (TPB) by Ajzen in 1985 (Ajzen, 1991)	Also based on the social psychology theory, it extends the TRA by including perceived behavioral control as an additional influence of behavioral intention.	Attitude towards behaviour; subjective norms; perceived behavioral control; behavioral intention and actual behaviour	N/A	Individual
Social cognitive theory (SCT) by Bandura in 1986 (Wood & Bandura, 1989)	SCT theorizes that human behaviour is determined by influences between personal factors, behaviour, and environmental factors.	Self-Efficacy, Performance Outcome Expectations, Personal Outcome Expectations, Affect, Anxiety	N/A	Individual
Technology Acceptance Model (TAM) by Davis in 1986 (Davis et al., 1989)	The development of TAM was influenced by the TRA and TPB. It is used to predict individual user's attitude, acceptance (behavioral intention) and usage of technology of technology	Perceived usefulness, perceived ease of use, attitude towards use, intention to use and actual use	N/A	Individual & organisational
Technology Organisation and environment framework (TOE) by Tornatzky & Fleischer in 1990 (Tornatzky & Fleischer, 1990)	The TOE framework posits that technological, organisational, and environmental factors affect the organisation's technology adoption process	Technology availability and characteristics, organisational size and culture, slack, communication processes, formal and informal structures, industry characteristics, market structure, technology support, infrastructure, government regulation, competitive pressure, managerial support	N/A	Organisational
Diffusion of Innovation Theory (DOI) by Rogers in 1962 (Rogers, 1995)	DOI is used to determine the adoption or non-adoption of new technology in a systematic way. It enables understanding of why and at what rate innovation diffuses	<i>Individual constructs</i> - relative advantage; ease of use; image; visibility; compatibility; results demonstrability. <i>Firm level constructs</i> -decision maker characteristics; organisational structure internal characteristics and external characteristics if the organisation	N/A	Individual & organisational
Technology Acceptance Model 2 (TAM 2) by Venkatesh and Davis, 2000 (Venkatesh & Davis, 2000)	TAM2 is an extension of TAM, and includes external variables influencing perceived usefulness, as well as experience and voluntariness as moderating variables	Perceived usefulness; perceived ease of use; subjective norm, image, job relevance, output quality, results demonstrability, attitude, behavioral intention	Experience Voluntariness	Individual
Unified Theory of Acceptance and use of	Integrated elements from TRA; TAM; MM; TPB; combined TAM-TPB:	Performance expectancy; effort expectancy; social	Experience Voluntariness Gender	Individual

Technology (UTAUT) by Venkatesh et al. in 2003 (Venkatesh et al., 2003)	MPCU: IDT and SCT to create a unified view of users' technology acceptance that can be used to determine behavioral intention and use behaviour.	Influence, facilitating conditions; behavioural intention and use behaviour	Age	
Technology Acceptance Model 3 (TAM3) by Venkatesh and Bala in 2008 (Venkatesh & Bala, 2008)	TAM3 is an integration of all previous TAM research. It includes individuals' differences; system characteristics, social influence and facilitating condition in its model. TAM 3 excluded the attitude construct in the model	Computer self-efficacy, computer anxiety, computer playfulness; job relevance, output quality, result demonstrability, perceived enjoyment, objective usability; subjective norm, image; facilitating conditions, perception of external control, perceived usefulness, perceived ease of use, behavioural intention and use behaviour	Experience Voluntariness	Individual

2.3.1 Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA), developed by Ajzen and Fishbein in 1975 (Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975; Madden et al., 1992), is the foundation for most technology acceptance theories (Alshammari & Rosli, 2020; Taherdoost, 2018). The TRA is used to predict human behaviour through three main constructs, attitude, subjective norms and behaviour intentions (Ajzen & Fishbein, 1980; Madden et al., 1992; Taherdoost, 2018), as shown in Figure 2.2. Masimba and Zuva (2021) notes that the TRA has proved to be highly predictive when the use of technology is voluntary, for example, when determining customers' behaviour towards a new technology.

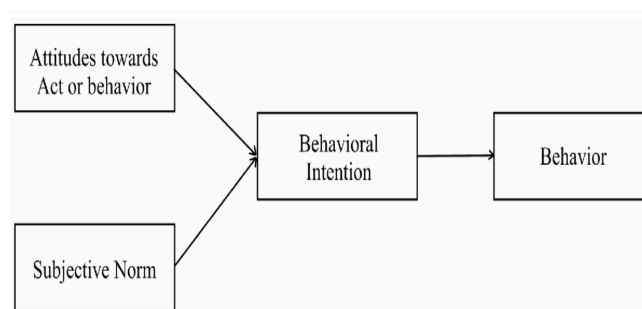


Figure 2.2 Theory of Reasoned Action

Source: (Madden et al., 1992)

Although the TRA is useful when explaining human behaviour, it has been criticised for being too general in nature (Alshammari & Rosli, 2020; Masimba & Zuva, 2021), and for assuming that one's behaviour is fully under one's control without consideration of situational, external and systematic factors that may influence an individual's behaviour (Al-Mamary et al., 2016;

Alshammari & Rosli, 2020; Masimba & Zuva, 2021). In addition, extending this theory to consider other factors into the model has been found to not significantly increase the explanatory power of the model (Alshammari & Rosli, 2020).

2.3.2 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour (TPB) was developed by Ajzen in 1985 (Ajzen, 1991). Although similar to TRA, the Theory of Planned Behaviour (TPB) is an extension of the TRA and includes the perceived behavioural control construct (Al-Mamary et al., 2016; Masimba & Zuva, 2021). Perceived behavioural control refers to the extent to which an individual believes that they have the ability to control personal or external factors that either facilitate or constrain their behaviour and performance (Masimba & Zuva, 2021). Figure 2.3 below depicts the TPB.

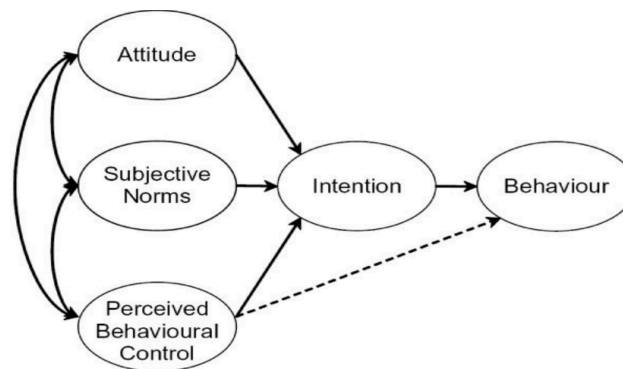


Figure 2.3 Theory of Planned Behaviour

Source: Ajzen (1991)

However, despite evidence of its ability to accurately predict behaviour (Masimba & Zuva, 2021), similar to the TRA, the TPB is more suited for situations where the use of a new technology is voluntary (Al-Mamary et al., 2016). Masimba and Zuva (2021) also note challenges raised by researchers when defining and measuring the constructs in the model as well as issues of multicollinearity between the independent variables.

2.3.3 The Technology Acceptance Model (TAM)

The Technology Acceptable Model (TAM) was developed by Davis in 1986, based on the TRA (Davis et al., 1989). It focuses on investigating external variables, individual's beliefs/perceptions of technology, attitude, behavioural intention and usage of a technology (Davis et al., 1989; Davis & Venkatesh, 1996). Over the years, the TAM has been recognised for its robustness (Dalcher & Shine, 2003; Davis & Venkatesh, 1996; Venkatesh & Davis,

2000) and for being a parsimonious model used to predict user acceptance (Venkatesh & Davis, 2000). It has been applied successfully to research on the adoption and acceptance of various technologies and in different contexts (Gangwar et al., 2015; Karunaratne & Abeyratne, 2020; Nath et al., 2013; Sohn & Kwon, 2020) and used as foundation for latter extensions of the TAM, for example TAM2 and TAM3 (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000), which are explained below. Figure 2.4 shows the original TAM.

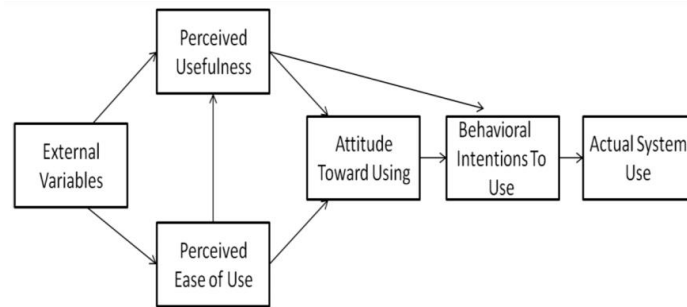


Figure 2.4 Technology Acceptance Model

Source: Davis (1989)

According to the original TAM, there are external variables that influence perceived usefulness and perceived ease of use (Davis, 1989). Perceived usefulness and perceived ease of use of a technology are primary determinants of attitude towards use of using a new technology (Davis, 1989). Attitude toward using a technology influences behaviour intention to use technology and in turn, the behavioural intention influences the actual usage of the technology (Davis, 1989). The behavioural intention construct has been used to determine the acceptance of a new technology (Alharbi & Drew, 2014; Sun & Zhang 2006).

The TAM has been critiqued for assuming that perceptions regarding the usefulness and ease of use of the new technology are always the primary determinants of attitude and acceptance of AI technologies, since they could be other key determinants of attitude that may need to be considered in order to explain the acceptance of technology (Alshammari & Rosli, 2020; Mathieson, 1991). TAM has also been criticised for ignoring the influence of social factors in technology acceptance (Qin et al., 2020), as well as for being too general and lacking consistency in the criteria for external variables to be included in the model (Mathieson, 1991; Qin et al., 2020). In addition, the influence of the attitude construct on behavioural intention has been inconsistent (Sun & Zhang, 2006), and was excluded in later TAM models (TAM2 and TAM3 and the UTAUT), as it was found to be an insignificant in determining behavioural intention (Kemp et al., 2019; Venkatesh et al., 2003).

2.3.4 The Technology Acceptance Model 2 (TAM2)

Venkatesh and Davis (2000) developed the Technology Acceptance Model2 (TAM2) shown in Figure 2.5 as an extension of the original TAM model. Social influence processes (*subjective norm, voluntariness and image*) and the cognitive instrumental processes (*job relevance, output quality, result demonstrability and perceived ease of use*) are included in the TAM2 model as factors influencing perceived usefulness (Venkatesh & Davis, 2000; Venkatesh et al., 2003). Voluntariness and Experience are included in the model as moderating variable (Venkatesh & Davis, 2000). Behavioural intention is determined by perceived usefulness, perceived ease of use and subjective norm, and influences usage of technology (Al-Mamary et al., 2016; Venkatesh & Davis, 2000).

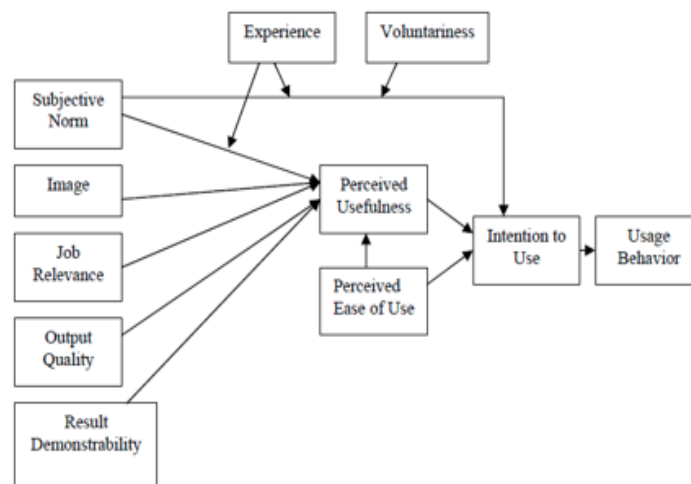


Figure 2.5 Technology Acceptance Model 2 (TAM2)

Source: Venkatesh and Davis (2000)

TAM2 has been recognised for considering both social influence processes and cognitive instrumental processes in determining behavioural intention and usage of a new technology (Masimba & Zuva, 2021). However, Alshammari and Rosli (2020) note that TAM2 has been criticised for theorising that all the external factors influence behavioural intention only through perceived usefulness and for neglecting the possible relationship and influence of these factors on perceived ease of use. In addition, the TAM2 was found to be inflexible when applied in different contexts, for example non-Western cultures, where its explanatory power in determining behaviour intention significantly lowered (Alshammari & Rosli, 2020).

2.3.5 The Technology Acceptance Model 3 (TAM3)

TAM3 was developed by Venkatesh and Bala (2008) shown in Figure 2.6 below, is a combination of all previous TAM models (Al-Mamary et al., 2016; Qin et al., 2020). TAM3 includes the categories of individual differences (computer self-efficacy, computer anxiety, computer playfulness); system characteristics (job relevance, output quality, result demonstrability, perceived enjoyment, objective usability); social influence (subjective norm, image); and facilitating conditions (perception of external control), as factors that influence perceived usefulness and perceived ease of use, which in turn influence behavioural intention and use of technology (Venkatesh & Bala, 2008). The moderating role of experience and voluntariness is also included in the model (Masimba & Zuva, 2021; Venkatesh & Bala, 2008).

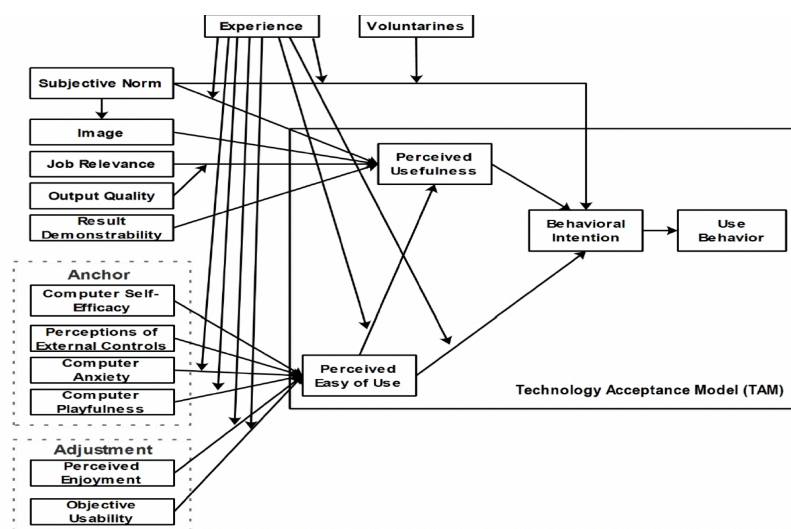


Figure 2.6 Technology Acceptance Model 3 (TAM3)

Source: Venkatesh and Bala (2008)

However, as with the TAM2, the TAM3 is criticised for its limitation in assuming that users can choose or volunteer to use a technology when this is not always the case in mandatory settings (Al-Mamary et al., 2016). Qin et al. (2020) also note that the detailed list of external variables limits its practical application.

2.3.6 Diffusion of Innovation Theory (DOI)

The Diffusion of Innovation Theory (DOI) was developed by Rogers in 1962 (Rogers, 1995; Rogers, 2003). It defines a process by which innovation spreads and is accepted through communication processes in a particular context (Rogers, 1995; Rogers, 2003; Rogers et al., 2005). The DOI provides a framework that can be used to describe the systematic adoption or non-adoption of technology (Al-Mamary et al., 2016), and can be used for both individual and organisational level analysis of technology adoption and acceptance (Masimba & Zuva, 2021; Rogers et al., 2005).

A 5 stage decision making process of the adoption and diffusion of technology is stated to entail the following stages: knowledge/awareness, persuasion, decision (to adopt or to reject new technology), implementation and confirmation/continuation of the use of technology (Al-Mamary et al., 2016; Rogers, 1995). The acceptance and the rate of adoption of any innovation is influenced by innovation characteristics such as relative advantage, compatibility, complexity, trialability, and observability (Rogers, 1995; Rogers, 2003). Moreover, five categories of adopters of innovation are provided which include early adopters, innovators, laggards, late majority, and early majority (Rogers et al., 2005).

However, this theory has been criticised for neglecting societal, cultural, economic and other contextual factors that determine how a new technology or innovation is adopted (Al-Mamary et al., 2016). In addition, Al-Mamary et al. (2016) and Masimba and Zuva (2021) note that the DOI has also been inconsistent in predicting individual and collective technology adoption and seems to be more applicable to educational settings compared to other settings. It is also argued to have less explanatory power and to be less practical in predicting outcomes of the use of technology compared to other adoption and acceptance models (Taherdoost, 2018).

2.3.7 The Social Cognitive Theory (SCT)

The Social Cognitive Theory (SCT) was developed by Bandura in 1986 (Wood & Bandura, 1989), and has been identified as an influential theory in human behaviour (Masimba & Zuva, 2021). The SCT depicted in Figure 2.7 defines human behaviour as an interplay and triadic structure between the person (personality, cognitive and demographic aspects), the behaviour (usage, performance and adoption issues) and the environment (physical and social factors) (Masimba & Zuva, 2021; Taherdoost, 2018; Wood & Bandura, 1989). According to this theory, an individual's behaviour is regulated through cognitive processes and is learnt through

observing the behaviour of others (Al-Mamary et al., 2016). The SCT model also integrates constructs such as self-efficacy, outcome expectations performance, anxiety, affect, and outcome expectations personal in evaluating the usage of a new technology (Taherdoost, 2018).

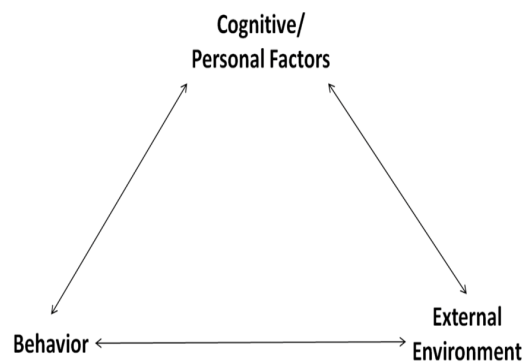


Figure 2.7 Social Cognitive Theory (SCT)

Source: Wood and Bandura (1989)

The SCT is applied when evaluating and determining technology usage and can be extended to different contexts to determine acceptance and use of technology (Taherdoost, 2018). However, the SCT has been criticised for being too general, too broad and unclear with regards to the extent to which each of these factors influence actual behaviour (Al-Mamary et al., 2016). In addition, Al-Mamary et al. (2016) and Masimba and Zuva (2021) state that this theory is difficult to apply and is more appropriate when focusing on education and motivation of using a new technology.

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

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003). The UTAUT provides a unified view of various technology acceptance theories by combining the theories discussed above (the TRA, TPB, TAM and its extensions, DOI and SCT), as well as the Motivation Model (MM) and the Model of PC utilization (MPCU) (Al-Mamary et al., 2016; Taherdoost, 2018). Figure 2.8 depicts the UTAUT and its constructs which include performance expectancy, effort expectancy, social influence constructs that influence behavioural intention, while behavioural intention and facilitating conditions influence the use of the new technology (Al-Mamary et al., 2016; Venkatesh et al., 2003). The UTAUT has been acknowledged for recognising individual

differences such as age, gender, experience and voluntariness as moderating variable when investigating technology acceptance (Alshammari & Rosli, 2020; Kim & Crowston, 2011).

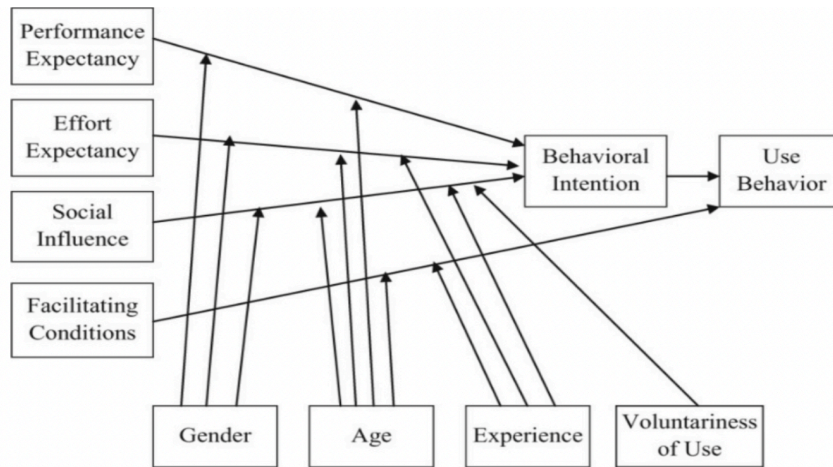


Figure 2.8 The Unified Theory of Acceptance and Use of Technology (UTAUT)

Source: Venkatesh et al. (2003)

Further, the UTAUT has been commended for being more predictive and integrative and for being able to explain 70% of the variance in usage intention, which is much higher than the previous models (Alshammari & Rosli, 2020; Masimba & Zuva, 2021). However, it has been criticised for having many constructs and for incorporating complex relationships between constructs which makes it inflexible and difficult to practically apply in certain contexts (Alshammari & Rosli, 2020; Qin et al., 2020). In addition, Alshammari and Rosli (2020) cite examples where the application of the UTAUT may be limited, for example in non-Western contexts, where the theory was only able to explain only 39% of the variance in users behavioural intention to use technology.

2.3.9 Technology-Organisation-Environment (TOE) Framework

The technology-organisation-environment (TOE) framework was developed by Tornatzky and Fleischer (1990) and is shown in Figure 2.9. It is used to examine factors influencing or inhibiting an organisation's decision to adopt a new technology (Alsheibani et al., 2019; Nam et al., 2020; Tripopsakul, 2018). The TOE framework investigates the impact of technological, organisational, and environmental factors on the adoption and acceptance of new technology. According to Tornatzky and Fleischer (1990), technological factors include

technological characteristics and availability of technology within and outside the organisations, as well as perceived characteristics such as relative advantage, compatibility, complexity, triability and observability. Organisational factors include organisational characteristics, such as resources, management support, organisational culture and size, communication processes (Al-Mamary et al., 2016; Tornatzky & Fleischer, 1990). Environmental factors include external factors that influence adoption of a new technology, for example customers, competitors, the market, the industry and regulators (Al-Mamary et al., 2016; Tornatzky & Fleischer, 1990).

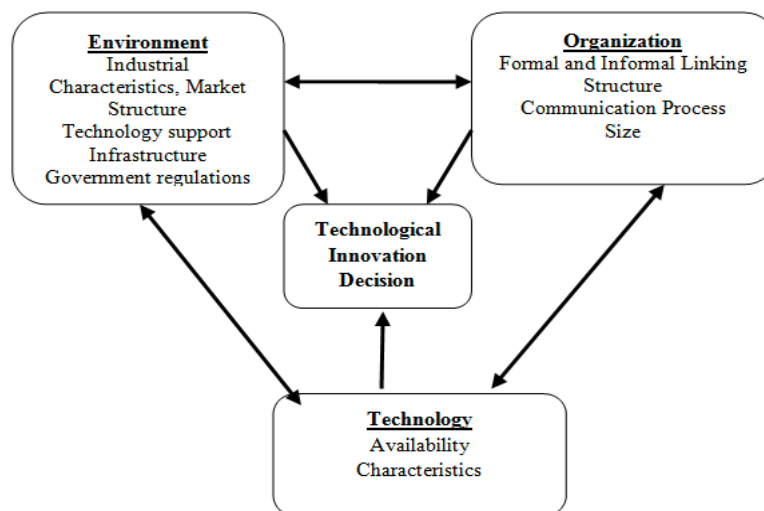


Figure 2.9 TOE Framework

Source: Tornatzky and Fleischer (1990)

The TOE framework is an organisational-level theory used to provide an analytic framework when investigating the adoption of a new technology (Al-Mamary et al., 2016). It has proved to be successful in allowing researchers flexibility to identify and select only specific factors or constructs relevant and applicable to the study at hand (Chen et al., 2020). However, the TOE framework has been criticised for simply categorising variables and lacking a solid theory to enable consistency in the application and definition of variable included in research (Al-Mamary et al., 2016; Bryan & Zuva, 2021).

The above mentioned adoption and acceptance theories have been used to explain the attitude, acceptance, adoption and usage of new technologies, including AI technologies, from the perspective of customers, employees or businesses at an individual and/or organisational level. All theories have limitations (Alshammari & Rosli, 2020), and there is no consensus on which theory is the best (Sohn & Kwon, 2020). What is also clear is that overall, these theories

in totality indicate how that the successful implementation and use of technology is not only based on technical factors but also on individual, social, organisational and environmental factors (Skafi et al., 2020). Researchers therefore need to consider the best suited theory or theories to combine, adapt and/or extend in order to fit the purpose and context of the research.

2.4 Conceptual framework for attitude and acceptance of AI technologies

Based on the literature review on the implementation and use of AI technologies, as well as a review of the technology adoption and acceptance theories and models, a conceptual framework for this research is developed. A conceptual framework is provided when one theory does not suffice when investigating a research phenomenon, and the researcher integrates different theories, models and concepts from both theoretical and empirical findings (Imenda, 2014; Ngulube et al., 2015). Given the complex nature of AI technologies, the paradoxes regarding its implementation as well as the different views of attitude and acceptance of AI technologies, there are clearly many variables and factors that need to be considered when investigating the attitude and acceptance of AI technologies.

2.4.1 Conceptual framework for this research

The following provides an explanation of the development of a conceptual framework that considers gaps and inconsistencies in the existing literature review and can be used to explain and understand attitudes and acceptance of AI technologies of employees within the South African financial services industry. Consideration is given to the most appropriate theories or models to apply when investigating attitude and acceptance of AI technologies in mandated settings such as financial services organisations. This conceptual framework is used to identify and organise relevant concepts and factors influencing the attitude and acceptance of AI technologies and used to develop a research model that will illustrate the expected relationship between these factors. Hypotheses to be tested will be formulated. The conceptual framework will also guide the research methodology, interpretations and explanation of data collected in this research.

2.4.1.1 Integrating the TAM and TOE framework

Considering the objective of the research, the type of research, the level or unit of analysis, the strengths and the weaknesses of each of the technology acceptance models and theories discussed above, the TAM and the TOE framework are selected for this research. Despite some

limitations with the TAM and TOE framework, the TAM and TOE framework have also been identified as the most prominent theories or models in conducting an individual level and organisational level analysis of technology adoption and acceptance respectively (Gangwar et al., 2015; Na et al., 2022; Qin et al., 2020).

The TAM has been identified as a widely used, robust and influential technology acceptance theory and model (Gangwar et al., 2015; Karunaratne & Abeyratne, 2020; Lee et al., 2003). It has been used to investigate technology acceptance and usage of various technologies amongst individual users (e.g. customers, students and employees) and within different and diverse contexts (Lee et al., 2003). The TAM has also been successfully applied in technology acceptance research of various AI technologies in manufacturing and production (Bröhl, Nelles, Brandl, Mertens, & Schlick, 2016), construction industry (Na et al., 2022), accounting and auditing (Damerji & Salimi, 2021), banking (Rahman et al., 2021) and in the healthcare sector (Alhashmi, Salloum, & Mhamdi, 2019; Ye et al., 2019).

van den Berg and van der Lingen (2019) and Gangwar et al. (2015) also note that although TAM was originally developed to study individual level technology adoption, the model can be extended and applied when conducting and organisational level analysis to examine the organisational level adoption of a new technology. For example, Yu and Tao (2009) extended the original TAM to include subjective norms, firm characteristics, and industry and environment characteristics, when investigating the business attitudes regarding the adoption of innovation internet-based information technology. In the process, they were able to successfully determine factors influencing business attitudes during the pre-adoption and adoption phase (Yu & Tao, 2009).

The TAM is popular because it has proved to be useful and valid for investigating and predicting attitude, acceptance and usage of technology (Ahmad et al., 2020; Gangwar et al., 2015; Hwang et al., 2016; Kasaj, 2016; Qin et al., 2020). To address the limitations of the TAM model discussed in section 2.3.3, the flexibility of the TAM makes it possible to extent the TAM to incorporate other adoption theories and models, as well as contextual factors applicable in the particular research context (Lee et al., 2003; Sun & Zhang, 2006). Alshammari and Rosli (2020) encourage extending and/or integrating the TAM with other technology adoption models and theories to be able to provide a valuable and comprehensive understanding of the complexities of technology acceptance. Kelly et al. (2023) in their

research on factors contributing to the acceptance of AI technologies recognise that the extensions of the TAM model with other technology adoption/acceptance models has been the most frequently used theory to assess acceptance of AI technologies.

The TOE framework has also been applied to investigate factors impacting the adoption of new technologies in diverse contexts and industries. For example, the TOE framework has been applied to investigate factors influencing the adoption of various AI technologies in the financial services industry (Gupta et al., 2022; Kruse et al., 2019; Thowfeek et al., 2020), healthcare industry (Ghaleb et al., 2021), manufacturing industry (Pillai et al., 2021), automotive industry (Smit & Eybers, 2022), auditing industry (Seethamraju & Hecimovic, 2022), hotel industry (Nam et al., 2020) and within various private and public companies (Phuoc, 2022).

Considering the limitations of the TOE framework discussed in section 2.3.9, it is important that when using the TOE framework, researchers provide a motivation and definition for each of the variables included in their framework, in line with the context and objective of their research. This research will apply the TOE framework to categorise factors identified as influencing attitude towards the use of AI technologies and define each of these factors based on the literature review and the context of this research.

Integrating the TOE framework with other technology adoption and acceptance theories when investigating technology adoption enables individuals factors to be catered for and provides a more holistic analysis of factors inhibiting or enabling the adoption and acceptance of technology (Chinia et al., 2019; Gangwar et al., 2015; Vang & Lind, 2023). Table 2.5 provides a summary of these studies.

Table 2.5 Studies integrating TOE with other theories

Researcher	Theory integrated with TOE	Innovation/ Technology	Context	Methodology and analysis
Gangwar et al. (2015)	TAM	Cloud computing	Manufacturing, IT and finance sectors, India	Quantitative, SEM
Awa et al. (2017)	UTAUT	Various computer hardware and software applications	SMEs, Nigeria	Quantitative, SEM
Abdekhoda et al. (2018)	TAM	Mobile technology-based services	Academic librarians, Iran	Quantitative. regression analysis
Matikiti et al. (2018)	TAM	Social media marketing technologies	Tourism industry, South Africa	Quantitative, multiple regression

Tripopsakul (2018)	TAM	Social media technology	Entrepreneurs, Thailand	Quantitative, SEM
Chiniah et al. (2019)	TAM	Cloud computing	ICT industry, Mauritius	Quantitative, regression
van den Berg and van der Lingen, (2019)	TAM, IDT, Fit-viability Model (FVM), and UTAUT	Mobile enterprise application	Various industries, South Africa	Quantitative, logistic regression
Chen et al. (2020)	DOI	Cloud computing	Telecommunication industry, China	Quantitative, SEM
Skafi et al. (2020)	Contextual Theory	Cloud computing	SMEs, Lebanon	Quantitative, logistic regression
Qin et al. (2020)	TAM	Building information technology	Construction industry, China	Quantitative, Dematel
Chatterjee et al. (2021)	TAM	AI used for digital manufacturing	Manufacturing and production, India	Quantitative, SEM
Ifikhar et al (2021)	TAM	Blockchain technology	Higher education institutes, Malaysia	Quantitative, multiple regression
Attencia & Mattos (2022)	TAM	Smart asset management	Construction, Brazil	Qualitative, case study
Na et al. (2022)	TAM	AI-based technology	Construction, South Korea	Quantitative, SEM
Smit and Eybers (2022)	IDT	AI use for data analytics	Automotive industry, South Africa	Qualitative, focus groups
Wang et al. (2022)	TAM	Blockchain technology	Construction, China	Quantitative, SEM
Mametja et al. (2023)	TAM	Digital technologies	Tourism, South Africa	Qualitative, interviews
Vang & Lind (2023)	TAM	Cloud computing	Government and public administration, USA	Quantitative, multiple regression

It is also clear from Table 2.5 above that the TOE framework has mostly been integrated with the TAM, indicating that although both the TAM and TOE have limitations when applied on their own (Mametja et al., 2023), they are often combined in order to complement each other and provide a more comprehensive analysis of the adoption, attitude, acceptance and use of new technologies (Chiniah et al., 2019; Gangwar et al., 2015; Mametja et al., 2023; Vang & Lind, 2023). The above also shows how the TAM and TOE framework have been integrated in research on the adoption, attitude and acceptance of AI technologies, for example in research by Chatterjee et al. (2021), Na et al. (2022) and Smit and Eybers (2022).

The flexibility of the TAM and the TOE framework make it possible to integrate the two in a way that is appropriate for the research objective. Gangwar et al. (2015) note the different ways in which the TAM and TOE can be integrated, for example, by having the factors in the TOE

framework included as external variables influencing the constructs in the TAM model, or by having both the TAM and TOE factors included as independent variables that are used to determine factors influencing the adoption, attitude and acceptance of new technologies.

2.4.1.2 Attitudes and acceptance of technology in mandatory settings

Research on technology adoption, attitude, acceptance, and usage has been conducted in both voluntary and mandatory settings. Although most TAM research was initially conducted in voluntary settings (Hwang et al., 2016; Venkatesh et al., 2003), extended TAM models, as well as the UTAUT, included consideration of technology acceptance in mandatory settings (Venkatesh & Davis, 2000; Venkatesh et al., 2003).

Voluntary settings refer to situations where the use of a new technology and voluntary and individuals have a choice on whether or not to adopt, accept or use a new technology (Linders, 2006; Po-An Hsieh & Wang, 2017; Venkatesh & Davis, 2000). On the other hand, mandatory settings are settings where individuals do not have a choice on whether to accept or use the technology but are instead required to use it because its use is compulsory (Brown et al., 2002; Hwang et al., 2016; Linders, 2006; Po-An Hsieh & Wang, 2017).

Linders (2006) notes that as organisations grow their investment in information technology, they mandate employees to use the technology they implement. In these mandatory settings, the decision to implement a new technology in an organisation is often determined by certain groups of people in the organisation such as senior management and IT experts (Hwang et al., 2016; Linders, 2006). As such, the views of the actual users of the technology, for example employees within organisations, who have no control in the decision to implement and use the new technology, are often neglected as they have no choice but to use the technology implemented (Schepman & Rodway, 2020).

Therefore, the application of the TAM to investigate attitude and acceptance of technology in mandatory settings within organisations has been questioned (Ajibade, 2018; Po-An Hsieh & Wang, 2017; Schepman & Rodway, 2020). It has been argued that TAM is more suitable in voluntary settings where individuals have a choice on whether or not to accept and use the new technology, than in mandatory settings where individuals do not have a choice to use the technology implemented (Ajibade, 2018; Po-An Hsieh & Wang, 2017; Schepman & Rodway, 2020).

Brown et al. (2002) emphasise the role of employees' attitudes when the use of technology within organisation is mandated. This is because, understanding and managing employees' attitudes towards a new technology, especially when these attitudes are negative, will enable management to minimize potential destructive behaviours such as employees misusing and/or sabotaging the use of the new technology, or employees continuing to use of old systems that need to be discontinued, which may affect the organisation's top line and bottom line (Brown et al., 2002). Linders' (2006) research also finds attitude toward a new technology to be a significant and key determinant of the success of a new technology in mandatory settings. Bhattacharjee et al. (2018) also highlight the importance of employees' attitudes towards a new technology by stating that in mandated settings, users that do not have a positive attitude towards the new technology or that do not accept it may start to be less engaged in their work, resent using the new technology in doing their work and/or may view the new technology as a threat to their jobs.

In addition, Brown et al. (2002) and Hwang et al. (2016) forewarn that just because a technology is mandated does not mean that employees will use it at all or use it appropriately as intended, which can negatively influence the implementation and use of technology. This highlights the need for researchers to be explicit about how they define technology acceptance in organisation, which this research will do in the sections that follow. In addition, as organisations are becoming more reliant on technology to digitalise and automate processes, using new technologies such as AI technologies has become necessary (Lui & Lamb, 2018). Broadening input from different employees across the organisation to obtain a more realistic and objective view of their attitude and acceptance of AI technologies is key to the successful implementation and use of AI technologies.

The above highlights the importance of investigating technology acceptance in mandatory settings. This research is conducted within the corporate environment in the financial services industry in South Africa, where decisions to use AI technology are mandated by senior management and IT/AI experts. Despite this, the research argues that the successful implementation and use of AI technologies will be determined by the employees' attitudes and acceptance of the AI technologies, across the different job roles and job levels.

2.4.1.3 Extending the TAM and TOE framework

The literature review has shown that implementing and using a complex technology such as AI should not only focus on the technical aspects of the technology but should consider a holistic approach that considers a wide range of contextual factors that may impact the adoption, attitude, acceptance and use of AI technologies (Alhashmi et al., 2019; Chatterjee et al., 2021; Füller et al., 2022; Kruse et al., 2019; Pumplun et al., 2019). This means that internal and external factors, human and non-human factors as well as social and technical factors that could impact employees' attitudes and acceptance of AI should be considered.

There are factors that can be identified from the literature review as impacting the attitude and acceptance of AI technologies that should be considered and investigated when implementing and using AI technologies, which are not included in the original TAM and/or TOE framework. For example, perceptions of fairness, employee wellbeing, social influence, experience with using AI technologies and an individual's job role, although not included in the TAM and TOE framework appear to have an influence on the attitude and acceptance of AI technologies. The combined effect of including these factors when integrating the TAM and the TOE framework in the investigation of attitude and acceptance of AI technologies amongst employees within the South African financial services industry has not yet been investigated. Therefore the TAM and TOE framework are integrated and extended to consider these additional factors expected to influence the attitude and acceptance of AI technologies.

After considering the above, Figure 2.10 provides an overview of the main concepts and factors for this research, which integrates and extends the TAM and TOE frameworks with other relevant concepts or variables expected to influence the attitude and acceptance of AI technologies. Some of the concepts and factors included in this conceptual framework are selected from the original TAM and the TOE framework, and others from prior research on attitude and/or acceptance of AI technologies as identified in the literature review.

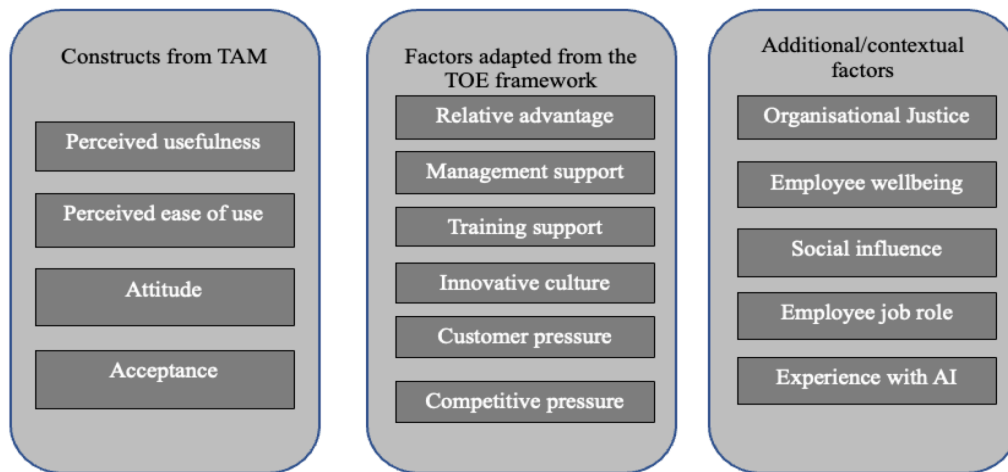


Figure 2.10 Conceptual framework

The usage of a new technology is often used to determine the successful implementation and use of a new system (Anandarajan et al., 2000; Hwang et al., 2016), and hence the usage construct from the TAM is often included in most technology adoption and acceptance research. However, the reliance on self-reported usage of a new technology has been criticised since it assumes that self-reported usage reflects actual usage (Lee et al., 2003). For this research, the usage construct is excluded, because first, the focus of this research is not to measure usage of AI technologies but to measure attitude and acceptance of AI technologies. Second, measuring usage in mandatory settings is immaterial because employees have to use the system whether they want to or not since its use is mandated (Brown et al., 2002; Hwang et al., 2016; Linders, 2006). Third, measuring usage in mandatory settings does not provide a comprehensive picture of how the employees really feel about the technology and what can be done to increase its usage in order to be able to use the technology to its full potential (Brown et al., 2002; Kim & Crowston, 2011).

2.4.2 Factors influencing attitude towards AI technologies

The conceptual framework depicted in Figure 2.10 indicates factors that are expected to influence the attitude and acceptance of AI technologies from the TAM and the TOE framework based on past research, as well as additional factors identified from the literature review. These factors are categorised into individual, technological, organisational, or environmental factors as shown in table 2.6 below. Each of these factors is discussed in the sections that follow and hypotheses are formulated indicating the proposed relationship of each of these factors with attitude towards use of AI technologies, based on past and similar research studies and literature on attitude and acceptance of AI technologies.

Table 2.6 Factors influencing attitude towards use of AI technologies

<i>Technological factors</i>	<i>Individual factors</i>	<i>Organisational factors</i>	<i>Environmental factors</i>
Perceived usefulness	Organisational justice	Management support	Social influence
Perceived ease of use	Employee wellbeing	Training	Customer pressure
Relative advantage		Innovative culture	Competitive pressure

2.4.2.1 Technological factors

Technological factors that are considered in this research to be impacting employees' attitude towards use of AI technologies are perceived usefulness, perceived ease of use of the technology, as well as the relative advantage of a new technology. Perceived ease of use and perceived usefulness are constructs from TAM, while relative advantage is a factor often included as a technological factor in various research using the TOE framework (Jere & Ngidi, 2020; Nguyen et al., 2022). Each of these factors will be discussed below.

Perceived usefulness

Perceived usefulness was defined by Davis (1989, p. 320) as the “the degree to which a person believes that using a particular system would enhance his or her job performance”. The usefulness of the technology can be determined by the extent to which the technology improves the individual's performance by enabling them to perform their work quicker, accurately, and effectively (Davis et al., 1989; Venkatesh et al., 2003). Davis (1989) argues that the perceived usefulness of the system is more important than its perceived ease of use, because even though users may consider the system to be too difficult to use, if users perceive it to be useful, they will still use the system because the benefits of using the system outweigh the effort of using the system. For this reason, the usefulness of a technology should be considered in the design, implementation and use of a new technology is vital.

Perceived usefulness has been shown to be a consistent significant variable in determining attitude and acceptance of a new technology across different contexts using diverse technologies (Brown et al., 2002; Karunarathne & Abeyratne, 2020; Sun & Zhang, 2006). Brown et al. (2002) also state that, specifically in mandatory settings, perceived usefulness is very important in encouraging positive attitudes towards use of a new technology.

The use of AI technologies is expected to enhance productivity, accuracy and performance of individuals and the organisation as a whole (Dwivedi et al., 2021; Wisskirchen et al., 2017). Research by Bhargava et al. (2020) on employees' perceptions of AI related technologies also provides an indication of how employees determine the usefulness of AI technologies, for example, by assessing the extent to which AI related technologies enhance their ability to do their work and enables them to use their time and skills more efficiently, as well as eliminates mundane, low value and strenuous tasks.

In this research, perceived usefulness is defined as the extent to which employees feel that the AI technologies implemented are useful in improving their performance. Given the potential of AI in complementing and improving employees' performance (de Saint Laurent, 2018; Lui & Lamb, 2018), a significant relationship between perceived usefulness of AI technologies and attitude towards the use of AI technologies is expected. In addition, it is expected that the more employees perceive the use of AI technologies to be useful and capable of contributing positively to their performance, the more positive their attitude towards the use of AI technologies would be. The following hypothesis is formulated:

Hypothesis 1 (H1): Perceived usefulness has a significant positive influence on attitude towards use of AI technologies.

Perceived ease of use

Davis (1989, p. 320) defined perceived ease of use as the “the degree to which a person believes that using a particular system would be free of effort”. Venkatesh and Davis (2000) elaborated this further to refer to an individual's perception of how easy it is to learn and use the technology. In addition, Davis (1989) argued that perceived ease of use influences perceived usefulness. Sun and Zhang (2006) note that a number of studies have shown perceived ease of use to have a positive influence on perceived usefulness. Recent studies by Chatterjee et al. (2021) and Na et al. (2022) also support this, as they find that perceived ease of use of AI technologies has a positive influence on the perceived usefulness of AI technologies.

Hughes et al. (2019) highlight the importance of technology that is easy to use or user friendly by stating that when a system is not easy to use, psychological barriers to using the system are created. Given that AI technologies are regarded as complex technologies (Chatterjee et al., 2021; Hanif, 2021; O'Shaughnessy et al., 2023), the use of AI technologies is sometimes

perceived to require specific skills and experience, which unfortunately may cause employees to have a perception that AI technologies are difficult to use.

Sun and Zhang's (2006) review of technology acceptance theories and models indicates that unlike the perceived usefulness construct, the relationship between perceived ease of use and attitude and or behavioural intention of technology has been inconsistent, and that this inconsistency could be explained by moderating variables such as experience, the complexity of the technology or gender.

Both Linders (2006) and van den Berg and van der Lingen (2019) acknowledge the importance of ease of use of technology in mandatory settings. However, they differ in terms of the construct that is more important in determining attitude toward a new technology between perceived usefulness and perceived ease of use. Linders (2006) argues that perceived usefulness is the main determinant of attitude followed by perceived ease of use. However, van den Berg and van der Lingen (2019) posit that perceived ease of use is more important because if a technology is perceived to be easy to use, this would outweigh the perceived usefulness of the technology, since the usefulness of the technology is not always clear and evident in mandatory settings.

For this research, perceived ease of use is defined as the extent to which employees perceive AI technologies to be user friendly and easy to use. This research proposes that employees' perception of the ease of use of AI technologies will have a significant influence on their attitude. In addition, the more employees perceive AI technologies to be user friendly, easy to interact with and use, the more positive their attitude towards its use would be. Therefore, the following hypothesis is formulated:

Hypothesis 2 (H2): Perceived ease of use has a significant positive influence on attitude towards use of AI technologies.

Relative advantage

Rogers (2003) defined relative advantage as the extent to which a technology is perceived to provide greater benefit for the organisation, compared to alternative or previous technology used. Relative advantage has been included in most studies that used the TOE framework as a key technological factor impacting the adoption and acceptance of new technology, for

example in the study of the adoption of blockchain by Wong et al. (2020) and in the research on the adoption of information and communication technology by Jere and Ndididi (2020).

Despite the slow adoption of AI technologies (Thowfeek et al., 2020; Weinert et al., 2022), as financial services organisations invest in digitalisation and automation of their processes and way of working, as well as consider upgrading their technologies from legacy systems (Jang et al., 2021; Kruse et al., 2019; Ndoro et al., 2020), the relative advantage of using of AI technologies over other systems and technologies is an important consideration. AI technologies are expected to be superior to other technologies and perform better, faster, and more accurately than humans and current or previous technologies used to carry out specific processes and activities (Füller et al., 2022; Hubbard & Rogers, 2019; Malik et al., 2021; Mehrotra, 2019). As such, it is expected that its use will increase efficiency, reduce costs, increase revenue, amplify human intelligence, as well as enable organisations to be more competitive (Agrawal et al., 2019; Füller et al., 2022; Lui & Lamb, 2018; Malik et al., 2021).

Recent research on the adoption of AI technologies also indicates that relative advantage is a key factor in the adoption of AI technologies. For example, Phuoc (2022), when investigating AI adoption within both public and private companies in Vietnam found that relative advantage was significantly and positively related to the adoption of AI application. Similarly, Gupta et al. (2022) investigated AI adoption within the financial services industry and found that relative advantage had a significant positive effect on the adoption of AI. This shows that although AI technologies are referred to as complex technologies (Füller et al., 2022; O'Shaughnessy et al., 2023), the potential benefits of AI technologies outweigh concerns regarding the complexity of the technology (Gupta et al., 2022).

Relative advantage in this research is defined as the extent to which using AI technologies is perceived to provide additional benefits over its alternative as well as current and/or previous technologies used. This research proposes that the more employees perceive the use of AI technologies to provide greater benefits to processes and ways of working, in comparison with alternative, current or previous technologies, the more positive their attitude would be. Therefore, the following hypothesis is proposed:

Hypothesis 3 (H3): The relative advantage of AI technologies has a significant positive influence on attitude towards use of AI technologies.

2.4.2.2 Individual factors

The TAM and the TOE framework do not include psychological aspects that may impact technology adoption and acceptance. However Kar and Kushwaha (2021) argue that introducing change through the use of a new technology, typically incites cognitive and emotional reactions. Literature reveals the divide between those that tend to be optimistic, excited and keen on embracing AI, and those that seem to be pessimistic, resistant or afraid of AI (Dwivedi et al., 2021; Lane & Saint-Martin, 2021; Tussyadiah & Miller, 2019). Contradictory views on the impact of AI, questions regarding the fairness of the implementation and use of AI technologies, as well the inconsistent views and research on AI's impact on jobs, way of working, work relationships, job satisfaction and overall wellbeing are evident (Ivanov et al., 2020; Malik et al., 2021; Wisskirchen et al., 2017). All these factors are likely to influence employees' attitude towards use of AI technologies. For this research, perceptions of organisational justice and employee wellbeing have been identified as factors to consider when investigating attitude towards use of AI technologies.

Perceptions of organisational justice

Organisational change such as the introduction of a new technology in organisations requires collaboration, communication, trust, transparency, and involvement of employees throughout the process in order to be successful (Baldwin, 2006; Ghislieri et al., 2018; Lichtenthaler, 2020; Manda & Soumaya, 2019). These aspects contribute to employees' perceptions of fairness within the organisation. The concept of organisational justice has been used to refer to the extent to which employees perceive fairness in the decisions, processes, and interactions within the organisation (Colquitt, 2001; Cropanzano et al., 2007). Employees perceive justice in the organisation when they perceive the organisation's process and procedures, interactions and outcomes to be fair (Baldwin, 2006).

The three main types of fairness are distributive fairness, procedural fairness, and interactional justice. Distributive fairness refers to the extent to which individuals perceive fairness in terms of the allocation of outcomes such as pay and other resources (Colquitt, 2001; Cropanzano et al., 2007). For example, in the case where AI is used to manage employees, Hughes et al. (2019) note that employees perceive a high level of distributive fairness when they feel that they are receiving outcomes aligned with their efforts, for example equal pay for equal work, or receiving a high performance rating for putting extra effort in their work. When they

perceive misaligned or inequality in the outcomes or allocation of resources, their perceptions of distributive fairness are low (Hughes et al., 2019).

Procedural fairness refers to the perceptions of fairness in the processes followed to make decisions rather than the actual outcome of the decisions (Cropanzano et al., 2007; Saunders, 2011). It also refers to the extent to which employees perceive fairness in terms of their involvement in the decision making process (Cropanzano et al., 2007; Saunders, 2011). For example, Ötting and Maier (2018) discuss how procedural fairness is experienced when employees feel that they can voice concerns regarding the implementation and use of AI and that these concerns will be addressed, as well as if they feel that the processes of implementing and using AI have been consistent and not biased. If they perceive inconsistency, bias and lack of transparency in the implementation and use of AI technologies, they will have low perceptions of procedural justice (Hughes et al., 2019; Ötting & Maier, 2018).

Interactional fairness refers to perceptions of fairness with regards to the extent to which employees experience fairness in the way they are treated within the organisation (Colquitt, 2001). Interactional fairness is often broken down into interpersonal justice, to refer to employees' perceptions of being treated with respect and dignity and informational justice, to refer to the extent to which employees perceive the presence of honest, fair, and adequate information sharing (Colquitt, 2001; Cropanzano et al., 2007). The extent to which employees feel that they are involved, informed, supported, respected and treated with dignity throughout the process of implementing and using AI technology will determine their perceptions of interactional justice (Hughes et al., 2019).

Employees' perceptions of fairness and justice in the organisation have been shown to have a positive impact on employees' commitment, performance, trust, job satisfaction (Baldwin, 2006; Cropanzano et al., 2007). On the other hand, perceptions of injustice have been shown to contribute to employee turnover, counterproductive behaviour, low performance and low morale at work (Baldwin, 2006; Cropanzano et al., 2007). Awareness of employees' perceptions of justice within the organisation, as well as factors contributing to these perceptions is therefore key.

In mandatory settings, management typically make decisions regarding changes to be implemented and the use a new technology, with limited or no input from employees

(Bhattacharjee et al., 2018; Brown et al., 2002). In such instances where employees are at the receiving end of decisions made by management, Saunders (2011) notes that employees form perceptions about the fairness of decisions made and procedures followed, which influences their adjustment to and acceptance of the changes implemented.

Georgalis et al.'s (2015) investigation on the role of employees' perceptions of organisational justice on the implementation of organisational changes finds that informational justice mediated the relationship between the organisational change and resistance to change. They, like Saunders (2011), emphasise the importance of employees' perceptions of fairness or justice in developing positive employee attitudes towards organisational changes, by promoting timely and accurate information sharing, involving employees throughout the change process, and ensuring transparency and fairness in making decisions (Georgalis et al., 2015).

Ötting and Maier's (2018) research on the effect of procedural justice on employees behaviour and attitude towards human-machine interactions, shows that procedural justice has a significant and positive effect on employees' attitudes and behaviours. Their research emphasises the role and importance of procedural justice when using and interacting with AI related technologies. Further, their research notes that employees' attitudes and behaviours are less influenced by unfavourable outcomes if their perceptions of procedural justice are high (Ötting & Maier, 2018). This aligns with previous findings by Saunders' (2011) that perceptions of procedural or interactional justice mitigated the negative effect of the unfavourable outcomes of decisions and changes made within the organisation.

Concerns raised regarding the use of AI resulting in biased and discriminatory decisions should not be overlooked. Hughes et al. (2019) and Robert et al. (2020) recommend that in cases where AI technologies are being used to plan, organise, supervise and manage employees, it is imperative that the AI technologies used are designed to ensure fairness, to prevent situation where employees perceive injustice in the way AI is used to manage them.

Given that the decision to use AI technologies is not the focus of this study, nor up to the employees in the organisation, this research will focus on perceptions of procedural and interactional justice, and not on distributive justice since the focus of the research is not on the allocation and distribution of the use of AI technologies. This is also in line with previous

studies, for example, the study by Georgalis et al. (2015) who investigated the role of employees' perceptions of fairness when organisational changes were being implemented, and omitted aspects related to distributive justice in their research and focused mainly on perceptions of fairness in terms of procedural and interactional justice. For the purposes of this research, organisational justice is defined as the extent to which employees perceive fairness in the procedures, processes, communication, and treatment they receive, throughout the implementation and use of AI technologies. It is therefore expected that the more employees perceive fairness in the implementation and use of AI technologies the more positive attitude they would have towards its use. The following hypothesis is proposed:

Hypothesis 4 (H4): Organisational justice has a significant positive influence on attitude towards use of AI technologies.

Employee wellbeing

The investigation of psychological factors, such as the wellbeing of employees in technology adoption and acceptance research has been growing (Lu et al., 2019; Schiff et al., 2020). As such, the need to focus on emotional and psychological aspects that enable as well as inhibit the wellbeing of employees when dealing with organisational changes, including changes in technology, has become more prominent (Litchfield, 2021; Loon et al., 2018; Pradhan & Hati, 2022; Schiff et al., 2020). The continued changes and pressures that organisations are experiencing internally as well as externally, are continuously placing new demands on employees to consistently adjust and adapt and this is impacting their overall wellbeing (Loon et al., 2018; Potgieter, 2019).

Ryff (1989) is often cited in wellbeing literature for providing a summary of six wellbeing dimensions that provide a holistic view of wellbeing. The dimensions include self-acceptance (a positive evaluation of oneself and one's past life), personal growth (a sense of continued growth and development), purpose in life (a sense of meaning and purpose in life), positive relations with others (quality relations with others); environmental mastery (ability to effectively manage oneself in their environment) and autonomy (a sense of control and personal authority) (Ryff, 1989).

A synthesis of the literature on the wellbeing at work also shows that wellbeing is a multidimensional construct (Loon et al., 2018; Potgieter, 2019; Pradhan & Hati, 2022). Various

definitions of wellbeing exist, as each definition considers different elements and meanings to refer to wellbeing, for example, mental wellbeing, psychological wellbeing, physical wellbeing, emotional wellbeing, subjective wellbeing and good health (Danna & Griffin, 1999; Pradhan & Hati, 2022). Nonetheless, the two main components of an individual's overall wellbeing include feeling good and functioning well (Keeman et al., 2017; Pradhan & Hati, 2022).

In describing employee wellbeing, Guest and Conway (2004) refer to six constructs that determine an employee's wellbeing which include manageable workload, personal control over the job, support from colleagues and supervisors, positive relationships at work, clear role and responsibilities and involvement in changes in the organisation. Pradhan and Hati's (2022) research on the development of a measurement for employee wellbeing concluded that employee wellbeing entails factors such as job satisfaction, psychological wellbeing, social wellbeing, workplace wellbeing and subjective wellbeing.

Despite the variations in how wellbeing is measured or defined, research on wellbeing in the workplace has been growing, as the impact of employees' wellbeing on key organisational outcomes such as productivity and performance has become more evident (De Simone, 2014; Ibrahim et al., 2020; Krekel et al., 2019). Employee wellbeing is related to lower employee turnover, higher productivity, increased efficiency, increased job involvement and innovation, increased organisational commitment and increased organisational performance (Garg et al., 2014; Litchfield, 2021; Loon et al., 2018; Pradhan & Hati, 2022). Low or poor wellbeing is related to poor health and poor career wellbeing, increased absenteeism, decreased productivity and low levels of satisfaction (Danna & Griffin, 1999; De Simone, 2014; Nawata, 2024).

The literature on the impact of AI on factors influencing employees' wellbeing has been contradictory. The optimistic view states that the use of AI technologies will have a positive impact on employees' work, their way of working, job satisfaction, engagements with others, and career wellbeing (Anderson et al., 2018; Kelley et al., 2019). At the same time, the pessimistic view highlights concerns of AI being a threat to employees' wellbeing through potential job losses, and negatively impacting employees' autonomy, work relationships and careers (Calitz et al., 2017; Ghislieri et al., 2018). In addition, concerns of individuals being at risk of technostress, described as the inability of individuals to handle work demands due use of new technologies (Malik et al., 2021), have also been raised. Although the implementation

and use of AI is intended to improve individual and organisational performance and bring autonomy and flexibility (Chiu et al., 2021), it appears to be potentially detrimental to employees' wellbeing in terms potential stress, and threat to their job security, autonomy, and careers. This is indicative to what Loon et al. (2018) refers to the above as the paradox of psychological wellbeing.

Although research on AI and wellbeing is limited, the importance of investigating the impact of automation and AI technologies on aspects that contribute to employee wellbeing has been recognised (Schiff et al., 2020). Nazareno and Schiff's (2021) investigation of the impact of automation technologies such as AI on employees' wellbeing finds that employees whose jobs have a high risk of being automated experience less stress initially but worse health and a minimal or negative impact on satisfaction, which indicates that although technologies can make work easier and reduce stress initially, the benefits come at a cost. However, research by Parker and Appel (2021) indicates that the use of AI related technologies has a positive impact on employees' wellbeing in terms of greater fulfilment in their work, reduced stress, and enhanced engagement. Wei and Li's (2022) research also reveals that the use of AI has a positive effect on employees' mental wellbeing. c

Given the above, employee wellbeing will be defined as the extent to which employees think or feel that using AI technologies will contribute more to their job satisfaction, career development, engagement with others and autonomy, and less to their work-related stress, anxiety and feelings of job insecurity. This research proposes that the more employees feel that the use of AI technologies contributes positively to their employee wellbeing, the more positive they would be in terms of their attitude towards the use of AI technologies. The following hypothesis is formulated:

Hypothesis 5 (H5): Employee wellbeing has a significant positive influence on attitude towards use of AI technologies.

2.4.2.3 Organisational factors

The TOE framework includes the organisational context as a key variable to be considered in technology adoption and acceptance research (Alsheibani et al., 2019; Nam et al., 2020; Tripopsakul, 2018). Factors such as an organisation's culture, characteristics, structures, size, availability of training, management support, are common organisational factors that have been

considered when investigating organisational factors impacting the adoption and acceptance of technology (Gangwar et al., 2015; Iftikhar et al., 2021; Li, 2020; Tjebane et al., 2022). Research on factors influencing the adoption, attitudes and acceptance of AI technologies has identified management support (Alsheibani et al., 2019; Li et al., 2019; Merhi & Harfouche, 2023; Na et al., 2022; Phuoc, 2022; Tjebane et al., 2022) an organisation's culture (Kruse et al., 2019; Merhi & Harfouche, 2023; Na et al., 2022; Tjebane et al., 2022) and the availability of training on AI to develop the lack of AI skills (Alsheibani et al., 2019; Kruse et al., 2019) as key organisational factors. An organisation's characteristics as well as the support it provides its employees has a significant impact on employees' attitude and acceptance of AI technologies (Na et al., 2022; Nguyen et al., 2022). For this research, management support, an innovative culture, and training are included as organisational factors to be considered when investigating determinants of attitude towards use of AI technologies.

Management support

Literature has shown that the implementation and use of AI technologies is often challenged with lack of understanding AI (Kelly et al., 2023; Ngoro et al., 2020), as well as uncertainty, and fear regarding its use and potential negative impact on employees' job and ways of working (Ghislieri et al., 2018; Lu, 2019; Strusani & Hounghonon, 2019). Therefore, management support given to employees by providing guidance, direction, and motivation to employees to minimise stress and anxiety during the implementation process is key to the successful implementation and use of AI technologies (Li et al., 2019; Tjebane et al., 2022).

Despite challenges and uncertainty regarding the use of AI technologies, employees look up to management for leadership, guidance, and support. Therefore, management's ability to provide employees with a clear AI strategy, clear processes to be followed as well as the support provided throughout the implementation and use of AI technologies is key (Pumplun et al., 2019; Weinert et al., 2022). This is why Phuoc (2022) notes that effective management support to overcome challenges with the implementation and use of AI technologies is dependent on management's capability to provide the required and adequate support.

Research on the adoption of technology shows that management support is key throughout the initiation, implementation, acceptance and use of technology (Ghaleb et al., 2021; Matikiti et al., 2018; Skafi et al., 2020). Chen et al.'s (2020) research on success factors impacting artificial

intelligence adoption in the telecommunications industry in China finds management support to be a key driver for AI adoption. They recommend that management promote the adoption and acceptance of AI by engaging with employees throughout the implementation process, by effectively coordinating organisational resources and by providing guidance to employees in terms of the vision, policies and objective of the implementation and use of AI technologies (Chen et al., 2020).

Chatterjee et al. (2021) and Gupta et al. (2022) report similar findings from their research as management support has a positive and significant influence on the adoption of AI technologies in the manufacturing industry and financial services industry respectively. Vasiljeva et al.'s (2021) research on attitudes towards the use of AI technologies across various industries in Latvia also confirm that management support has a significant effect on attitudes towards the use of AI technologies. Tjebane et al.'s research on organisational factors that impact AI adoption in the South African construction industry indicated that management support was a key determinant for successful implementation of AI technologies. Merhi and Harfouche's (2023) research on enablers of AI in production systems also find that management support is a key organisational factor.

Although Ivanov et al.'s (2020) research on drivers and solutions for fears towards automation technologies such as AI amongst Bulgarians citizens reveals that respondents have a low fear of automation, they urge management to not get complacent. Instead, they encourage management to involve employees in decisions made regarding the use of these new technologies, and to be supportive to employees throughout the implementation and use of these technologies.

For this research, management support is defined as the extent to which employees feel that management provide sufficient guidelines on the use of AI technologies, access to training, resources and software as well opportunities for employees to provide feedback on the use of AI technologies. It is expected that the more employees feel that there is adequate support from management, the more positive they would be regarding the implementation and use of AI technologies. Therefore, the following hypothesis is formulated:

Hypothesis 6 (H6): Management support has a significant positive influence on attitude towards the use of AI technologies.

Training support

Training support is found to be a significant organisational factor in research on the adoption, attitude, and acceptance of new technology (Gangwar et al., 2015; Ghaleb et al., 2021; Matikiti et al., 2018). Although it has been argued that the goal of AI is to empower and complement employees in their way of working, the lack of AI skills to effectively implement and use AI technologies remains a challenge (Kruse et al., 2019; Ndoro et al., 2020; Zhang et al., 2021). For this reason, training and development of AI skills is essential to ensure AI readiness, as well as the successful implementation and use of AI technologies (Gangwar et al., 2015; Kruse et al., 2019).

Understanding what AI is and what it can do is highlighted as a challenge to working with AI technologies, based on research on AI adoption by Bhargava et al. (2020), Ndoro et al. (2020) and Zhang et al. (2021). Lack of training to gain a better and more accurate understanding of what AI is and what it can do, may result in individuals having a skewed and unbalanced view of the benefits and potential challenges of using AI, which can contribute to uneasiness, stress resistance, and fear towards the use of AI technologies (Baggio & Omana, 2019; Lichtenthaler, 2020).

As AI becomes more pervasive (Chatterjee et al., 2021; Kurshan et al., 2021), employees who lack training on AI may also feel disadvantaged from being able to participate actively in an AI dominated world (Korinek & Stiglitz, 2018). Lane and Saint-Martin (2021) cite research by Accenture (2018) which suggests that employers may sometimes underestimate the willingness of employees to undergo training and acquire the skills necessary for them to work effectively with AI technologies, as there are employees keen to develop their skills to work positively with AI technologies. Training on AI technologies can therefore expose employees to different types of AI technologies to get a better understanding and appreciation of AI (Gu et al., 2022; Strich et al., 2021). This will enable employees to familiarise with AI and reduce resistance, stress, fear, and anxiety when working with AI technologies (Robb et al., 2020; Wisskirchen et al., 2017).

Vasiljeva et al. (2021) adds that for organisations to be able to leverage the benefits and potential of technological developments such as the use of AI technologies, they will need to train and develop their employees to acquire new skills and competencies. Since there are

debates surrounding the impact of AI technologies on job creation and job losses, training employees to enable them to develop AI skills and/or reskilling or upskilling them for future roles will help mitigate the negative impact of AI on employment (Arakpogun et al., 2021; Lane & Saint-Martin, 2021; Moldenhauer & Londt, 2018).

Magwentshu et al. (2019) recommend that in South Africa where there are extremely high levels of unemployment, there is a need to have aggressive plans and action to ensure that individuals have access to the relevant training and are sufficiently trained or reskilled to enable them to benefit from the use of new technologies such as AI technologies.

Research by Ndoro et al. (2020) on the uses, benefits, and challenges of using AI technologies within the financial services industry in the Western Cape in South Africa highlights the lack of AI skills as a main challenge when it comes to working with new technologies. These research findings highlight the need to provide employees with opportunities to be exposed to and learn about AI technologies. In examining AI readiness in South Africa, Schoeman et al. (2021) also note the concerns of workforce readiness in terms having adequate skills to work with AI.

Training support in the context of this research refers to the extent to which employees feel that there is sufficient training provided to help them understand AI, be more comfortable and confident when using AI technologies as well as be more receptive towards the use of AI technologies. The presence of training support is expected to positively influence attitude towards the use of AI technologies. This research proposes that the more employees feel that they have adequate training opportunities and support to enable them to be exposed to and learn about AI technologies, the more positive their attitude towards the use of AI technologies would be. The following hypothesis is formulated:

Hypothesis 7 (H7): Training support on the use of AI technologies has a significant positive influence on attitude towards use of AI technologies.

Innovative Culture

Although organisational culture can be defined in different ways (Hogan & Coote, 2014; Martínez-Caro et al., 2020) it encompasses an organisation's structure, policies, way of working, and shared beliefs and values (Hogan & Coote, 2014; Hubbard & Rogers, 2019;

Martínez-Caro et al., 2020; Zemanova et al., 2022). Zemanova et al. (2022) developed a framework that can be used to characterise key attributes of an innovative culture, which are clustered into four clusters, communication and cooperation; innovation and change as core values; employee participation and employee engagement.

An innovative organisational culture is an important factor in the TOE framework (Neumann et al., 2022) and has been found to have a significant influence on the adoption and acceptance of a new technology (Brdešec et al., 2012; Neumann et al., 2022; Pateli et al., 2020). This is because an organisation's culture influences the what, how and why of implementing a new technology, as well as the processes, policies, attitudes and expectations of the new technology (Na et al., 2022).

Innovative cultures are organisational cultures that are agile, encourage collaboration and focus on promoting a digital mindset, and are therefore likely to have more success with the implementation, integration and use of AI technologies (Alsheibani et al., 2019; Hubbard & Rogers, 2019; Jöhnk et al., 2020). They are also likely to promote knowledge sharing and open communication and enable policies and processes that support employees throughout the changes, implementation and use of AI technologies, and put employees at ease throughout the process (Holmström, 2022; Hubbard & Rogers, 2019).

Research on the implementation and use of AI technologies also acknowledges the role and impact of an organisation's culture in determining the successful implementation and use of AI technologies. For example, Calitz et al.'s (2017) research on the use of collaborative robots within South African manufacturing companies indicate that an organisation's culture is significant in the human–robot interaction and enables employees to develop trust towards their interaction with robots.

Ahn and Chen's (2022) research findings on the perception of government employees and their willingness to use AI also emphasises the importance of organisations having a more collaborative culture that promotes innovation and digital transformation in order to be able to leverage the potential of AI. Neuman et al.'s (2022) research on the adoption of AI technologies in public organisations in Switzerland indicates that an innovative culture, that is agile, encourages experimentation and is open to failure when using AI technologies is likely to be supportive to AI adoption and acceptance. Research by Tjebane et al. (2022) on organisational

factors impacting AI in the South African construction industry also shows that the success and flow of innovation within an organisation depends on the extent to which the organisational culture supports it. Merhi and Harfouche (2023) share similar findings from their research as organisational culture is identified as an enabler of AI in the implementation of production systems.

Despite progress in implementing and using AI technologies, financial services institutions such as banks and insurance companies have been criticised for not being flexible and agile enough to be able to quickly and continuously adapt and make use of AI-related technologies due to their rigid traditional hierarchical structures and red tape (Kruse et al., 2019; Thowfeek et al., 2020). This could explain the slow implementation and use of AI technologies.

For this research, an innovative culture refers to the extent to which employees feel that their organisation's culture is innovative and promotes collaboration, openness, agility, flexibility and is capable of effectively implementing AI technologies in their way of working. An innovative culture is expected to positively influence attitude towards the use of AI technologies. This research therefore proposes that the more employees perceive the culture of their organisation to be innovative in terms of promoting innovation, collaboration, openness, agility, flexibility, and the ability to effectively implement AI technologies in their way of working, the more they would be positive towards the use of AI technologies. The following hypothesis is formulated:

Hypothesis 8 (H8): An innovative organisational culture has a significant positive influence on attitude towards the use of AI technologies.

2.4.2.4 Environmental factors

The TOE framework is notable for considering the impact of environmental factors in the adoption of new technology, given that organisations operate as part of a broader ecosystem, where they are influenced by and influence various factors external to the organisation. As such, environmental factors can enable as well as inhibit an organisation from effectively adopting a new technology (Nguyen et al., 2022; Thowfeek et al., 2020). Some of the common environmental factors considered in previous research that applied the TOE framework include customer needs and pressure (Matikiti et al., 2018; Nam et al., 2020; Tripopsakul, 2018), competitive pressure (Chatterjee et al., 2021; Chiniah et al., 2019; Gangwar et al., 2015;

Iftikhar et al., 2021; Na et al., 2022; Pateli et al., 2020; Qin et al., 2020), government regulations and/or policies (Gupta et al., 2022; Iftikhar et al., 2021; Qin et al., 2020), social pressure/social norms/public opinion (Na et al., 2022; Tripopsakul, 2018) partner support (Chatterjee et al., 2021; Chiniah et al., 2019; Malik et al., 2021; Pillai et al., 2021) and market dynamics or uncertainty (Chen et al., 2020; Gupta et al., 2022).

Based on the literature review on external factors influencing the adoption, attitude and acceptance of AI technologies, social influence (which includes other people's views, public opinion, and the media), customer pressure as well as competitive pressure are included in this research as environmental factor influencing attitude towards the use of AI technologies.

Social influence

The concept of social influence which is sometimes referred to as subjective norm (Flavián et al., 2021; Gansser & Reich, 2021) is based on the Theory of Reasoned Action (TRA), and (Fishbein and Ajzen (1975) described it as the extent to which an individual feels that those important to him or her think that he or she should perform a specific behaviour or use a specific technology (Ajzen & Fishbein, 1980). Na et al. (2022) include social influence as an environmental variable in their research on the acceptance of AI technologies in the construction industry, by combining subjective norms, social norms as well as public image. For the purposes of this research, social influence refers to the extent to which others' positive beliefs about the use of AI technologies influences employees' attitude towards the use of AI technologies. Others' beliefs include views shared by peers and people regarded as being important to the individual, as well as the media. The views that employees are exposed to regarding a new technology, whether positive or negative, influence their attitudes and acceptance of a new technology. Afterall, employees are social beings and do not live in a vacuum (Rufus, 2020).

Although not initially included in the original TAM due to its uncertain theoretical and psychometric properties (Davis et al., 1989; Linders, 2006), this construct is included in later and extended TAM models (Gansser & Reich, 2021; Venkatesh & Davis, 2000). However, the sources and influence of social influence in technology acceptance within organisations have been debatable. Hwang et al. (2016) state that social influence comes from second-hand information including colleagues and friends which influences their attitude and acceptance of

a new technology. However, Ajibade (2018) argues that only those that have a directive influence over an employees, such as an employee's superior can influence an employee's attitude and behaviour.

Public perceptions of AI, driven by the media also contribute to the attitude and acceptance of AI technologies (Fast & Horvitz, 2017; Robb et al., 2020). Depending on what an individual is exposed to, the media's view and portrayal of AI can be negative, positive, or even inaccurate (Fast & Horvitz, 2017; Kelley et al., 2019; Robb et al., 2020). Garvey and Maskal (2020) note that because the definition and use of new technologies such as AI is still flexible and growing, the public and media can easily shape how they present this to the public. Their research on the sentiment analysis of the news media on AI indicates that although AI news coverage has been positive, public perceptions tend to be negative since the use of AI technologies is often seen to pose a threat to many people (Garvey & Maskal, 2020).

The significance of social influence in the adoption, attitude, acceptance, and usage of technology has been inconsistent (Kim & Crowston, 2011; Lee et al., 2003; Sun & Zhang, 2006). For example, Mathieson (1991) did not find subjective norms or social pressure to influence technology adoption. Although Venkatesh and Davis (2000) find social influence to significantly impact acceptance of technology, the effect of social influence on the acceptance of a new technology lessened over time. They suggest that this could be because as individuals gain experience with the new technology over time, they rely more on their experience and less of their social influence when deciding whether or not to accept a new technology (Venkatesh & Davis, 2000).

Anandarajan et al. (2000) find social influence to be a strong motivating factor of microcomputer usage, while Ye et al. (2019) conclude that subjective norms is the most important predictor of intention to use AI devices amongst all variables. Similarly, Prastiawan et al. (2021) find that social influence has a positive influence on attitude towards the use of mobile banking. The inconsistencies in research findings can be explained by Venkatesh et al. (2003) who note that the inconsistency in terms of the influence of social influence on technology acceptance could be due to factors such as experience with the new technology, or variables such as well as gender, profession, and type of technology.

Research by Anandarajan et al. (2000) highlights how the significance of social influence in technology acceptance is influenced by the context and culture. Their research on technology acceptance in the banking industry in Nigeria, indicates that because African countries and societies tend to be collectivist cultures, the effect of social pressures on technology acceptance is likely to be more significant than the perceived usefulness or enjoyment of the technology (Anandarajan et al., 2000). This is because individuals may only use the new technology because of pressure from others, in order to be perceived as being technological sophisticated by those they consider important to them (Anandarajan et al., 2000).

Venkatesh et al.'s (2003) research in the development of a unified model to be used to determine acceptance of a new technology indicates that social influence has a significant direct effect on behavioural intention towards a new technology in mandatory but not in voluntary settings. Hwang et al.'s (2016) review of literature on technology acceptance in mandatory environments also highlights significant role of social influence in the acceptance of technology acceptance, especially within mandatory settings.

Given that this research is conducted within mandatory settings, a significant relationship between social influence and attitude towards use of AI technologies is expected. Given that social influence in this research is regarded as the extent to which others' positive beliefs about the use of AI technologies influences employees' attitude towards the use of AI technologies, this research proposes that the greater the social influence, the more positive the employees' attitude towards the use of AI technologies would be. The following hypothesis is formulated:

Hypothesis 9 (H9): Social influence has a significant and positive influence on attitude towards use of AI technologies.

Customer Pressure

Customer pressure refers to the extent to which employees perceive that the pressure to implement and use a new technology comes from customers' need and demands (Tripopsakul, 2018). However, its role in technology adoption, attitudes and acceptance has not been consistent. For example, research by Matikiti et al. (2018) on the acceptance of social media technology in South Africa find that customer pressure has no significant influence on the attitude towards use social media marketing technologies. On the contrary, research by Tripopsakul (2018) on social media adoption in Thailand identifies customer pressure as the main environmental factor influencing the adoption of social media. Nam et al.'s (2020)

research on factors influencing the adoption of AI technologies and robots in the hotel industry also highlight customer pressure as a main factor influencing the adoption of a new technology.

The literature review shows that customers' needs and expectations are continuously changing (Lui & Lamb, 2018; Rufus, 2020; Sartori & Bocca, 2022). This puts pressure on organisations to find innovative ways of using technology to keep up with customer needs as well as technological trends. The use of AI technologies to create and promote a great customer experience, customer trust, customer satisfaction and commitment is emphasised (Dwivedi et al., 2021; Kelly et al., 2023; Kruse et al., 2019; Ndoro et al., 2020). For example, creating a more digital and personalised banking experience and providing customers with more convenience through instant and interactive 24/7 support services is becoming the norm (Guo & Polak, 2021; Jang et al., 2021; Lui & Lamb, 2018). Sheth (2020) and Biswas et al. (2020) note the impact of the Covid-19 pandemic, specifically during the time when lockdown regulations were implemented and enforced, and how this disrupted and modified customer behaviours, resulting in customers having to embrace digital technologies in order for them to be able to access services and products online from their homes, since they could not do so physically or in person. As a result, customers' digitally driven relationships have grown (Lu et al., 2022; Manser Payne et al., 2021).

However, literature alludes to the fact that caution should be taken when implementing AI technologies for service customers. Lui and Lamb (2018) bring attention to the fact that although organisations are trying to offer convenience when engaging with their customers by using various AI technologies such as chatbots, trust and confidence in using AI technologies may be challenged. This is because, in some instances, humans are still preferred to advise customers when dealing with more complex needs or complaints that require social and emotional skills, which machines do not have (Lui & Lamb, 2018). This is why, Lui and Lamb (2018) advocate for the promotion of augmented intelligence, where both humans and AI are integrated to be able to provide customers with seamless services. Siderska and Alsaqoor (2023) share similar views and stress the fact that because humans and AI offer different opportunities and strengths, the focus should be on findings constructive ways to develop augmented or hybrid intelligence.

Nevertheless, this research proposes that the more customer pressure that employees experience or perceive, the more positive their attitude towards the use of AI technologies

would be. This is because the more employees believe that the adoption and use of AI technologies enhances customer relationships, customer satisfaction and customer growth, the more likely they are to have a positive attitude towards the use of AI technologies. If employees are enabled to effectively service their customers by using AI technologies, this will improve their own performance as well as the organisation's performance and in so doing, benefit employees directly or indirectly through increased job security, salaries, bonus, etc. Therefore, the following hypothesis is formulated:

Hypothesis 10 (H10): Customer pressure has a significant positive influence on attitude towards the use of AI technologies.

Competitive pressure

Pressure from competitors is often included as a factor in the environmental context to indicate the extent to which the competitors are perceived to influence the adoption, attitude, and acceptance of a new technology (Chatterjee et al., 2021; Chiniah et al., 2019; Gupta et al., 2022). Competitive pressure has been found to influence technology adoption or acceptance of cloud computing (Gangwar et al., 2015), social media technologies (Matikiti et al., 2018; Tripopsakul, 2018) and blockchain technology (Wong et al., 2020). However, Chen et al. (2020) and Nguyen et al. (2022) did not find competitive pressure to influence AI adoption within the telecommunications industry in China and within private and public organisations in Vietnam respectively.

In the financial services industry, the implementation of AI is seen as a necessity to stay competitive and survive in the market (Lui & Lamb, 2018; Møller et al., 2018; Noreen et al., 2023). Traditional financial services organisations are urged to use AI technologies to avoid being left behind in terms of technology used and keep up with competitive pressure from Fintechs (Belanche et al., 2019). Fintechs are described as new financial intermediaries that use technology-enabled innovations to support new business models and changes in business processes, while offering exciting, different, flexible and improved products and services (Belanche et al., 2019; Zhang et al., 2021).

Thowfeek et al. (2020) also note that conventional banking services sometimes fail to provide the needed flexibility and innovation required for them to effectively service customers' needs. Fintechs, however, use advanced technologies and agile processes to provide efficient and

advanced customer-focused solutions, reduce costs of servicing customers and to gain competitive advantage in the market (Guo & Polak, 2021; Zhang et al., 2021). This is also the case in African financial services environments, where mobile operators and Fintechs are said to be using AI technologies aggressively and outcompeting traditional financial services institutions (Adeleye et al., 2019), while also bridging the gap between the banking industry and millions of unbanked across the continent (Kheira, 2021).

As organisations are competing through technology and innovation (Adeleye et al., 2019), failure to experiment and adopt new technologies effectively in order to gain competitive advantage puts the organisation at risk of losing their competitive advantage and losing customers (Biswas et al., 2020; Moldenhauer & Londt, 2018). This research proposes that the more employees perceive competitive pressure to implement and use of AI technologies as something that is necessary for the organisation's survival, success and competitiveness, the more positive their attitude would be towards the use of AI technologies. Employees may also desire to work for an organisation that is innovative and competitive, as this would also have a positive impact on their career development and job security. The following hypothesis is formulated:

Hypothesis 11 (H11): Competitive pressure has a significant positive influence on attitude towards the use of AI technologies.

2.4.3 Attitude towards use of AI technologies

The attitude construct in technology acceptance literature has been used to determine the extent to which an individual is positive or negative, or favourable or unfavourable towards use of a new technology (Fishbein & Ajzen, 1975). Ghaleb et al. (2021) note that a positive attitude towards technology encourages individuals to embrace new technologies, while negative attitudes lead to uneasiness and feelings of insecurity which inhibit the successful adoption and acceptance of technology.

Investigating individuals' attitude when introducing change through the use of a new technology is crucial in explaining how and why individuals feel the way they do about the new technology (Tjebane et al., 2022; Vasiljeva et al., 2021). This will enable management to be aware of and manage possible resistance that may hamper the successful implementation and use of the technology (Bhattacharjee & Sanford, 2009; Djasasbi et al., 2009; Hwang et

al., 2016; Lichtenthaler, 2020; Linders, 2006; Vasiljeva et al., 2021). Negative attitudes towards a new technology that are left unaddressed can lead to suboptimal use of the technology, sabotage or misuse of technology, as well as destructive or counterproductive behaviours, which will be costly to the organisation and obstruct the effective implementation and use of the new technology (Brown et al., 2002; Hwang et al., 2016; Lichtenthaler, 2020).

In the context of AI technologies for example, Lichtenthaler (2020) discusses how individuals with negative attitudes and are not in favour of the use of AI technologies, tend to be afraid and/or resistant to interacting with AI technologies as they focus mainly on the potential negative effects of using AI technologies. On the other hand, individuals with a positive attitude towards AI technologies tend to be in favour of and more open to using AI technologies, as they focus more on the potential benefits of using AI technologies to optimise processes (Lichtenthaler, 2020). These individuals also tend to have a more balanced view of the positive and negative consequences of AI (Lichtenthaler, 2020). However, Lichtenthaler (2020) also highlights the paradox of employees' attitudes towards the use of AI technologies in that depending on the situation, an employee may have both positive and negative attitudes towards AI technologies. For example, an employee may prefer to work and collaborate with real humans than virtual colleagues, but at the same time be keen to use AI technologies when its beneficial for them (Lichtenthaler, 2020).

In technology acceptance research, the relationship between attitude and behavioural intention (acceptance of technology), specifically the extent to which the attitude constructs influences acceptance is inconsistent and widely debated (Davis & Venkatesh, 1996; Hwang et al., 2016; Sun & Zhang, 2006). For this reason, the attitude constructs has been removed from the revised TAM models and subsequent extension of the TAM and technology acceptance theories (Brown et al., 2002; Hwang et al., 2016; Sun & Zhang, 2006). For example, although research by Davis and Venkatesh (1996), Venkatesh and Davis (2000) and Nath et al. (2013) find attitude to have a limited or non-significant influence on acceptance or use of technology, the attitude construct indicates a significant relationship in the technology acceptance and use of computer systems (Davis, 1989), healthcare information systems (Djamasbi et al., 2009), document management systems (Bhattacharjee & Sanford, 2009), technology-enabled financial services (Wentzel et al., 2013), social media marketing (Matikiti et al., 2018) and use of mobile banking (Prastiawan et al., 2021).

Research on the acceptance of AI technologies in various contexts indicates the significant role of attitude on acceptance of AI, for example, in the healthcare sector in the UAE (Alhashmi et al., 2019), in various companies in the UK (Cao et al., 2021), within the construction industry in South Korea, (Na et al., 2022) and within the banking services in Malaysia (Rahman et al., 2021) and in the banking industry across five different Asian countries (Noreen et al., 2023). These research findings support the view by Lichtenthaler (2020) that independent of a positive or negative attitude, employees' attitudes strongly influence technology acceptance decisions, which in turn impact an organisation's innovation outcomes, performance and ability to leverage the potential of AI technologies.

Brown et al. (2002) acknowledge the need to investigate and understand employees' attitudes in mandated settings, they argue that attitude is not a predictor of behavioural intention (acceptance) as indicated in the TAM since employees do not have the choice on whether to accept the new technology or not. Their research also found the relationship between attitude and behavioural intention to be insignificant. Hwang et al. (2016) concur with these findings and state that employees have to use the new technology implemented regardless of their attitude towards using it. However Chiu et al.'s (2021) research on factors that contribute to employees' attitudes (affective and cognitive) towards AI technologies and how they influence employees' behavioral responses such as intention to use AI technologies found that attitude toward AI technologies positively influences intention to use AI technologies.

In emerging market economies, research on attitude towards AI technologies is limited as most research is dominated in developed countries (Ahmad et al., 2020; Georgieff & Hyee, 2022). Nonetheless, the available research findings on attitude towards the use of AI technologies in emerging market economies highlights factors to be considered which impact the attitude and acceptance of AI technologies. For example, in South Africa, Roberts et al.'s (2021) research on the public's attitude and acceptance of AI technologies such as automation or robotics concludes that resistance to these technologies remains high, although this varies across different contexts, demographic differences (age, race, class), perceived labour market vulnerability, experience with AI technologies and confidence in the government to manage adverse human consequences. Ivanov et al.'s (2020) research on attitudes toward AI amongst Bulgaria citizens also shows similar findings in terms of differences in fear of AI technologies due to demographic differences. They also note that factors driving fear towards automation and use of AI -related technologies include the potential dehumanising effects of automation,

peer-pressure, job automatability, and a person's self-perception of professionalism (Ivanov et al., 2020).

From the above, this research argues that as the use of AI technologies continues to grow, it becomes more imperative to understand employees' attitudes towards AI technologies as this has an impact on the adoption and acceptance of AI technologies. For this research, attitude is defined as the extent to which an employee is positive and in favour of the use of AI technologies. Despite the inconsistencies in research on the relationship between attitude and acceptance (behavioural intention), it is expected that employees' attitude towards the use of AI technologies will have a significant influence on the acceptance of AI technologies. Therefore, the attitude construct from the original TAM model is retained. The following hypothesis is formulated:

Hypothesis 12 (H12): Attitude towards the use of AI technologies has a significant positive influence on the acceptance of AI technologies.

2.4.4 Acceptance of AI technologies

In technology acceptance research, Sun and Zhang (2006) note that the attitude, usage and behavioural intention constructs have been used to measure technology acceptance of technology. As a result, there has been inconsistency in the in the meanings and measurement of acceptance of technology (Nadal et al., 2019; Sun & Zhang, 2006). However, a review of theories and models of technology acceptance indicates that the behavioural intention or the intention to use constructs have been used to measure acceptance of a new technology (Alharbi & Drew, 2014; Karunarathne & Abeyratne, 2020; Taherdoost, 2018). This, together with usage of a new technology has been used to measure the success of a new technology (Hwang et al., 2016). For example, Bröhl et al.'s (2016) research on the acceptance of human-robot cooperation in production systems indicate that acceptance is a significant factor in predicting successful cooperation between humans and robots. Hwang et al. (2016) also note that decision makers in organisations have recognised that the that lack of acceptance from users of a new technology can cost the organisation money and resources.

However, Linders (2006) has argued that in mandatory settings where employees do not have a choice on whether to or not to use or accept the new technology, measuring behavioural intention/intention to use a technology (i.e. acceptance of technology) is irrelevant. Hwang et al. (2016) also concur by stating that in mandatory settings where the use of technology is

mandatory, measuring intention to use a new technology or the usage of a new technology does not provide a clear indication of how individuals feel and/or truly accept a new technology since individuals may merely use the technology because its use is compulsory. For this reason, they propose that other measures of success when implementing a new technology be considered, for example, user satisfaction (Hwang et al., 2016).

Taking the above into account, this research argues that the acceptance of technology in mandatory settings be broadened and defined to suit the context of mandatory settings. The following considerations highlighted in literature are considered in redefining acceptance in mandatory settings. First, since employees in mandatory settings have no choice when it comes to the use of new technologies within the organisation in doing their work, employees can easily use the technology as a tick-box exercise to avoid punishment or negative consequences (Brown et al., 2002; Hwang et al., 2016).

Second, if individuals do not like the new technology, they may try to find ways of reverting back to the old system or only use the new technology for specific tasks (Brown et al., 2002). Floridi et al. (2018) note that the underuse of AI technologies may result in opportunity costs as employees and the organisation may fail to use AI technologies to their full potential.

Third, an intention-behaviour gap (Bhattacharjee & Sanford, 2009) or innovation dissonance (Karahanna & Agarwal, 2006; Rawstorne et al., 1998) may arise. This is generally evident in mandatory settings where there sometimes a significant discrepancy between employees' initial adoption or acceptance of a new technology and their actual behaviour to use the new technology (Bhattacharjee & Sanford, 2009; Rawstorne et al., 1998). This happens when employees may accept and use the new technology initially, but over time, demonstrate limited use of the technology (Brown et al., 2002; Po-An Hsieh & Wang, 2017).

All these behaviours can sabotage or hinder the successful implementation and use of new technologies (Bhattacharjee & Sanford, 2009; Brown et al., 2002; Karahanna & Agarwal, 2006). Failure to use a new technology or system to its full extent will prevent an organisation from leveraging the potential of the new technology and attaining a positive return on investment (Po-An Hsieh & Wang, 2017). Magwentshu et al.'s (2019) research findings also support this argument, as they find that organisations with employees who embrace innovation and the use of new technologies generate greater revenue and employment growth than those

that demonstrate limited application of the new technologies. Given this, defining acceptance of a new technology in mandated settings to incorporate not only employees' eagerness and contentment with the new technology or system, but the comprehensive and persistent use of the new technology or system, even when its use is mandated, seems appropriate.

The concept of extended use was proposed by Saga and Zmud (1994) as cited by Po-An Hsieh & Wang (2017) and refers to the use of technology beyond the routine or standardised use, as well as the use of broader technology features to explore its full potential in performing one's work. In addition, Po-An Hsieh and Wang (2017) stress the importance of focusing on employees' behaviours and the extent to which they mentally and fully accept the technology beyond its initial use, as this will determine the extent to which employees fully accept the new technology. The continued or discontinued use of the new technology after employees' initial use of the technology is therefore a key element to consider.

Bhattacharjee et al. (2018) argue that users with a positive attitude towards a new technology accept it enthusiastically, engages and experiments with it and find ways to keep learning how to use it. Acceptance of a new technology in mandatory settings is determined when employees demonstrate positive attitudes and behaviours towards the new technology not only because the use of the technology is mandated, but because they themselves see value in accepting and using the new technology (Bhattacharjee et al., 2018). On the other hand, individuals who have a less positive or negative attitude towards the new technology may initially accept it, but not put effort to use it or experiment with it further, which may result in very limited use of the technology (Bhattacharjee et al., 2018).

For the purposes of this research, acceptance will refer to the extent to which employees express openness, willingness, and commitment to fully integrate and embrace AI technologies in their way of working, while continuing to use it and to learn more, despite its use being mandated. This research proposes that employees' attitude towards the use of AI technologies will influence the extent to which they accept AI technologies.

2.4.5 Factors moderating the attitude-acceptance of AI relationship

In examining the relationship between factors included in the research, possible moderating variables are considered to enable better explanation and understanding of the relationship

between these factors or variables. Moderating variables are variables that can either strengthen, weaken, or alter the direction of the relationship between variables, and can account for the limited explanatory power and inconsistencies in research (Sun & Zhang, 2006). Technology adoption and acceptance research has considered factors such as age, gender, experience, and voluntariness as moderating variables (Sun & Zhang, 2006; Venkatesh et al., 2003). Research on the use and attitude towards AI technologies has also considered and investigated the moderating role of factors such as experience (Flavián et al., 2021; Karunaratne & Abeyratne, 2020), and individuals' job role (Bhargava et al., 2020; Noponen, 2019).

In investigating the attitude-acceptance relationship, the effect of two variables, namely, employees' job role and employees' experience with using AI technologies on the attitude-acceptance relationship is hypothesised and investigated. This is because, especially in mandatory settings where the role of attitude in technology acceptance has been challenged, understanding possible variables impacting the attitude-acceptance relationship is key to explaining the variance and the exploratory power of the model.

2.4.5.1 Experience

Experience in technology adoption and acceptance research refers to an individual's exposure, knowledge, and experience with using a new technology. The role of an individual's characteristics such as experience with using the new technology in the adoption, attitude and acceptance of technology has been investigated extensively (Alharbi & Drew, 2014; Lee et al., 2003; Sun & Zhang, 2006; Taherdoost, 2018; Venkatesh et al., 2003). Sun and Zhang (2006) ascertain that the users' experience is a consideration and possible reason for not only explaining some of the inconsistencies in research in terms of the relationships between the variables used in the TAM model for example, but for enhancing the explanatory power of the technology acceptance models. Hence, experience is included as a moderating variable in most technology acceptance studies using extensions of the TAM and the UTAUT (Sun & Zhang, 2006; Venkatesh & Davis, 2000; Venkatesh et al., 2003)

Research that considers experience in investigating technology adoption and acceptance indicates differences in terms of how experience is defined or measured (Sun & Zhang, 2006). For example, Davis et al. (1989) investigate the role of experience in technology acceptance by measuring exposure to technology at different stages or intervals throughout the pre-and

post-implementation of the technology. Venkatesh et al. (2003) measure experience at different times over 6 months. Bröhl et al. (2016) in their research on acceptance of working with robots in production systems, ask participants to indicate whether or not they have prior experience to using AI technologies and then formulate items subjectively for individuals that do not have experience working with robots in doing their work.

Experience with using a new technology is found to influence the adoption, attitude and acceptance of technology. For example, in their research on the role of training and experience on the adaptation of computerised maintenance systems, Karunarathne and Abeyratne (2020) find that experience with the technology influences the ease of use of a technology but not its usefulness. Robb et al.'s (2020) research on the public's perceptions of engaging with robots concludes that negative attitudes, perceptions, fears and uncertainties of robots and AI-related technologies can be reduced by providing exposure and experience to these technologies. Po-An Hsieh and Wang's (2017) research on understanding the extended use of complex system also reveals that experience with the new system significantly influences an individual's acceptance, their need to continue using the system, as well as satisfaction with the system. Flavian et al.'s (2021) research on intention to use robo-advisors (analytical AI services) indicates that although experience does not directly affect intention to use robo-advisors, previous experience moderates the influence of technology insecurity (distrust of technology) on intention to use robo-advisors. Horowitz and Kahn (2021)'s research on factors that influence attitudes towards AI adoption also shows that individuals already using AI technologies are more trusting and supportive of the use of AI technologies.

Chiu et al. (2021) argues that the more employees increase their knowledge of AI, the more they would be able to make a positive evaluation of AI technologies, and develop realistic expectations of AI, which also impacts their behaviour and acceptance of AI. In mandatory settings, where employees typically have limited input into the use of AI technologies and do not have a choice on whether to use a new technology implemented (Hwang et al., 2016; Linders, 2006), experience with using AI technologies will enable employees to make informed decisions about their attitude towards the use of AI technologies and its continued use.

Therefore, this research proposes that as employees gain experience with using AI technologies in their work, their knowledge and appreciation of AI's capabilities and limitations will increase, which influences their attitude and acceptance of AI technologies. Further, given that

attitude towards use of AI is expected to positively influence acceptance of AI technologies, experience with using AI technologies is expected to strengthen the positive relationship between attitude and acceptance of AI technologies. The following hypothesis is stated:

Hypothesis 13 (H13): Employees' experience with using AI technologies moderates the relationship between attitude and acceptance of AI technologies.

2.4.5.2 Job role

An employee's job role describes the function and core activities the individual performs in a specific job within an organisation, what is expected from them, the skills and experience required in a specific role, as well as the extent to which the individual is involved in the decision making processes of the organisation (Ivanov et al., 2020). Li's (Li, 2020) research on the role of individuals perceptions in technology adoption emphasises the importance of considering the impact of an individual's job role when investigating technology adoption and acceptance in an organisation, since different members in the same organisation may have different views of the new technology.

Literature on the attitude and acceptance of AI technologies highlights the debates and inconsistencies regarding how the use of AI technologies is expected to impact individuals' job roles (Lane & Saint-Martin, 2021; Strich et al., 2021). What is evident is that although it might not be clear yet in terms of how or the extent to which most jobs will be impacted by the use of AI technologies, all job roles will be impacted in one way or another (Brougham & Haar, 2018; Lane & Saint-Martin, 2021; Li, 2020).

Research on the use of AI technologies also points to the fact that an individual's job role should not be ignored when investigating the adoption, attitude, and acceptance of AI technologies. Noponen's (2019) research on the impact of AI technologies on management indicates that different types of managers had different views, expectations, and objectives regarding the use of AI technologies in their work. Therefore, Noponen (2019) highlights the need to not treat employees as a homogenous group as employees are likely to view and be impacted using AI technologies differently. Further, Raisch and Krakowski's (2021) review of the automation-augmentation paradox highlights the conflicting objectives of managers who despite prioritising and driving the use of AI technologies to improve efficiency within the organisation, also feel that the use of AI technologies may put them at risk of losing their jobs.

Ivanov et al.'s (2020) research on the drivers and solutions for automation technologies such as AI technologies find that the extent to which an individual's tasks are at risk of being automated or taken over by the use of AI technologies in their job will depend on the type of job or work they do, as well as the job level of their position. For example, they argue that individuals in managerial or executive level positions have a lower risk of having their jobs fully automated due to the nature of their jobs (Ivanov et al., 2020). People in these job roles tend to be fewer compared to individuals in other roles, and they also perform tasks that cannot be easily automated, such as making strategic decisions for the organisation, including decisions to implement new technologies, compared to other job roles in the organisation (Ivanov et al., 2020). As such, they are likely to feel less threatened by the use of AI technologies, and be positive about its use, as well find ways to promote its use across the organisation. Bhargava et al.'s (2020) research on employees' perceptions of the impact of AI related technologies on job satisfaction, job security and employability also reveals that employees in lower skilled manual job roles appear to be more fearful of the use of AI related technologies than managers, professionals, and highly educated employees.

Lichtenthaler (2020) postulates that individuals in certain job roles may struggle to understand the benefit of using AI technologies in their job roles and may perceive AI technologies to be a threat to their jobs. As a result, they may be negative towards its use and resist the use of AI technologies. On the other hand, employees in certain job roles may perceive the use of AI technologies to be useful and beneficial to their job roles and way of working, and capable of creating opportunities for growth and increased performance (Lichtenthaler, 2020). They may therefore be enthusiastic and positive towards its use and be more willing to accept and embrace it (Lichtenthaler, 2020).

What is clear is that, depending on an individual's job role, their attitudes and acceptance of AI technologies is likely to vary and their job role will likely have an impact on the attitude and acceptance relationship. Since attitude is expected to have a positive effect on the acceptance of AI technologies, this relationship is likely to be strengthened or weakened depending on the employees' job roles. Based on the literature review, it is proposed that the relationship between attitude and acceptance of AI technologies would be strengthened or weakened depending on an the employees' job role. The following hypothesis is formulated:

Hypothesis 14 (H14): The relationship between attitude towards use of AI technologies and acceptance of AI technologies is moderated by employees' job roles.

2.5 Research questions

In order to address the objectives of this research, the above literature review provided a discussion of factors to be considered when investigating the attitude and acceptance of AI technologies. The relationship between these factors seem to be inconsistent and complex, resulting in many unanswered questions and a gap in research with regards to employees' attitude and acceptance of AI technologies in mandated settings. The below provides an overview of the research questions to be answered, in order to contribute to the understanding and limited research on employees' attitude and acceptance of AI technologies within mandated settings in South Africa, an emerging market economy. The following research questions are formulated:

Q1: To what extent do the technological, individual, organisational, and environmental factors independently influence employees' attitude towards the use of AI technologies in the financial services industry in South Africa?

Q2: Which technological, individual, organisational and environmental factors are the most influential determinants of employees' attitude towards the use of AI technologies?

Q3: To what extent do employees' attitude towards the use of AI technologies influence acceptance of use of AI technologies?

Q4: To what extent do employees' job roles and employees' experience with using AI technologies moderate the relationship between attitude towards use of AI technologies and acceptance of the use of AI technologies?

Q5: What model can organisations use to facilitate the successful implementation and acceptance of AI technologies?

2.6 Research model

For this research, an integration and extension of the TAM and TOE framework is proposed. Based on the literature review of factors proposed to be influencing attitude and acceptance of AI technologies, only specific factors from TAM and the TOE framework that are relevant to this study were discussed above and will be investigated. Additional individual and contextual factors identified in literature to be influencing attitude and acceptance of AI technologies have also been included in the research model. Figure 2.11 below depicts the research model as well as the 14 hypotheses to be tested (H1-H14).

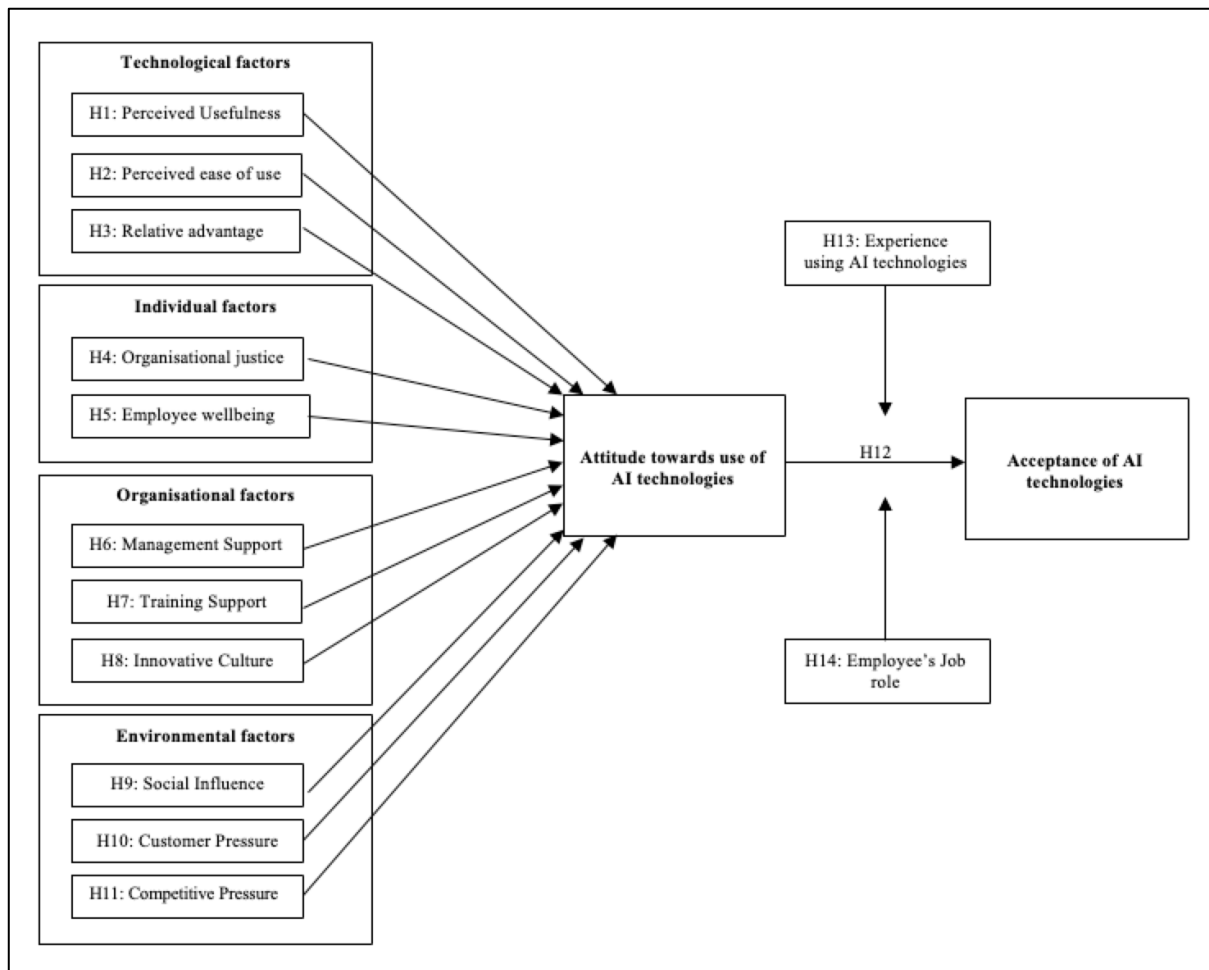


Figure 2.11 Research model

2.7 Linking research questions and hypotheses

Table 2.7 below provides an overview of which hypotheses will be tested to answer each specific research question and meet the objectives of this research.

Table 2.7 Research questions and hypotheses

Research Question	Hypothesis to be tested
Q1: To what extent do the individual, technological, organisational, and environmental factors independently influence employees' attitude towards the use of AI technologies in the financial services industry in South Africa?	H1; H2; H3; H4; H5; H6; H7; H8; H9; H10; H11
Q2: Which technological, individual, organisational and environmental factors are the most influential determinants of employees' attitude towards the use of AI technologies?	H1; H2; H3; H4; H5; H6; H7; H8; H9; H10; H11
Q3: To what extent do employees' attitudes towards the use of AI technologies influence acceptance of use of AI technologies?	H12
Q4: To what extent do employees' job roles and employees' experience with using AI technologies moderate the relationship between attitude towards use of AI technologies and acceptance of the use of AI technologies?	H13 and H14
Q5: What model can organisations use to facilitate the successful implementation and acceptance of AI technologies?	Based on outcome of all the hypotheses

2.8 Summary

This chapter provided a literature review of AI, with specific reference to AI technologies within the financial services industry in line with the context of this study. The AI paradoxes that exist for both businesses and employees when using AI technologies were highlighted. A critical review of technology acceptance theories and models used to investigate the adoption, attitude and acceptance of new technologies was provided. Based on this, a conceptual framework was developed by integrating and extending the TAM and TOE framework with factors identified to be impacting the attitude and acceptance of AI technologies from the literature review. Each of these factors was discussed and defined in the context of this research and hypotheses to be tested are formulated. Specific research questions to be answered were stated and a research model was presented. The following chapter, Chapter 3, details how the research was conducted within the financial services industry in South Africa

CHAPTER 3: METHODOLOGY

3.1 Introduction

This chapter provides an overview of the research methodology applied in conducting research on the attitude and acceptance of the use of AI technologies within the financial services industry in South Africa. The chapter discusses the research strategy, the research design, the research sample, as well as the data collection and analysis process. The chapter also discusses how reliability, validity and ethical considerations were addressed. Limitations of this research are also noted.

3.2 Research strategy

There are three main types of research strategies, quantitative research, qualitative and mixed methods research design (Creswell, 2014). Quantitative research involves the development and testing of hypotheses to determine the relationship between variables by proving or disproving the hypotheses proposed (Creswell, 2014). Clear measures for each variable are developed and standard measures of collecting data are employed and numerical data is collected and analysed using relevant statistical tools (Bryman, 2012; Neuman, 2011). In quantitative research, samples are considered to be representative of the population, making it possible to generalise research findings to the population (Queirós et al., 2017). Although being a more objective research method and being capable of providing an analysis of the relationship between variables, this method lacks the ability to obtain an in-depth analysis and explanation of participants' experiences to provide a deeper understanding of the problem investigated (Neuman, 2011; Rahman, 2020).

Qualitative research typically focusses on conducting research to obtain an in-depth understanding of the problem under investigation (Queirós et al., 2017). Qualitative research is often appropriate in exploratory research, where the objective is to discover meaning and/or enhance understanding of a particular topic or experience, and is used to develop theory (Creswell, 2014; Neuman, 2011). Measurement instruments are often flexible and unstructured, and data collected is often in the form of words, images observations and transcripts (Neuman, 2011). Qualitative research is sometimes criticised for being less objective and susceptible to the researcher's bias, as well as for neglecting contextual, social, and cultural influences by focusing more on meanings and experiences (Rahman, 2020).

Qualitative research approaches are also criticised for being susceptible to bias when interpreting research findings, for being time consuming and for using small samples which makes it difficult to generalise research findings (Neuman, 2011; Rahman, 2020).

Mixed methods research combines both quantitative and qualitative research methods in conducting a research study (Bryman, 2012; Creswell, 2014). Although the mixed method approach is often applied to address the limitations of using either a quantitative or qualitative research approach on its own, Bryman (2012) stresses that this approach should not be considered superior to the individual use of qualitative and quantitative research methods. In addition, this approach requires a lot of time and effort and therefore one should be clear on the reasons and benefits of using mixed methods approach for the specific study at hand from the onset (Bryman, 2012).

The majority of TAM studies have used either quantitative research methods or mixed methods (Wibowo, 2019). As such, most TAM studies have applied a quantitative research approach to test hypotheses and identify factors that significantly influence attitude and acceptance of new technologies. Studies that have applied the TAM or its extension in research on the acceptance of some of emerging technologies, for example studies by Bröhl et al. (2016) on the acceptance of human-robot cooperation and by Eltayeb and Dawson (2016) on the attitude and acceptance of cloud computing, as well as studies on the attitude and acceptance of AI technologies in the healthcare sector by Alhashmi et al (2019) and in the construction industry by Sorce and Issa (2021) have taken a quantitative approach.

TOE studies on the adoption of AI technologies have applied either qualitative or quantitative research methods. Qualitative research methods have been conducted using the TOE framework to investigate AI adoption in various industries such as the financial services industry (Kruse et al., 2019), the hotel industry (Nam et al., 2020), the automotive industry (Smit & Eybers, 2022) and within the auditing practice (Seethamraju & Hecimovic, 2022). Quantitative research on AI adoption using the TOE framework include research by Pillai et al. (2021) within the manufacturing industry, research by Nguyen et al. (2022) within private and public companies in Vietnam and research by Gupta et al. (2022) within the insurance industry. Few studies using the TOE framework have applied mixed-methods approaches in research on attitude, adoption and/or acceptance of AI technologies, for example, Vasiljeva et

al. (2021), when investigating factors influencing the public and business' attitude towards the use of AI technologies.

The aim of this research is to investigate and determine factors influencing the attitude and acceptance of AI technologies with the South African financial services industry and provide guidelines to organisations on factors to consider and manage when implementing and using AI technologies to enable them to leverage the potential of AI technologies. An integration and expansion of the TAM and TOE framework is used to provide a conceptual framework for this research. 14 hypotheses to be tested are formulated and the relationship between variables is to be investigated. This approach is in line with previous studies that extended the TAM (Alhashmi et al., 2019; Bröhl et al., 2016; Wentzel et al., 2013) and/or the TOE framework (Malik et al., 2021; Skafi et al., 2020), as well as studies that have integrated the TAM with the TOE framework (Chiniah et al., 2019; Gangwar et al., 2015; Iftikhar et al., 2021; Vang & Lind, 2023) and specifically in research on the adoption, attitudes and acceptance of AI technologies, as done by Chatterjee et al. (2021) and Na et al. (2022).

Researchers that integrate the TAM and TOE framework to investigate technology adoption have favoured a quantitative approach. For example, research by Matikiti et al. (2018) and Tripopsakul (2018) on the adoption of social media marketing technologies, research by Qin et al. (2020) on the adoption of building information technologies and research by Wang et al. (2022) on the adoption of blockchain technology. Research integrating the TAM and TOE to investigate the adoption, attitudes and/or acceptance of AI-related digital technologies has also mostly been quantitative, for example research by Chatterjee et al. (2021) in the manufacturing industry, Na et al. (2022) in the construction industry and Mametja et al. (2023) in the tourism industry.

Given that the implementation and use of AI is still in its early stages in South Africa (Tjebane et al., 2022), and that researchers are still exploring and developing understanding on this, research on the adoption, attitude, or use of AI technologies in South African organisations has largely been qualitative in nature. For example, in investigating the current and future use of cobots and its impact on employees, Calitz et al. (2017) employed a qualitative research design with 12 employees. Ngoro et al. (2020) conducted a qualitative research with 11 individuals when investigating the uses, benefits and challenges of AI within the financial services industry in the Western Cape. Although Parker and Appel (2021) collected both qualitative and

quantitative data to investigate the effect of a robotic solution in a financial services firm, their study was largely qualitative in nature as it focused on understanding employees' perceptions and experiences with using the robotic solution. In their research, quantitative data was collected mainly to measure the impact of the robotic solution on productivity (Parker & Appel, 2021).

Although Tjebane et al. (2020) conducted quantitative research on organisational factors key in driving the adoption of AI in the South African construction industry, sample targeted was similar to that in studies by Ngoro et al. (2020) and Calitz et al. (2017) in that it comprised of mainly management and IT experts and was not representative of employees across the organisation who are main users of the AI technologies implemented.

The objective of this research is to investigate and determine the factors influencing employees' attitude and acceptance of AI technologies, using a more representative sample of employees at different levels in the organisation. The literature review indicates that there are several factors that need to be considered as influencing the attitude and acceptance of AI technologies, however in some instances, the relationship between these factors has been inconsistent or inconclusive. As such, this research developed a conceptual framework that shows the proposed relationships between these factors. Hypotheses to be tested were formulated. Only three short open ended questions were included at the end of the questionnaire to allow participants to share any additional information regarding their attitude towards the use of AI technologies as well as factors they would like to be considered in the implementation and use of AI technologies. As highlighted above, there is a need for more quantitative research studies examining the adoption, attitude, and acceptance of AI technologies in South Africa, to be able to develop effective strategies and models for AI implementation and use. This research therefore employed a quantitative research strategy.

3.3 Research design

Neuman (2011) and Bryman (2012) provide a description of research designs used when conducting quantitative research, which include the cross-sectional design (collecting or examining data on many cases at a single point time) and longitudinal design (collecting or examining data from many cases at more than one point in time). This research was cross-sectional design as data was collected, from several participants, at a single point in time.

The cross sectional design is sometimes referred to as a survey design, and makes use of questionnaires (Bryman, 2012). Given that the objective of this research is to examine the relationship between factors proposed to be influencing the attitude and acceptance of AI technologies, the cross-sectional design enabled research data to be collected simultaneously in the form of a survey and be analysed to examine the relationship between variables. The next section describes the research sample and the questionnaire that was used as the research instrument in conducting this research.

3.4 Research sample

A sample is a small part or unit selected from a larger group or population to which the results are generalised (Bryman, 2012; Neumann, 2011). A population is a collection or list of possible objects from which data will be gathered from (Neumann, 2011). For this study, the population entailed employees working in various job roles and job levels within the financial services industry. The financial services industry was chosen because first, it is one of the industries in various countries where the use of AI technologies continues to grow (Adeleye et al., 2019; Kurshan et al., 2021; Mamela et al., 2020; Mogaji & Nguyen, 2021), due to the potential savings, and expected increase in efficiency and productivity expected from using AI technologies (Mehrotra, 2019; Parker & Appel, 2021; Waliszewski & Warchlewska, 2020). Second, the financial services industry is one of the largest contributors to the South Africa's GDP and formal employment in the country (Statistics South Africa, 2023). The successful implementation and use of AI technologies in the financial services industry is expected to create new jobs, increase productivity and improve access to key financial services provided to individuals (Mamela et al., 2020).

According to the Q3 Quarterly Labour Force Survey by Statistics South Africa (2023), the finance industry employs about 2 521 000 people, which is about 22% of people employed in the formal sector³. Based on the ten occupational categories provided by Statistics South Africa (2023) and the Employment Equity Act (1998), 4 of the 9 occupational categories (manager, professional, technician and clerk) reflect the main categories of employees' roles considered to be relevant to the target population for this study. This is because the research targeted employees employed in the financial services organisations (e.g. banking, insurance, financial advisory, wealth management, risk and compliance) and working in various management,

³ The formal sector refers to the employment of employees paying income tax and those not paying tax but working in firms with five or more (Statistics South Africa, 2023)

leaderships and supervisory roles, working as professionals in information technology (IT) or technical roles and professionals working in non-IT or technical roles, as well as those working in clerical or administrative roles (e.g. different types of administrators or assistants). Employees occupying roles different to the ones targeted⁴ were not part of the target population. Based on the target population for this research, the size of the estimated population of employees working in the financial services industry was estimated to be about 2 000 000 employees.

Given the estimated population size, to prevent sampling error or biases and be able to generalise the research findings from this research (Taherdoost, 2017), the ideal sample size was calculated. Gill et al. (2010) proposed a calculation of sample sizes based on the desired accuracy with confidence levels of 95% or 99%, and a population percentage variability of 50%. The level of confidence for this research is set at 95%, which is commonly used in social and management research (Taherdoost, 2017). This means that at this confidence level, one can be 95% confident that the results are accurate and accurately reflects the characteristics of the population and also be 95% certain that if the population was to be sampled again, the sample would produce approximately the same results (Taherdoost, 2017). Bartlett et al. (2001) also notes that the population percentage of variability of 50% is what is generally used by most researchers to be able to maximize variance and determine the maximum sample size. Using this calculation, the appropriate sample size would need to be 385.

Additional methods of determining an appropriate sample size proposed by Bartlett et al. (2001) and Hair et al. (1998) were also considered. Hair et al. (1998) recommends that the minimum sample size should be five times larger than the total measurement items for constructs included in the measurement scale. Using this guideline, the total measurement items in the questionnaire is 57 (excluding 6 questions on demographic information and experience with use of AI technologies and 3 open ended questions), which was represented by 13 constructs. Therefore the minimum sample size for this research is 285.

Bartlett et al. (2001) highlights additional factors to be considered when determining an appropriate sample size, based on the type of data collected (continuous vs categorical), alpha levels, acceptable margin of error and data analysis methods such as multiple regression and

⁴ Service and Sales Workers, Skilled Agricultural and Fishery Workers, Craft and Related Trades, Plant and Machine Operators and Assemblers, Elementary Occupations. A full description can be found in Annexure 3 of the Regulations to the Employment Equity Act (1998).

factor analysis. For example, they recommend that factor analysis should not be conducted with a sample size of less than 100 and that for multiple regression analysis, the ratio of the sample size to the total number of independent variables should not be below 10 (Bartlett et al., 2001). In this case, given that there are 11 independent variables expected to influence attitude towards use of AI technologies, the minimum sample size should be 110.

The random sampling technique, which is a probability sampling method was used instead of a non-probability sampling method within the financial services industry, because this method makes it possible to obtain a sample that is likely to be representative of the population (Neuman, 2011). Using the researcher's professional network, the Google search engine and the LinkedIn professional platform, a search of financial services organisations as well as of individuals in senior level positions was conducted, to request assistance and permission for employees in their organisation to participate in this research survey. Where required, discussions were held with specific heads of departments to explain the objective of the research. Appendix A is a sample of the permission letter to conduct the research that was also sent to individuals in senior level positions to discuss with the relevant management team and get assistance and approval for this research. The permission letter provided context of the research and highlighted the confidentiality and anonymity of the organisation and their employees participating in this research.

Employees that participated in this research were from five financial services organisations that will remain anonymous. These organisations included one of the largest South African banks, one of the largest insurance organisations, two medium sized short-term insurance organisations and a small sized financial services advisory and regulatory firm. 432 employees participated in this research and 432 survey responses were collected. 410 participants with valid responses to the questionnaire were retained upon removing responses with missing data. This sample size is sufficient given that the sample of 410 participants is above the minimum sample sizes recommended by Hair et al.'s (1998), Bartlett et al. (2001) and Taherdoost (2017).

3.5 Research instrument

The instrument used to collect data in this research was a questionnaire which was designed to collect data on employees' attitude and acceptance of AI technologies. This online self-administered questionnaire made it possible to collect data in the absence of the researcher,

making it possible to collect and analyse data in an objective way. The questionnaire included 66 questions and took participants between 15 and 20 mins to complete. The research questionnaire is included in Appendix B.

The first three questions asked participants to select responses that match their demographic information such as age, gender, and job role. Financial services organisations are typically characterised with traditional hierarchical structures and a variety of roles with different skills and experiences (Kruse et al., 2019; Thowfeek et al., 2020). For this research, job roles were classified using input from classifications of management and non-management roles used in previous research by Kolbjørnsrud et al. (2017) and Noponen (2019). In addition, a distinction between professional IT roles (developers and users of technology) and professional non-IT roles (mainly users of technology) was also made since research has shown that there are differences between IT technical and non-IT technical professionals in terms of their attitude and acceptance of AI related technologies (Kar & Kushwaha, 2021). The following roles were considered for participants to select from: Top Management/executives, Senior Manager of a business unit/division, Middle management, Manager of processes/projects, Team lead/Supervisor, Professional (IT/Technical), Professional (non-IT/Technical) and Administrative.

The next two questions asked participants to select the main services provided by their financial services organisation as well as indicate the business applications of AI technologies that currently apply or would apply in their organisations. Participants were then asked to indicate whether or not they had experience with using AI technologies in doing their work. Items were formulated subjunctively for individuals that did not have any experience with using AI technologies in their daily work. This followed a similar procedure used by Bröhl et al. (2016) when conducting research on the acceptance of human-robot cooperation amongst individuals that used robots and those that did not.

The following items included in the questionnaire were used to measure the variables included in this research. The items included in this study were formulated based on the literature review on the constructs or factors included in this research. Most of the items included in the questionnaire were obtained from previously validated measures that were used and tested in earlier studies, which were then adapted and adjusted to fit the context of this research and

ensure content validity. Table 3.1 below provides an overview of the factors or variables included in this study and items included in the questionnaire.

A 7-point Likert-scale was used, 1 - strongly disagree to 7 – strongly agree. Although Dolnicar et al. (2011) argue against the use of the Likert scale due to potential response bias and the time it takes respondents to complete the questionnaire, the 5-point or 7-point Likert scales have been successfully used in technology adoption and acceptance research (Malik et al., 2021; Pateli et al., 2020; Vang & Lind, 2023), in measures of employee wellbeing (Keeman et al., 2017; Krekel et al., 2019) and in measures of perceptions of organisational justice (Colquitt, 2001). Bryman (2012) also notes that the Likert scale is commonly used in research investigating attitudes.

In deciding on whether to use the 5-point or the 7-point Likert scale in this research, the recommendation from Finstad's (2010) research on system usability of enterprise software applications which provides a comparison between using a 5-point or 7-point scale was considered. The research finds the 7-point Likert scale to be a more accurate measure of participants evaluation of the system, as well as more suitable for questionnaires distributed electronically, in unsupervised settings (Finstad, 2010). In addition, more recent TAM and TOE framework studies on the adoption, attitude, and acceptance of AI technologies for example, research by Chatterjee et al. (2021) and Na et al. (2022) have also used the 7-point Likert scale.

Table 3.1 Research variables and measurement items

Variable	Definition	Items	Source adapted from
Perceived usefulness	The extent to which an employee believes that using AI technologies is useful in their work and will enhance their performance	• I find AI technologies useful in doing my work. • Using AI technologies would help me finish tasks quicker. • Using AI technologies enhances my job performance. • Using AI technologies makes it easier for me to do my work.	Davis (1989); Davis et al. (1989)
Perceived ease of use	The extent to which an employee believes that AI technologies will be easy to use	• I find AI technologies easy to use (user-friendly). • It will be easy for me to become skillful at working with AI technologies. • The AI technologies we use are clear and understandable. • I do not get frustrated when working with AI technologies.	Davis (1989); Davis et al. (1989)
Relative advantage	The extent to which an employee believes that the use of AI technologies is perceived to have greater benefits than its alternatives	• AI technologies enable more efficient processes and ways of working. • Using AI technologies enables better integration of our processes and services. • Using AI technologies gives me greater control over my work. • There are more advantages than disadvantages to using AI technologies.	Moore and Benbasat (1991) and Gangwar et al. (2015)
Organisational justice	The extent to which an employee perceives fairness with processes followed and the treatment they receive throughout the implementation and use of AI technologies	• The use and application of AI technologies in the organisation is explained to me clearly. • The implications of the use of AI technologies on my work has been discussed with me clearly. • I can express my views and concerns regarding the use of AI technologies. • The use of AI technologies has been applied consistently within the organisation. • Overall, the implementation and use of AI technologies has been fair.	Bies and Moag (1986); Colquitt (2001); Thibaut and Walker (1975)
Employee wellbeing	The extent to which an employee believes that using AI technologies will contribute positively to their job satisfaction, career development, collaboration with others and decrease feelings of being stressed, losing control and being anxious about losing their job	• Using AI technologies contributes positively to my job satisfaction. • Using AI technologies enhances my career development opportunities. • Using AI technologies makes my work less strenuous. • Using AI technologies enables me to engage and collaborate better with others. • Using AI technologies reduces autonomy in my work. • Using AI technologies make me feel anxious and/or stressed. • I think my job could be replaced with AI technologies.	Brougham and Haar (2018) and Pradhan and Hati (2022)
Management support	Management support – the extent to which employees feel that management provides sufficient guidelines on the use of AI technologies, access to training, resources and software as well opportunities for employees to provide feedback on the use of AI technologies	• Management provides clear guidelines on the use and implementation of AI technologies. • Management supports training on the use of AI technologies. • Management provides the necessary access to resources and software needed to make use of AI technologies. • Management seeks feedback on the use of AI technologies	Han et al. (2008); Gangwar et al. (2015) and Garrison et al. (2015)
Training	The extent to which employees feel that there is sufficient training provided to help them understand AI, be more comfortable and confident when using AI technologies as well as be more receptive towards the use of AI technologies	• The organisation provides training on the use of AI technologies. • Training provided helps me understand AI technologies better. • Training provided gives me confidence to use AI technologies in my work. • I am more receptive to using AI technologies because of the training I have received.	Gangwar et al. (2015)
Innovative Culture	The extent to which employees feel that their organisation's culture is innovative and promotes collaboration, openness, agility, flexibility and is capable	• Our culture is flexible and agile. • Our culture is innovative and supports the use of new technologies such as AI. • Our culture supports collaboration across different areas of the organisation using AI technologies.	Martínez-Caro et al. (2020)

	of effectively implementing AI technologies in their way of working	• Our culture enables us to effectively integrate AI technologies in our way of working.	
Social influence	The extent to which others' positive beliefs about the use of AI technologies influences employees' attitude towards the use of AI technologies.	• People close to me positively influence my views towards using AI technologies. • People who are important to me think that it is good for me to use AI technologies. • The media positively influences my views on the use of AI technologies.	Taylor and Todd (1995) and Venkatesh and Davis (2000)
Customer pressure	The extent to which employees perceive that the pressure to implement and use AI technologies within the organisation comes from customers	• Our customers expect us to use AI technologies in servicing them. • Using AI technologies improves the products and services we offer our customers. • The use of AI technologies helps us retain our customers. • The use of AI technologies helps us attract more customers.	Pillai et al. (2021) and Reyes et al. (2016)
Competitive pressure	The extent to which employees perceive that the pressure to implement and use AI technologies within the organisation comes from competitors	• The use of AI in our industry puts pressure on us to use AI technologies. • Most of our competitors are using AI technologies. • I think our competitors are doing well because they use AI technologies. • Using AI technologies enables our organisation to be competitive.	Gangwar et al. (2015) and Rogers (2003)
Attitude towards use of AI	The extent to which employees are positive or negative towards the use of AI technologies	• I like using AI technologies in doing my work. • Using AI technologies makes my work interesting. • I feel positive about using AI technologies. • I see value in using AI technologies in doing my work. • Overall, I am in favor of the use of AI technologies in the organisation.	Davis et al. (1989) and Taylor and Todd (1995)
Acceptance of AI technologies	The extent to which employees express openness, willingness and commitment to integrate and embrace AI technologies in their way of working, and continue to use and learn more about AI technologies	• I will continue to find ways of making use of and integrating the use AI technologies in my work. • I will continue to learn and increase my knowledge of AI technologies. • I will provide support to others using of AI technologies in their work. • I will recommend the use of AI technologies to others. • It is valuable for me to learn more about AI technologies even when it may not be compulsory/mandatory.	Moore & Benbasat (1991); Taylor and Todd (1995) and Venkatesh and Davis (2000).

Since this was a quantitative research, the questions included in this questionnaire were largely closed-ended questions. However, textual responses in the form of three open-ended questions were included at the end of this questionnaire. The inclusion of open-ended questions has been used often in quantitative research studies to give respondents an opportunity to elaborate on their responses and/or add information they think is missing from the survey (Lloyd & Devine, 2015; Rohrer et al., 2017). The researcher wanted to provide participants who wished to do so, an opportunity to provide additional information in terms of their overall attitude towards the use of technology in doing their work, factors they would like to be considered when using AI technologies in doing their work, and factors they thought should be considered when using AI technologies in the organisations.

Given that the use of AI technologies in South Africa is still in its early stages (Tjebane et al., 2022), the objective was to use the feedback from these open-ended questions to complement and add richness to the research findings. Participants were provided with an opportunity provide their sentiments towards the use of AI technologies, to give feedback and insight into additional aspects to be considered when implementation and using AI technologies which impact their attitude and acceptance of the use of AI technologies. If ignored, these factors may hinder the successful implementation and use of AI technologies. This data collected was also used to provide input into the development of a model for organisations to use when implementing and using AI technologies, which was one of the objectives of this research.

3.6 Data collection

The survey questionnaire was loaded onto Qualtrics and an anonymous survey link was created to be shared with survey participants. Before distributing the online link to start the research, it was important to test the survey link and conduct a pilot study. The questionnaire was distributed to individuals in the financial services industry using the researcher's social network and contacts from LinkedIn. A pilot study resulted in 12 valid samples of employees within the financial services industry, with the objective of being able to assess the ease and process of distributing the online questionnaire, collecting responses, as well as check for clarity, appropriateness and potentially misinterpretations of items included in the questionnaire.

Given the objective of the pilot study, a sample size of 12 was sufficient based on the recommendation by Hertzog (2008) of a minimum sample size of 10. The results of the pilot

study indicated the reliability and validity of the scales. In addition, one industry expert and one academic expert also reviewed the questionnaire and provided suggestions on items to be adjusted. Based on this, some items were adjusted and reworded accordingly. The pilot data was not merged with the final data collected in order to avoid possible contamination.

When conducting the actual research, the online survey link was shared with management and/or heads of departments in financial services organisations who assisted with distributing the questionnaire to employees in their departments, as well as in other departments. Data was collected between July 2022 and December 2022. The online survey link provided participants with a participants' information note, which notified the participants the purpose of the study, the nature of the study, the estimated time required from them to complete the survey, as well as the researcher's and supervisor's details. Appendix C provides a sample of the participants information note.

The participations information note also made it clear that anyone could participate in this study, whether or not they were currently using AI technologies in their work. Participants were also informed that participation was voluntary and that there was no risk or obligation to participate in the study. It was also stated that no sensitive or confidential information that would identify participants would be required from them in order to ensure that confidentiality and anonymity. Participants also had an opportunity to indicate whether or not they give consent to participate in this survey, before actually starting to complete the survey.

3.7 Research and data quality measures

As stated by Neuman (2011), it is important to ensure that items in the questionnaire measure what they are intended to measure consistently to ensure credibility and generalisability of the research findings. The validity and reliability of the measurements instrument and the research data were examined.

3.7.1 Validity

3.7.1.1 Measurement validity

The validity of the measurement instrument was tested. Measurement validity refers to the quality of the measurement and the extent to which a measurement instrument measures what it is intended to measure (Bryman, 2012; Salkind, 2017). According to Bryman (2012) and Neuman (2011) measurement validity includes content validity (the extent to which the

measurement instrument is representative of what it intends to measure), criterion validity (which is determined by comparing the measurement of a construct with another measure of the same construct), face validity (the extent to which the measurement instrument is perceived by others to reflect the concepts or variables being investigated) and construct validity (the extent to which indicators of the same construct converge or how well indicators of different constructs diverge, which is referred to as convergent and discriminant validity respectively).

To ensure measurement validity, a conceptual framework was established from the literature review, which guided this research. Items included in the questionnaire were adopted and adapted from literature and items included in previous studies using TAM and/or the TOE framework, as well as from research investigating perceptions of organisational justice or employee wellbeing. A pilot study was conducted to assess measurement validity and items were adjusted based on feedback received. Items in the questionnaire were stated clearly and only items relevant to the constructs being measured were included in the questionnaire.

3.7.1.2 Convergent validity and discriminant validity

Factor analysis was conducted using principal component analysis with the varimax rotation method which has been used widely to analyse the validity of the items included within each variable (Costello & Osborne, 2005; Howard, 2016). Principal component analysis is used to identify patterns in the data, highlight the extent to which items converge or diverge and explain the total variance in the variable (Alavi et al., 2020). It is used as a reduction method to determine the number of factors that account for the maximum variance in the data (Costello & Osborne, 2005). By using the varimax rotation method, the variance of the factor loadings will increase, making it possible for each item to clearly load or not load onto another factor (Howard, 2016).

Costello and Osborne (2005) note that principal component analysis is used to assess the variable's unidimensionality, by examining the extent to which items within each variable load highly onto the same and single component (indicating convergent validity) and low on other components (indicating discriminant validity). Howard (2016) and Guvendir and Ozka (2022) note that researchers have applied varying cut-offs in terms of what is considered acceptable for factor loadings, as values used vary from 0.3 to 0.6.

In addition, the criterion to be used to identify and remove items that are crossloading has also varied. Although Guvendir and Ozka (2022) used a difference of less than 0.10 to identify items crossloading between the primary and alternative factor/variable, they also cited other researchers such as Can (2008) that used a criteria of less than 0.15. Howard (2016) notes that some researchers propose a cut off of a difference of less than 0.1 between the primary and alternative factor/variable to be used when identifying items crossloading, however, they recommend using a cut off of 0.2.

The above principles were applied to determine the extent to which items measured the constructs or variables they were meant to measure, and which items needed to be removed. Items with a factor loading of 0.6 and above for a factor were retained, while items crossloading with a high loadings of above 0.5 and/or a difference of less than 0.1 between the primary and alternative components were removed.

In addition, to ensure more accurate analysis, communalities were assessed. Costello and Osborne (2005) notes that item communalities of 0.8 and above are high, while communalities of 0.4 to 0.7 are considered low to moderate. Values less than 0.4 indicate that the item may not be related to other items. Communalities also represent the correlation coefficients of the items (Costello & Osborne, 2005). Communalities of at least 0.6 were preferred in this study.

3.7.1.3 Internal validity

Internal validity refers to the extent to which the relationship between the independent and dependent variable can be clearly established, having controlled extraneous variables and eliminated confounds (García-Pérez, 2012). Based on the literature review a clear relationship between each of the factors influencing attitude and acceptance of AI technologies has been proposed. Hypotheses formulated will be tested to evaluate this.

3.7.1.4 Statistical conclusion validity

Statistical conclusion validity (SCV) refers to the appropriateness and accuracy of statistics used, to analyse data as well as the extent to which results from the statistical analysis used are adequate to explain the relationship between the independent and dependent variables (García-Pérez, 2012). Given that a probability sampling technique using random sampling was used, the possibility of errors was likely (Neumann, 2011). Bartlett et al. (2001) note that Type 1

error may occur, when the null hypothesis is rejected when it is actually true, which means that the conclusion made is that there is a statistically significant difference when that is not true, and Type II error which occurs when the null hypothesis is accepted when it should not be accepted and it is concluded that the results are not statistically significant when the results actually are.

The level of statistical significance was set at $p < 0.05$ based on most educational and social research (Bartlett et al., 2001), to indicate that results would be due to chance only 5 in 100 times or that one can be 95% confident that the results are due to a real relationship in the population and not due to chance factors (Neumann, 2011). The results of the study from the hypothesis testing would only be statistically significant if the p value is less than 0.05 and the null hypotheses is rejected.

3.7.1.5 External validity

External validity refers to the scope of generalisation, in other words the extent to which the research findings can be generalised to other settings (Bryman, 2012; Neuman, 2011). Sample size and randomisation were considered in the context of obtaining external validity. The random sampling technique was used to ensure a representative sample of the population, which would enable the generalisability of the research findings. In addition, a sample size of just over 400 participants, comprising of employees in various job roles in the financial services industry took part in their research. As discussed in section 3.4 above, the size of the research sample is appropriate. Findings of this research can therefore be generalised to the financial services industry population as well as similar industries.

3.7.2 Reliability

Reliability examines the extent to which the measurement instrument is accurate and measures the variables consistently (Neuman, 2011; Salkind, 2017). Reliability of a research instrument can be assessed by using any of the following techniques or measurements, test-retest, parallel forms, internal consistency, and interrater reliability (Salkind, 2017). For this research, internal consistency reliability was evaluated. Internal consistency refers to the extent to which items included in the measure are consistent with each other in measuring the variable they are meant to measure (Salkind, 2017). Cronbach's alpha was used to measure the internal consistency of items measuring each variable in the questionnaire. Tjebane et al. (2022) notes that the

Cronbach alpha is recognised as the most appropriate measure of reliability when using the Likert scales.

If the Cronbach's alpha coefficient is close to 1, the construct is considered to be internally consistent and highly reliable, and if closer to 0, it is considered to have a low degree of reliability (Liu et al., 2021). Although some researchers investigating the technology adoption, attitudes and acceptance of AI technologies have considered values of over 0.7 to indicate an acceptable level of reliability (Na et al., 2022; Pillai et al., 2021; Tjebane et al., 2022), some researchers have considered values of 0.6 and above (Sohn & Kwon, 2020; Vasiljeva et al., 2021). For this research, acceptable levels of reliability were set at 0.7 and above.

3.8 Data analysis

The primary objective of this research was to investigate and determine factors influencing employees' attitude and acceptance of AI technologies within mandatory settings in the South African financial services industry. Upon identifying factors proposed to be influencing employees' attitude and acceptance of AI technologies, a list of hypotheses were formulated which were to be tested in order to determine the relationship between these factors and employees' attitude and acceptance of AI technologies. The questionnaire was designed to collect quantitative data from the closed-ended questions where participants selected responses from the options provided. Using SPSS, descriptive analysis and hypotheses testing was conducted on this quantitative data. Limited textual data were also collected from the three open ended questions included at the end of the questionnaire. The below details how this data collected was analysed.

3.8.1 Preliminary analysis

Preliminary analysis was carried out to screen data, to identify missing information, to code data, as well as to regroup the data where applicable (Neuman, 2011). Reverse coding which needed to be done on specific negatively worded items measuring subjective wellbeing was also conducted.

3.8.2 Descriptive analysis

Descriptive statistics were conducted to organise, describe and summarise the research data collected (Salkind, 2017). An analysis of the profile of the participants in this research was conducted. Charts, graphs, tables and frequency distribution diagrams were presented and used to visualise the data. Cross-tabulation was used to summarise categorical data collected (Salkind, 2017), which included age, gender, experience with using AI, job role and type of financial services organisation the participants worked in. The relationship between this categorical data was examined further using the chi-square statistic (Kremelberg, 2011).

Univariate analysis was conducted to analyse each variable and evaluate the distribution of scores for each variable (Bryman, 2012). Measures of central tendencies such as the mean, the median and the mode, as well as measures of variability to determine how scores differ from one another, such as standard deviation were conducted (Salkind, 2017).

Various methods to analyse the distribution and normality of data were applied to ensure that appropriate statistical techniques are used when analysing the data and testing hypothesis. For example, graphical methods such as the use of box plots and histograms were used (Orcan, 2020). The presence of outliers which indicates extreme values which are either very high or very low values, and which may distort the mean or range of the data collected were assessed (Bryman, 2012).

The skewness and kurtosis values for each variable were also used as a method to evaluate the normality of the data. Given that there is no consensus on the values for skewness and kurtosis that indicate normality (Orcan, 2020), guideline's provided by Lei and Lomax (2015) were considered. They note that non-normality can be categorized into slight non-normality for absolute values less than ± 1.0 ; moderate non-normality for values between ± 1.0 and ± 2.3 and severe non-normality for values above ± 2.3 . Z-scores which measure the number of standard deviations a value is from the mean were also calculated to determine where scores lie on the normal distribution curve (Salkind, 2017). In addition, normality tests such as the Kolmogorov–Smirnov normality test were also conducted to determine if the distribution of the sample was from normal distribution ($p > 0.05$) or if the distribution was different from a normal distribution ($p < 0.05$) (Razali & Wah, 2011).

Bono et al. (2017) note that in social research, data is not always normally distributed, which means that when this is the case, appropriate statistics need to be used to analyse the data collected. The use of parametric and nonparametric tests when conducting hypothesis testing for the differences between means was examined. Parametric tests such as two-sample t-tests and the analysis of variance (ANOVA) are used when data is normally distributed (Jett & Speer, 2016). If data is not normally distributed, nonparametric tests such as the Mann-Whitney U test, and the Kruskal-Wallis one way analysis of variance are used (Jett & Speer, 2016; Salkind, 2017). Jett and Speer (2016) examined the power of parametric and nonparametric tests and found that parametric tests outperformed nonparametric tests when data was normally distributed, while nonparametric tests outperformed parametric tests when data was not normally distributed (Jett & Speer, 2016).

3.8.3 Hypothesis testing

Hypothesis testing was conducted using various inferential statistics to examine the relationship between variables, test the hypotheses and determine the extent to which the research findings can be generalised to the population (Neumann, 2011; Salkind, 2017). Bivariate analysis, using correlation analysis, was used to investigate the extent to which two variables were related, while multivariate analysis was used to investigate the relationship between 3 or more variables (Salkind, 2017).

For this research, correlation analysis and multiple linear regression were used to examine the relationship between the proposed factors identified as influencing attitude toward the use of AI technologies (technological, individual, organisational and environmental factors) and the attitude towards the use of AI technologies construct. Correlation analysis explains the direction and strength of the bivariate relationship (Tranmer & Elliot, 2008). Multiple regression describes the nature and association of the relationship between dependent and independent variables, and how the independent variables combine to predict the dependent variable (Tranmer & Elliot, 2008).

In doing so, hypotheses H1 to H11 were tested. This investigation was intended to answer research question 1 – *To what extent do each of the technological, individual, organisational, and environmental factors influence employees' attitude towards the use of AI technologies in the financial services industry in South Africa?*

In the process, various regression analysis assumptions were assessed to ensure that the results are trustworthy, in order to prevent a Type 1 or Type II error, as well as biases leading to the overstating or understating the significance of effect sizes (Osborne & Waters, 2002). Based on Tranmer and Elliot (2008) and Osborne and Waters (2002) the following assumptions were considered in the regression analysis.

The independent and dependent variables should be continuous (Tranmer & Elliot, 2008). The relationship between the independent and dependent variable should be linear, which can be derived from theory or previous research as well as from examining the scatter plot residuals (Osborne & Waters, 2002; Tranmer & Elliot, 2008). Using the normal p-p plot, the residuals should lie approximately on the diagonal as this would indicate that the residuals are normally distributed (Osborne & Waters, 2002; Tranmer & Elliot, 2008). Histograms of standardised residuals should follow a normal distribution (Tranmer & Elliot, 2008). The residuals should also indicate homoscedastic which can be visualised from scatter plots that indicate residuals that are randomly scattered (Tranmer & Elliot, 2008). As a general guideline, a clear cone shape would indicate heteroscedasticity, whereas a plot that shows a more random pattern indicates homoscedastic residuals (Tranmer & Elliot, 2008)

The reliability of the measurement should be acceptable, 0.7 and above (Osborne & Waters, 2002). There should be limited multicollinearity, indicated by a variance inflation factor (VIF) of not more than 10 and a collinearity tolerance that is not close to 0 (Tranmer & Elliot, 2008). This means that the correlation between the regressors should not be very high (Tranmer & Elliot, 2008). Although independent or predictor variables are often correlated with one another, significant correlations between the variables can result in multicollinearity which may complicate the analysis and interpretation of the results from the multiple regression (Kraha et al., 2012). Kim (2019) notes that a VIF greater than 5 and collinearity tolerance lower than 0.2 would indicate the presence of multicollinearity. These guidelines were applied in this research.

Tranmer and Elliot (2008) note that linear regression method can be used if there are some violations to the assumptions above, however consideration should be given to the limitations of the findings, and where necessary, the interpretation of the results may need to be adapted, or data may need to be transformed.

Multivariate analysis techniques such as multiple regression and stepwise regression were also used to determine the most influential determinants of attitude towards the use of AI technologies. Several studies integrating the TAM and the TOE frameworks have also used multiple regression, for example research by Abdekhoda et al. (2018) when investigating factors influencing the adopting of mobile technology-based services by academic librarians and research by Chiniah et al. (2019) as well as Vang & Lind (2023) when investigating cloud computing adoption. Similarly, Vasiljeva et al. (2021) and Ghani et al. (2022) also applied multiple regression analysis in their research on factors influencing the adoption, attitude, and acceptance of AI technologies in various industries in Latvia and in the manufacturing industry in Malaysia respectively. These analyses were used to answer research question 2 – *Which factors are the most influential determinants of employees' attitude towards the use of AI technologies?*

Further, correlation analysis and linear regression was used to investigate the relationship between attitude towards the use of AI technologies and the acceptance of AI technologies, to test hypothesis H12. In doing so, research question 3 was answered – *To what extent do employees' attitude towards the use of AI technologies influence acceptance of use of AI technologies?*

An analysis of moderating factors that were proposed to moderate the attitude-acceptance relationship was carried out using linear regression. Therefore hypotheses 13 and 14 were tested to investigate the moderating role of employees' experience with AI and employees' job role respectively. In doing so, the objective was to answer research question 4 – *To what extent do employees' job roles and employees' experience with using AI technologies moderate the relationship between attitude towards use of AI technologies and acceptance of the use of AI technologies?*

Results from the hypothesis testing and open-ended questions were also used to determine key factors that would enable the construction of a model that management and organisations can use to ensure the successful implementation and use of AI technologies. This was to address research question 5 - *What model can organisations use to facilitate the successful implementation and acceptance of AI technologies?*

3.8.4 Analysis of textual responses

Unlike in qualitative studies that typically generate long and comprehensive tests, responses to open-ended questions in a survey are generally one worded or very few words (Rohrer et al., 2017). Textual responses to open-ended questions in this study were analysed to determine key themes relevant for this study, as well as to investigate the link between responses from textual data and variables included in the research study.

The overall process followed in analysing textual data was guided by approaches and processes followed by Rohrer et al. (2017) and Baburajan et al. (2022). Data collected from Qualtrics was entered into Excel. Preliminary analysis included data cleaning, checking and correcting typos. The next step involved reviewing and coding the data to summarise the data collected. Codes were grouped into categories and these categories represented main themes that were then prepared for visualisation in the form of word cloud using an online tool called WordItOut. Word cloud is a technique used to visualise key words from textual data based on the frequency of the word from the text analysed (DePaolo & Wilkinson, 2014). The more the word appears in the text analysed, the bigger the size of the word in the word cloud in comparison to other words (DePaolo & Wilkinson, 2014).

Given that responses to the open ended questions in the questionnaire was voluntary and that responses to these questions were mostly one word responses or short phrases, the use of word cloud was justified. Further, given that the research study was mainly quantitative in nature, textual responses in this research were included to provide a quick and easy way to supplement the findings of the quantitative data and analysis.

The open-ended questions asked participants to share their attitude towards AI technologies and factors they would like to be considered in the implementation and use of AI technologies within their work and within their organisation. Therefore one would expect some similarity between participants responses to these open-ended questions and the items included in the questionnaire. This overlap between factors included in the closed-ended questions and responses to open-ended questions also enables the assessment of convergent validity (Rohrer et al., 2017). In addition, responses to open ended questions were valuable input into the development of a model to be used by organisations when implementing and using AI technologies.

3.9 Ethical considerations

Ethical standards and guidelines were maintained throughout the research process to avoid negative outcomes on the research findings and a negative experience for the participants (Neuman, 2011). The researcher went through a process to obtain ethical clearance from the University of Witwatersrand's Research Ethics Committee, see Appendix D. This is done to ensure that the research conducted is done so in a way that adheres to strict ethical principles that protect the interest of research participants and ensures that the research is carried out in a professional manner.

The anonymity of organisations and employees that participated in this research was guaranteed, as indicated in the request for permission for the organisations to participate in this research (Appendix A), as well as in the participants' information note (Appendix C). As mentioned previously, each research participants was given an opportunity to indicate their informed consent before participating in this research. Participants were also informed that participation in this research survey was voluntary, and that no one was forced to participate in this research. The privacy and anonymity of information shared by the participants was also highlighted. No detailed information to identify individuals participating in this research was collected, such as participants names. Participants were informed that only general demographic information would be collected (e.g. age, gender, job role). Further, participants were notified that they could withdraw from participating in this research at any time, without any negative consequences. By indicating the above upfront to assure participants of their voluntary participation, anonymity, as well as requesting them to give and indicate their informed consent to participate in this research, it was expected that this would increase the chances of participants being more truthful in their responses.

As this was an online survey on Qualtrics, access to the Qualtrics portal was password protected. The data that was downloaded and saved in folders on the researchers personal laptop, which is also password protected. Only the researcher has access to this laptop and password and this has not been shared with anyone. All research data collected throughout this research process has not only been kept securely, but has also remained confidential and not shared with companies that participated in this research. In addition, no individual responses will be reported on as data included in this research report is anonymised and aggregated.

3.10 Limitations

This research was a cross-sectional study, as the research was conducted over a specific period of time and was not intended to measure changes in employee's attitude and acceptance of AI technologies. The cross-sectional design was used for this research because it was cheaper and convenient for the researcher than a longitudinal study. Unfortunately, attitude and acceptance of AI technologies may change over time, especially after the extended use of AI technologies. For example, Fast and Horvitz's (2017) longitudinal study of the public perceptions of artificial intelligence reveal changes in individuals' views and attitude over time, a 30-year period. Given that the use of AI technologies in South Africa is still in its early stages (Tjebane et al., 2022), and that understanding of AI is still limited (Ndoro et al., 2020), individuals' attitude and acceptance of AI technologies may change once they have more experience and understanding of AI technologies. Therefore, the findings of this research may be limited to employees' attitudes and acceptance of AI technologies at that specific point in time when data was collected, and their attitudes and acceptance may change over time due to increased exposure and understanding of AI technologies.

Online self-administered questionnaires provide many advantages such as being cost-effective, quick to administer as well as being convenient for the researcher and the respondents (Bryman, 2012). In addition, the researcher's objectivity is maintained (Kelley, 2019). However, self-reported questionnaires are often seen to be subject to response bias, such as social desirability bias, as participants may respond in a way they think they should be responding or are expected to respond (Neumann, 2011). Further, response bias may occur as participants may rush through the questions because they are lazy to read the questions properly, and/or end up selecting specific responses out of habit (Neumann, 2011). Participants may also easily misinterpret the survey questions given the limited understanding and misconceptions surrounding the use of AI technologies noted in literature above.

In survey research where an online questionnaire is distributed to participants to complete, the actual research sample may be affected by non-response bias (Bryman, 2012). In this research, this could mean that employees who participated in the survey are employees that have an interest in or have exposure to AI technologies. To try and mitigate this potential risk or bias, a participants' note was included at the start of the survey to specify that employees did not need to have experience with using AI technologies for them to participate in this research.

Although open-ended questions were included to add to the of the research findings, interpretation of results and provide input into the development of a model for organisations to use when implementing and using AI technologies, completing the open-ended questions was voluntary and these questioned were not answered by everyone. This was expected, since the research was largely quantitative. However, it does make it difficult to determine the extent to which results from the open -ended these results can be applied to the total sample of this research.

This research was conducted within South African financial services organisations, which means the results of this study may be more applicable in this context, compared to other context or industries. Caution must be taken when interpreting the research findings to avoid overgeneralising the results of this research in other contexts.

3.11 Summary

This chapter provided a description of the research strategy, the research design, the research instrument, the research sample, the data collection process and how the quantitative and qualitative data was analysed. Guidelines to be followed when reporting on and interpreting the data were provided. Ethical considerations and measures considered and taken to ensure research and data quality are explained. Limitations with this research are noted. The following chapter presents the research findings based on the analysis conducted.

CHAPTER 4: RESEARCH RESULTS

4.1 Introduction

The purpose of this study was to investigate and determine factors influencing employees' attitude and acceptance of AI technologies within the South African financial services industry. The literature review identified factors proposed to be influencing attitudes towards the use of AI technologies, as well as factors moderating the relationship between attitude towards the use of AI technologies and acceptance of AI technologies. This chapter presents the research results from the research conducted. A discussion of these results follows in the next chapter, Chapter 5.

To begin with, data was cleaned, and preliminary analysis was conducted to remove missing data and outliers. The validity and reliability of the questionnaire items and data collected was assessed. Descriptive statistics on the research sample are provided. The results of the univariate analysis of each factor included in this research, as well as results of the bivariate and multivariate analysis carried out to test the hypotheses and answer the research questions are presented. In addition, the results of the analysis of key determinant of employees' attitude towards the use of AI, as well as the results of the analysis of the attitude-acceptance relationship and effect of the proposed moderators on this relationship are presented. Responses from open-ended responses were analysed and illustrated in the form of word clouds.

4.2 Preliminary analysis

Qualtrics, an online survey platform was used to collect survey responses. The raw data collected from participants in this survey was downloaded from Qualtrics into an excel format and the following details the steps taken to clean the data and prepare it for analysis.

4.2.1 Data screening and cleaning

432 survey responses were collected. Data was analysed for missing data and responses to ensure that accurate data was available for analysis. After data screening and removing cases with missing data, which included removing missing demographic information, 410 valid responses were retained. Thereafter, data was coded and responses regrouped (specifically jobs roles and type of financial services institutions). Numerical values were assigned to responses collected in the raw data. Data was then loaded onto SPSS for further analysis.

4.2.2 Reverse scoring

Items that were negatively worded needed to be reverse scored to enable data and the results of the analysis to be meaningfully interpreted. This process entailed reverse scoring the last 3 items included in the measurement of subjective wellbeing, EW5, EW6 and EW7⁵. Therefore, instead of using the numerical scoring of 1=strongly disagree to 7=strongly agree, the numerical scoring used was reversed to 7 = strongly disagree to 1 = strongly agree for these items.

4.3 Respondents profile

Of the 410 participants, 53% identified themselves as females and 47% as males as shown in figure 4.1. The majority of the participants were aged between 31 and 50 years old, which was 73% of the participants shown in figure 4.2.

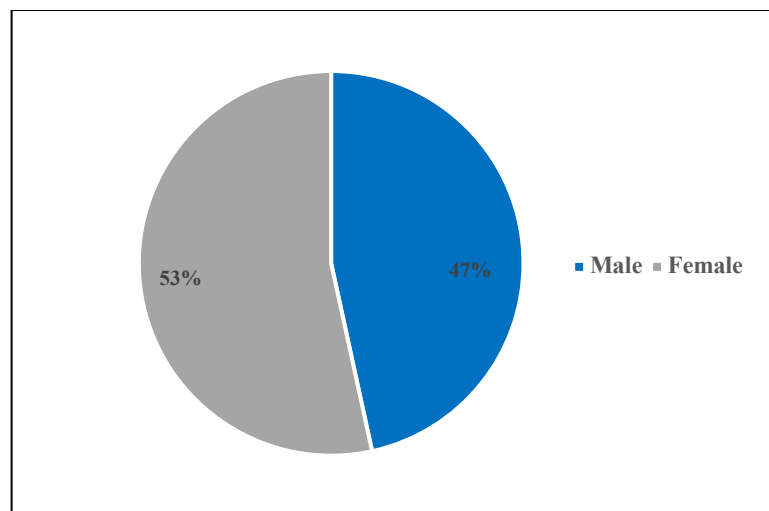


Figure 4.1 Gender distribution

⁵ EW5 - Using AI technologies reduces autonomy in my work.
EW6 - Using AI technologies make me feel anxious and/or stressed.
EW7 - I think my job could be replaced with AI technologies.

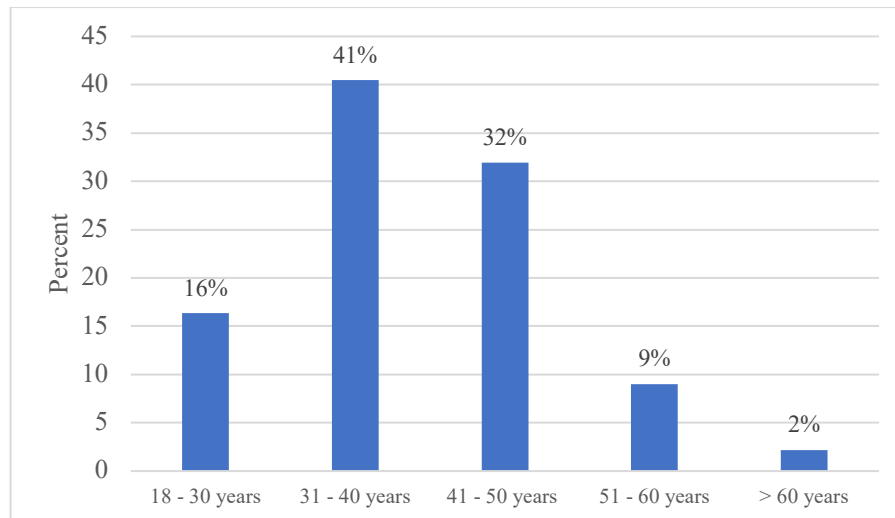


Figure 4.2 Age group distribution

Figure 4.3 illustrates that 59% (243) of all the participants did not have experience using AI technologies in doing their work. From those that indicate that they have experience using AI technologies in doing their work, males have more experience with using AI technologies than females, 60% compared to 40% respectively. From the 59% of the total participants that did not have experience using AI technologies in doing their work, more than half were females (63%).

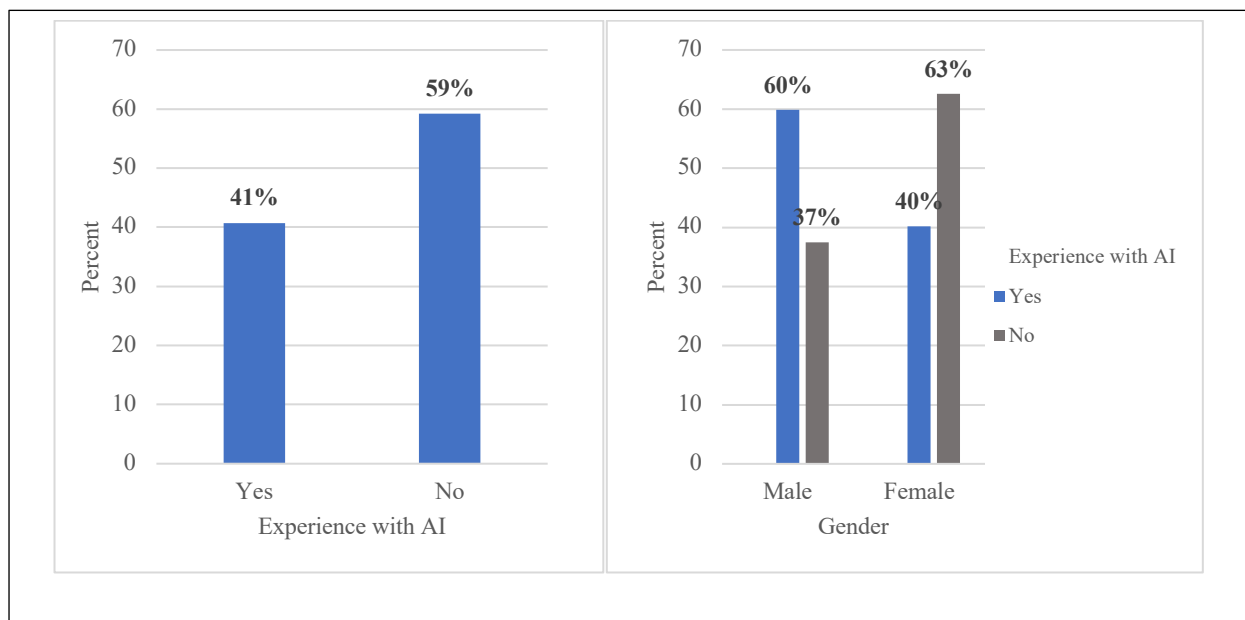


Figure 4.3 Experience with using AI technologies

The cross tabulation in Table 4.1 provides an overview of the distribution between gender and experience with using AI technologies. A chi-square test of independence was conducted to

examine the relation between gender and experience with using AI technologies. The relationship between these variables is significant, $X^2(1, N = 410) = 20, p < 0.001$. Men are more likely than females to indicate that they have experience with using AI technologies.

Table 4.1 Cross tabulation of gender and experience

		Experience with AI	
		Yes	No
Gender	Male	24.4%	22.2%
	Female	16.3%	37.1%
Total		40.7%	59.3%

Figure 4.4 indicates that most of the participants, 69%, indicate their role to be either middle management (25%); professional IT (24%) or non-professional IT (20%). Table 4.2 provides a cross tabulation between gender and job role, indicating that there are more males than females in top management/executive roles, middle management and IT roles (35%) compared to females (22%). However, there are more females in first line management, professional non-IT and administrative roles (32%) compared to males (11%).

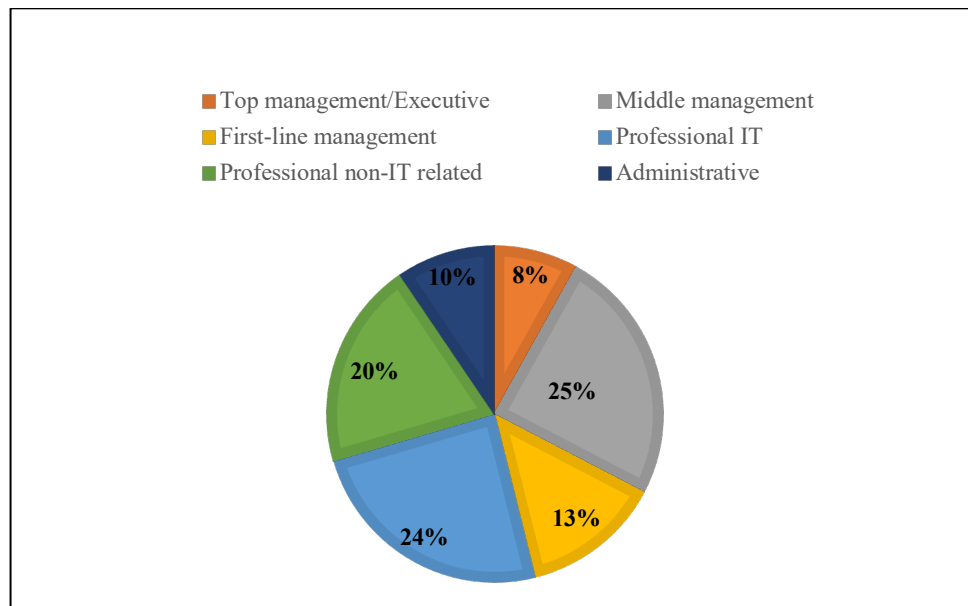


Figure 4.4 Job role distribution

Table 4.2 Cross tabulation between gender and job role

Gender * Job role Crosstabulation							
	Top management/ Executive	Middle management	First-line management	Professional IT	Professional non-IT related	Administrative	Total
Male	5.8%	12.0%	4.4%	17.6%	6.3%	0.5%	47%
Female	2.2%	12.7%	9.0%	6.8%	13.7%	9.0%	53%
Total	8.0%	24.7%	13.4%	24.4%	20.0%	9.5%	100%

Table 4.3 shows that of the 167 participants (41%) that have experience with using AI technologies, those in an IT role have the most experience with using AI technologies (46%), while those in administrative roles have the least experience with using AI technologies (3%). The chi-square tests indicates a significant relationship between employees' job role and experience using AI technologies $X^2 (5, N = 410) = 90, p < 0.001$. Those in Professional IT roles were more likely than those in other roles to have experience with using AI technologies.

Table 4.3 Experience with using AI technologies per role

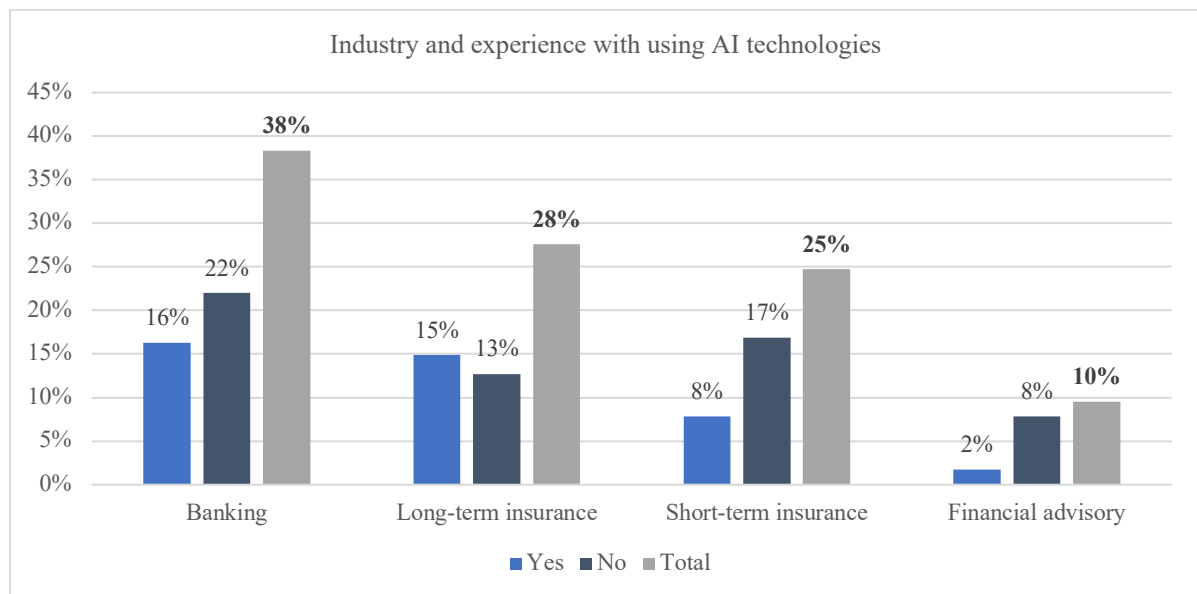
	Experience with AI		Total
	Yes	No	
Top management/Executive	2.4%	5.6%	8.0%
Middle management	9.3%	15.4%	24.7%
First-line management	5.8%	7.6%	13.4%
Professional IT	18.8%	5.6%	24.4%
Professional non-IT related	3.2%	16.8%	20.0%
Administrative	1.2%	8.3%	9.5%
Total	40.7%	59.3%	100.0%

Participants were asked to indicate which business application of AI technologies they think are relevant in their organisation, and results are shown in table 4.4 below. Participants responses indicate what they view as the practical application of AI technologies from the options provided but were also able to share other practical applications of AI technologies within their organisations, that were not included in the options provided. This enabled the researcher to also get a view of employees' view or knowledge of areas in which AI technologies can be applied within their organisation. Additional application of AI technologies indicated by participants were the use of AI technologies in HR processes, robotics, financial reporting and compliance and reporting.

Table 4.4 AI Business application

	N	% of all participants
Credit vetting, scoring and decisions	347	84.6%
Data analysis for insights recommendations and predictions	366	89.3%
Detect fraudulent activities and cybersecurity attacks	358	87.3%
Chat bots and virtual assistant	352	85.9%
Authenticate and authorise users	351	85.6%
Document analysis and processing	329	80.2%
Automation of workflow processes	338	82.4%
Other	6	1.5%

38% participants indicate that the main service provided by their financial services institution is banking, followed by long-term insurance 28% and short-term insurance 25% and financial advisory 10%. As shown in figure 4.5, compared to other financial services institutions, participants from the long-term insurance institutions had more people with experience using AI than those that did not (15% vs 13%).

**Figure 4.5 Industry and experience using AI technologies**

4.4 Validity and reliability of measures

The following provides an overview of how the data and the measurement used was analysed for validity and reliability. Items that violate validity are removed. The reliability of the remaining scales is assessed through the measurement of internal consistency, Cronbach alpha.

4.4.1 Validity

Principal component analysis is used to validate the measurement instrument. To demonstrate convergent and discriminant validity, items measuring the same construct load highly onto the same component and show low cross loadings on components that they are not intended to measure. As discussed in the previous chapter, items with a factor loading of 0.6 and above are deemed acceptable and demonstrate convergent validity. To ensure discriminant validity, items with a high loading (above 0.5) on more than one component or factor as well as a difference of less than 0.1 between the primary and alternative components are removed.

Data inspection techniques such as the Bartlett's test of sphericity and the Kaiser–Meyer–Olkin (KMO) were applied (Howard, 2016). The KMO is applied to indicate the common variance within the dataset, and a KMO above 0.6 is deemed to be acceptable (Guvendir & Ozkan, 2022; Howard, 2016). The Bartlett's test should be significant in order to indicate a relationship within the data set, making it appropriate for further analysis (Howard, 2016). The varimax rotation method is applied to the technological, individual, organisational and environmental items, as it is used to increase the variances of factor loading and enable items to clearly load or not load onto each factor or variable (Guvendir & Ozkan, 2022). A variance of more than 60% which is considered acceptable by Guvendir and Ozkan (2022) is also applied. Communalities are also assessed to determine if they are at least above 0.6.

4.4.1.1 Attitude towards use of AI technologies

Factor analysis is conducted on the attitude variable. Table 4.5 shows that the KMO measure is 0.92 and the Bartlett's test of sphericity is significant ($p < 0.000$), which indicates that there is a relationship between the items measuring attitude towards the use of AI technologies and that it is appropriate to proceed with the factor analysis. All five items load highly onto one component as indicated below, with values above 0.9, and are all retained. Convergent validity is demonstrated. The total variance explained by all the 5 items is 93%. The communalities are all high, over 0.9.

Table 4.5 Principal component analysis of attitude towards use of AI technologies

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.916
Bartlett's Test of Sphericity	Approx. Chi-Square	3435.874
	df	10

	Sig.	.000
Cumulative % variance		93.096
Item	Attitude	Communalities
AT1	0.964	0.929
AT2	0.965	0.931
AT3	0.968	0.937
AT4	0.972	0.944
AT5	0.956	0.914

4.4.1.2 Acceptance of AI technologies

Factor analysis is conducted on the acceptance variable. Table 4.6 shows the KMO measure is 0.90 and the Bartlett's test of sphericity is significant ($p < 0.000$), which indicates that there is a relationship between the items measuring acceptance of AI technologies and that it is appropriate to proceed with the factor analysis. All factors load highly onto one component as indicated below, with values above 0.8, which are all retained. Convergent validity is demonstrated. The total variance explained by all the five items is 92%. The communalities are all high, over 0.8.

Table 4.6 Principal component analysis of Acceptance of AI technologies

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.896
Bartlett's Test of Sphericity	Approx. Chi-Square	3229.132
	df	10
	Sig.	.000
Cumulative % variance		91.621
Item	Acceptance	Communalities
AC1	0.962	0.926
AC2	0.970	0.941
AC3	0.963	0.927
AC4	0.956	0.915
AC5	0.934	0.872

4.4.1.3 Technological factors

Items intended to measure perceived usefulness, perceived ease of use, and relative advantage which represent technological factors in this research are analysed for convergent and

discriminant validity. The KMO measure is 0.94 and the Bartlett's test of sphericity is significant ($p < 0.000$) as indicated in Table 4.7. Varimax rotation is applied to assess how items load highly onto one factor and low on the other components. No cross loading was evident. All items have a factor loading above 0.7. The cumulative variance explained by the three technological factors is 93%, as perceived usefulness, perceived ease of use and relative advantage each account for a variance of 31.816%, 31.756% and 28.941% respectively. The communalities are all high, over 0.8.

Table 4.7 Principal component analysis of technological factors

KMO and Bartlett's Test				
Kaiser-Meyer-Olkin Measure of Sampling Adequacy			.938	
Bartlett's Test of Sphericity	Approx. Chi-Square		8632.198	
	df		66	
	Sig.		.000	
Cumulative % variance			92.513	
Item	Perceived usefulness	Perceived ease of use	Relative advantage	Communalities
PU1	0.802			0.959
PU2	0.819			0.974
PU3	0.815			0.974
PU4	0.799			0.964
PEOU1		0.805		0.918
PEOU2		0.785		0.904
PEOU3		0.830		0.916
PEOU4		0.829		0.898
RA1			0.702	0.865
RA2			0.772	0.917
RA3			0.774	0.886
RA4			0.809	0.927

4.4.1.4 Individual factors

Individual factors in this research are assessed using items that measure perceptions of organisational justice and employee wellbeing. The KMO measure is 0.93 and the Bartlett's test of sphericity is significant ($p < 0.000$) as indicated in Table 4.8. Varimax rotation is also applied to assess how items loaded highly onto one factor and low on the other components. Item EW4 from the employee wellbeing factor is removed because of evidence of high cross loading on the employee wellbeing factor (0.655), and also on the organisational justice factor

(0.504). The remaining items each have a factor loading above 0.7 and no evidence of cross loading. The cumulative variance explained by these individual factors is 80%, as the employee wellbeing factor accounts for a total variance of 40.263% and organisational justice has a total variance of 39.997%. The communalities are all high, over 0.7.

Table 4.8 Principal component analysis of individuals factors

KMO and Bartlett's Test			
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.931	
Bartlett's Test of Sphericity	Approx. Chi-Square	5774.044	
	df	66	
	Sig.	.000	
Cumulative % variance		80.261	
Item	Employee wellbeing	Organisational justice	Communalities
EW1	0.757		0.812
EW2	0.764		0.761
EW3	0.734		0.784
EW5	0.821		0.731
EW6	0.868		0.825
EW7	0.819		0.745
OJ1		0.844	0.854
OJ2		0.867	0.869
OJ3		0.852	0.845
OJ4		0.877	0.861
OJ5		0.848	0.861

4.4.1.5 Organisational factors

Management support, training support and innovative culture are all included as organisational factors influencing attitude towards the use of AI technologies. The KMO measure is 0.92 and the Bartlett's test of sphericity is significant ($p < 0.000$) as indicated in Table 4.9. Varimax rotation is applied to assess how items load highly onto one factor and low on the other components. Item TS1 from the training support factor is removed because of evidence of high cross loading on the training support factor (0.641) and also on the management support factor (0.581). All other items indicated a factor loading of 0.8 and above, with no evidence of cross loading. The cumulative variance explained by these three organisational factors is 91%. Management support, innovative culture and training support each account for a variance of 31.350%, 31.504% and 27.908% respectively. The communalities are all high, over 0.8.

Table 4.9 Principal component analysis of organisational factors

KMO and Bartlett's Test				
Kaiser-Meyer-Olkin Measure of Sampling Adequacy			.922	
Bartlett's Test of Sphericity	Approx. Chi-Square		7082.565	
	df		66	
	Sig.		.000	
Cumulative % variance			90.972	
Item	Management support	Training support	Innovative culture	Communalities
MS1	0.833			0.903
MS2	0.844			0.936
MS3	0.860			0.943
MS4	0.848			0.863
TS2		0.874		0.926
TS3		0.894		0.953
TS4		0.864		0.907
IC1			0.884	0.903
IC2			0.904	0.939
IC3			0.892	0.908
IC4			0.886	0.917

4.4.1.6 Environmental factors

Social influence, customer pressure and competitive pressure were identified as environmental factors influencing the attitude towards use of AI technologies. The KMO measure is 0.92 and the Bartlett's test of sphericity is significant ($p < 0.000$) as indicated in Table 4.10. Varimax rotation is applied to assess how items loaded highly onto one factor and low on the other components. All items have a factor loading above 0.7 and no factors are removed for cross loading. The cumulative variance explained is 90%. Competitive pressure, customer pressure and social influence each account for a variance of 32.838%, 31.370% and 25.455% respectively. The communalities are all high, over 0.8.

Table 4.10 Principal component analysis of environmental factors

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.915
Bartlett's Test of Sphericity	Approx. Chi-Square	5874.564
	df	55
	Sig.	.000
Cumulative % variance		89.663

Item	Competitive pressure	Customer pressure	Social influence	Communalities
CoP1	0.834			0.904
CoP2	0.856			0.931
CoP3	0.821			0.919
CoP4	0.858			0.910
CP1		0.832		0.866
CP2		0.858		0.926
CP3		0.819		0.918
CP4		0.795		0.895
SI1			0.857	0.866
SI2			0.847	0.891
SI3			0.829	0.836

4.4.2 Internal consistency reliability

Of the original 47 items measuring factors influencing employees attitude towards use of AI technologies, 2 are removed and 45 retained. Once relevant items are identified and retained, composite scores for each variable are created. As proposed by Boone and Boone (2012), composite scores are calculated by taking the sum or mean of the relevant Likert-type items. Therefore, given the equal weighting of each question and response to items included in the questionnaire, Likert-type items are combined into a single composite score using the mean to provide and represent a quantitative measure of each variable.

Cronbach's alpha is used to determine the internal consistency reliability. The variables in this research indicate a high level of internal consistency reliability as the minimum value of internal consistency is 0.916 for the social influence scale and the highest is 0.989 for the perceived usefulness scale, which indicates high levels of internal consistency for each of the constructs in this study and confirms that the data is at least 95% reliable with a 5% acceptable error margin.

The internal consistency values reported in this study are consistent with findings from previous TAM-TOE studies on the adoption and acceptance of AI technologies, that have also reported high levels of internal consistency (above 0.8). For example, Chatterjee et al. (2021) in their study on the adoption of AI technologies in the manufacturing industry reported a Cronbach alpha of 0.9 and above for each constructs and Na et al.'s (2022) research on the acceptance of AI technologies in the construction industry reported a Cronbach alpha above

0.8 for each construct. Table 4.11 below provides an overview of the internal consistency for each construct or factor included in this research.

Table 4.11 Internal consistency for each variable

Variable	N	Number of items	Cronbach's alpha
Perceived usefulness	410	4	0.989
Perceived ease of use	410	4	0.966
Relative advantage	410	4	0.960
Organisational justice	410	5	0.959
Employee wellbeing	410	6	0.918
Management support	410	4	0.965
Training support	410	3	0.965
Innovative culture	410	4	0.969
Social influence	410	3	0.916
Customer Pressure	410	4	0.960
Competitor Pressure	410	4	0.969
Attitude	410	5	0.981
Acceptance	410	5	0.976

4.5 Descriptive statistics

Univariate analysis was carried out and a summary of descriptive statistics which includes measures of central tendency and the distribution of the data is provided in table 4.12 below. A 7-point Likert-scale was used to collect responses, 1 - strongly disagree to 7 – strongly agree, and the means of each of the variables is above $M = 5$, indicating generally positive responses to the variables in the study. Acceptance of AI technologies ($M = 6.08$, $SD = 0.78$) has the highest mean, followed by perceived usefulness ($M = 5.99$, $SD = 0.82$) and competitive pressure ($M = 5.92$, $SD = 0.79$). This shows that most of the participants agreed the most on their acceptance of AI technologies, perceptions of the usefulness of AI, as well as the pressure experienced from competitors to use AI technologies.

Acceptance, innovative culture and training support indicate the lowest standard deviation of $SD = 0.78$, indicating that these variables have the least variation of responses, compared to other variables, especially employee wellbeing and perceived ease of use that indicate the highest standard deviation, $M = 5.14$, $SD = 1.25$ and $M = 5.48$, $SD = 0.93$ respectively. The

greatest variation of scores is noted for the employee wellbeing variable where the scores range from 1.83 to 7.00, SD = 1.25.

Table 4.12 Descriptive statistics

Variables	N	Min	Max	Mode	Median	Mean	Std. Dev	Skewness	Kurtosis	K-S test
Perceived usefulness	410	3.50	7.00	6.00	6.00	5.99	.82	-.634	.184	<0.001
Perceived ease of use	410	3.00	7.00	5.50	5.75	5.48	.93	-.163	-.543	<0.001
Relative advantage	410	3.25	7.00	6.00	6.00	5.82	.83	-.450	-.058	<0.001
Organisational justice	410	3.20	7.00	5.60	5.60	5.45	.82	-.201	-.409	<0.001
Employee wellbeing	410	1.83	7.00	7.00	5.33	5.14	1.25	-.346	-.722	<0.001
Management support	410	3.00	7.00	6.00	5.75	5.52	.87	-.446	-.023	<0.001
Training Support	410	3.00	7.00	6.00	6.00	5.95	.78	-.419	-.071	<0.001
Innovative culture	410	2.00	7.00	5.00	5.00	5.28	.78	-.369	.674	<0.001
Social influence	410	3.00	7.00	5.00	5.33	5.32	.86	-.104	-.406	<0.001
Customer Pressure	410	3.50	7.00	6.00	6.00	5.74	.84	-.537	.143	<0.001
Competitive pressure	410	3.50	7.00	6.00	6.00	5.92	.79	-.643	.450	<0.001
Attitude	410	3.60	7.00	6.00	6.00	5.88	.85	-.410	-.255	<0.001
Acceptance	410	3.60	7.00	6.00	6.00	6.08	.78	-.600	-.025	<0.001

The distribution of the data and the normality of data was also analysed for each available. The 410 survey responses were examined for outliers, which is an examination of extreme scores in terms of scores with unusually low or high values (Salkind, 2017). Graphical methods such as histograms, box plots and stem leaf plots were applied to determine outliers. An analysis of the standardized scores was conducted to determine the z-scores. Although there are variations in terms of the cut off for the value of z-scores used to determine what constitutes an outlier, it seems that at the very extreme, any z-score above +3.29 or below -3.29 is considered to be an outlier (Mowbray et al., 2019).

Further, the assumption for normality was assessed using numerical methods such as the skewness and kurtosis coefficients, as shown in table 4.12 above. Acceptable ranges for normality are said to be generally in the range of ± 1 for both the absolute values of skewness and kurtosis (Chan, 2003). Lei and Lomax (2015) note that non-normality can be categorized into slight non-normality for absolute values less than ± 1.0 ; moderate non-normality for values between ± 1.0 and ± 2.3 and severe non-normality for values above ± 2.3 . Normality tests such

as the Kolmogorov–Smirnov normality test were also conducted as indicated in table 4.12, to determine if the distribution of the sample was from normal distribution ($p>0.05$) or if the distribution was different from a normal distribution ($p<0.05$) (Razali & Wah, 2011). The K-S results are all is significant.

From the above analyses, it is evident that the data had some outliers. In cases were outliers are detected, a number of processes can be applied, but the most common ones are removing/deleting outliers, windsorisation or leaving the outliers as is and conducting specific statistical analysis such as non-parametric statistics which are more robust to outliers (Mowbray et al., 2019; Osborne & Overbay, 2004). Removing or deleting refers to the process of identifying and removing outliers from the data set. Windsorisation on the other hand is the process of adjusting extreme score by changing their value to the nearest valid value that is not considered an outlier. Sometimes outliers are left as is because removing them or transforming them can improve normality but complicate the interpretation of the results (Osborne & Waters, 2002). Past research has noted that there is validity in applying either one of the methods, as long as the approach chosen is sufficiently motivated (Mowbray et al., 2019).

Each case identified as an outlier was reviewed to determine whether the values appeared valid or erroneous. All outlying values appeared to be valid (i.e. no evidence of random answering or mistake in entering data). Given that the literature review in Chapter 2 has also shown the variations in views and factors influencing attitudes towards the use of AI, there is a need to capture those variations as much as possible. Due to the mixed views of individuals' perceptions, experiences regarding AI technologies, there is likely to be variations amongst employees' responses. Therefore, having employees whose responses may not necessarily fit the norm can be expected. In this case, the outliers are identified as legitimate and are retained.

The K-S normality results are all is significant for each factor, which indicates deviation from data that is normally distributed. Although the data indicated slight non-normality, therefore the use of non-parametric is applied for specific analysis of the data, such as correlation analysis and comparisons between group, to prevent making interpretation and inferences that may not be reliable or valid (Razali & Wah, 2011).

4.6 Correlation between attitude towards use of AI and its determinants

Bivariate analysis was carried out to determine the relationship between all the eleven factors identified as determinants of attitude towards use of AI technologies and the attitude towards use of AI technologies constructs. The correlation between each individual factor and attitude towards use of AI technologies was investigated to determine the strength and the direction of the relationship.

Given that the univariate analysis revealed that the data was not normally distributed, the Spearman rank correlation coefficient test, which is a non-parametric correlation test is used. Table 4.13 provides the results of the correlation analysis. The results of the Pearson correlation, a parametric assessment used when data is normally distributed, are also provided for comparison and indicate minimal differences between the coefficient values. The Spearman correlation coefficients will be used for reporting on the relationship between the variables below. Guidelines provided by Salkind (2017) are used in interpreting the strength of the relationship between each of the independent variables (factors affecting attitude towards the use of AI technologies) and attitude the use of AI technologies. Correlation coefficients of 0.80 to 1.0 indicate a very strong relationship, 0.6 to 0.8 indicates a strong relationship, 0.4 to 0.6 indicates a moderate relationship and ranges below 4 indicate a weak or no relationship (Salkind, 2017).

Table 4.13 Correlation between attitude and its determinants

Variable	Spearman correlation with Attitude towards use of AI technologies	Pearson correlation with Attitude towards use of AI technologies
Perceived usefulness	0.790**	0.813**
Perceived ease of use	0.793**	0.800**
Relative advantage	0.791**	0.799**
Organisational justice	0.662**	0.665**
Employee wellbeing	0.835**	0.832**
Management support	0.701**	0.718**
Training Support	0.653**	0.643**
Innovative culture	0.584**	0.560**
Social influence	0.596**	0.622**
Customer Pressure	0.676**	0.724**
Competitive Pressure	0.748**	0.798**

**p<0.01 (n=410)

4.6.1 Correlation between attitude towards use of AI and technological factors

Technological factors which include perceived usefulness, perceived ease of use, and relative advantage each demonstrate a significant positive and strong relationship with attitude towards use of AI technologies. The correlation between each of these technological factors and attitude towards use of AI technologies is similar, $r(408) = .79, p < .01$.

4.6.2 Correlation between attitude towards use of AI and individual factors

Although the relationship between each of the individual factors and attitude towards use of AI technologies is positive and statistically significant, the relationship between employee wellbeing and attitudes towards use of AI, $r(408) = .84, p < .01$, is stronger than the relationship between organisational justice and attitude towards use of AI technologies, $r(408) = .66, p < .01$. Amongst all the determinants of attitude towards the use of AI technologies in this study, employee wellbeing has the strongest association with attitude towards the use of AI technologies.

4.6.3 Correlation between attitude towards use of AI and organisational factors

The relationship between organisational factors and attitude towards use of AI technologies is also positive, strong, and statistically significant. Management support has the highest correlation with attitude towards use of AI technologies, $r(408) = .70, p < .01$. The correlation between training support and attitude towards use of AI technologies is $r(408) = .65, p < .01$. Innovative culture has the lowest association and moderate correlation with attitude towards use of AI technologies, $r(408) = .58, p < .01$.

4.6.4 Correlation between attitude towards use of AI and environmental factors

All environmental factors which include social influence, customer pressure and competitive pressure have a significant and positive relationship with attitude towards the use of AI technologies. Compared to other environmental factors, social influence has the lowest but moderate correlation with attitude towards the use of AI technologies, $r(408) = .60, p < .01$. The relationship between customer pressure and attitude towards use of AI technologies is strong, $r(408) = .68, p < .01$, while the relationship between competitive pressure and attitude towards use of AI technologies is very strong, $r(408) = .75, p < .01$.

4.7 Multiple regression of factors influencing attitude towards AI

The previous section demonstrated the bivariate analysis conducted, as the correlation between each of the factors and attitude towards use of AI technologies was analysed. However, to further analyse the relationship between attitude towards use of AI technologies and its determinants and predict attitude towards use of AI technologies, multivariate analysis using multiple regression analysis is performed. This was also used to test the hypotheses formulated.

The regression analysis assumptions that were discussed in the previous chapter, Chapter 3, need to be met when carrying out regression analysis. It should be noted that although the univariate analysis conducted indicated evidence of non-normality in the data, regression analysis is still a valid statistical analysis to test the hypotheses in this research. This is because in regression analysis, a normal distribution refers to the normality in the distribution of residuals and not necessarily normality in the data for the independent variables (Tranmer & Elliot, 2008). This normality of the distribution of residuals is assessed by analysing the visual presentation of normal p-p plots of regression standardised residuals and histograms of residuals (Tranmer & Elliot, 2008).

The analysis of multivariate outliers was done by analysing the Mahalanobis Distance, where a high value indicates deviation of a case from the typical values (Field, 2013). However, measures of a case's influence on the model such as the Cook's distance and leverage value (Field, 2013), are considered before deciding on what to do with outliers detected. The Cook's distance is used to assess if a case should be removed in order to improve the fit of the model (Tranmer & Elliot, 2008). A Cook's distance of more than 1 would indicate the need for further investigation or would mean that the case needs to be deleted as the case would have a potentially large effect on the regression analysis (Field, 2013; Tranmer & Elliot, 2008). A maximum leverage value of 1 indicates that the case has a large influence on the regression analysis (Field, 2013). Residual statistics for each regression analysis indicating the minimum and maximum values for the Cook's distance and leverage were evaluated to determine if there were significant outlier issues influencing the model fit.

Unlike the unstandardised coefficients, the standardised coefficients are more suitable to use for comparison between variables because the variables are all standardised to fit a normal distribution with a mean of zero and a standard deviation of 1 (Tranmer & Elliot, 2008). The standardised beta values for each variable are noted and compared to determine the degree of

importance in the model, as well as to indicate the number of standard deviations the dependent variable will change as a result of one standard deviation change in the independent variable(s) (Field, 2013).

4.7.1 Technological factors and attitude towards use of AI technologies

The effect of technological factors on attitude towards the use of AI technologies is investigated using multiple regression. The three independent variables include perceived usefulness, perceived ease of use and relative advantage. Since all the three technological factors indicate a linear and positive relationship with attitude towards use of AI technologies based on the correlation analysis, all three factors are included in the regression analysis. Table 4.14 provides the model summary, ANOVA table and coefficients used to interpret the results.

The overall regression model is statistically significant, $R^2 = .74$, $F(3, 406) = 386.726$, $p < .001$. The three independent variables explain 70% of the variance in attitude towards use of AI technologies. No issues of multicollinearity are found as the VIF is below 5 for all variables and the collinearity tolerance values are above .2. The Durbin-Watson value of 1.8 is within the acceptable range of between 1.5 and 2.5. The residual statistics section indicates that the Cook's D is below 1 (min = .000 and max .076), indicating that there is no significant influence of outliers on the regression analysis ($D < 1$). In addition, the centered leverage values are satisfactory (min = 0.000 and max = .051).

Figure 4.6 does not show serious deviation from normality as the residuals in the histogram present a reasonably symmetric histogram and the normal p-p plots present data points that are linear, grouped around the upward sloping curve and fall approximately on a straight line. In the scatterplot, the residuals indicate homoscedasticity as residuals are randomly scattered.

Table 4.14 Multiple regression with technological factors

Model Summary ^b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.861	.741	.739	.43426	1.827
a. Predictors: (Constant), Relative advantage, Perceived ease of use, Perceived usefulness					
b. Dependent Variable: Attitude					
ANOVA ^a					
Model	Sum of Squares	df	Mean Square	F	Sig.

1		Regression	218.787	3	72.929	386.726	<.001 ^b	
		Residual	76.564	406	.189			
		Total	295.351	409				
a. Dependent Variable: Attitude								
b. Predictors: (Constant), Relative advantage, Perceived ease of use, Perceived usefulness								
Coefficients ^a								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.619	.163		3.807	<.001		
	Perceived usefulness	.354	.053	.340	6.722	<.001	.249	4.014
	Perceived ease of use	.304	.041	.333	7.408	<.001	.315	3.173
	Relative advantage	.253	.052	.247	4.846	<.001	.246	4.070
a. Dependent Variable: Attitude								
Residuals Statistics ^a								
		Minimum	Maximum	Mean	Std. Deviation	N		
Predicted Value		3.5929	6.9971	5.8785	0.73139	410		
Std. Predicted Value		-3.125	1.529	0.000	1.000	410		
Standard Error of Predicted Value		0.022	0.101	0.041	0.013	410		
Adjusted Predicted Value		3.5531	7.0063	5.8783	0.73131	410		
Residual		-1.87056	1.40715	0.00000	0.43266	410		
Std. Residual		-4.307	3.240	0.000	0.996	410		
Stud. Residual		-4.331	3.286	0.000	1.002	410		
Stud. Deleted Residual		-4.429	3.326	0.000	1.007	410		
Mahal. Distance		0.043	21.003	2.993	2.771	410		
Cook's Distance		0.000	0.076	0.003	0.008	410		
Centered Leverage Value		0.000	0.051	0.007	0.007	410		
a. Dependent Variable: Attitude								

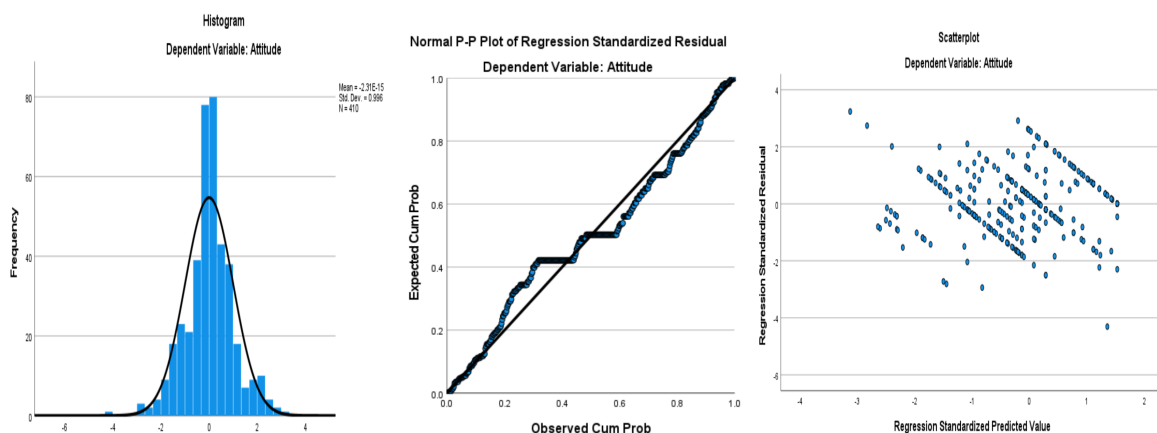


Figure 4.6 Histogram, normal p-p plot and scatterplot for technological factors

Each of the technological factors have a significant effect on attitude towards use of AI technologies. Perceived usefulness slightly has a stronger significant effect on attitude towards the use of AI technologies ($\beta = .34, t = 6.72, p < .001$) compared to perceived ease of use ($\beta = .33, t = 7.41, p < .001$). Relative advantage has the lowest effect, $\beta = .25, t = 4.85, p < .001$.

4.7.2 Individual factors on attitude towards use of AI technologies

Multiple regression analysis is used to investigate the effect of individual factors on attitude towards use of AI technologies. For this analysis, individual factors include organisational justice and employee wellbeing as independent variables, and attitude towards use of AI technologies is the dependent variable. Table 4.15 provides the model summary, ANOVA table and coefficients used to interpret the results.

The overall regression model is statistically significant, $R^2 = .71, F(2, 407) = 485.82, p < .001$. These two independent variables explain 71% of the variance in attitude towards use of AI technologies. No issues of multicollinearity are found as the VIF is below 2 for both variables and the collinearity tolerance values are above .5. The Durbin-Watson value of 1.9 is within the acceptable range. The residual statistics section indicates that the Cook's D is below 1 (min = .000 and max .113), indicating that there is no significant influence of outliers on the regression analysis ($D < 1$). In addition, the centered leverage values are satisfactory (min = 0.000 and max = .048).

Figure 4.7 shows evidence of normality as the residuals in the histogram present a reasonably symmetric histogram and the normal p-p plots present data points that are linear, grouped around the upward sloping curve and falling approximately on a straight line. In the scatterplot, the residuals indicate homoscedasticity as residuals are randomly scattered.

Table 4.15 Multiple regression with individual factors

Model Summary ^b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.840 ^a	.705	.703	.46285	1.944
a. Predictors: (Constant), Organisational Justice, Employee Wellbeing					
b. Dependent Variable: Attitude					
ANOVA ^a					
Model	Sum of Squares	df	Mean Square	F	Sig.

1	Regression	208.158	2	104.079	485.820	<.001 ^b		
	Residual	87.193	407	.334				
	Total	295.351	409					
a. Dependent Variable: Attitude								
b. Predictors: (Constant), Organisational Justice, Employee Wellbeing								
Coefficients ^a								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	2.489	.143		16.167	<.001		
	Employee Wellbeing	.490	.026	.723	19.044	<.001	.503	1.987
	Organisational Justice	.160	.039	.155	4.083	<.001	.503	1.987
a. Dependent Variable: Attitude								
Residuals Statistics ^a								
		Minimum	Maximum	Mean	Std. Deviation		N	
Predicted Value		3.9623	7.0381	5.8785	0.71340		410	
Std. Predicted Value		-2.686	1.625	0.000	1.000		410	
Standard Error of Predicted Value		0.023	0.104	0.038	0.011		410	
Adjusted Predicted Value		3.9615	7.0408	5.8783	0.71325		410	
Residual		-1.71857	1.59222	0.00000	0.46172		410	
Std. Residual		-3.713	3.440	0.000	0.998		410	
Stud. Residual		-3.751	3.462	0.000	1.002		410	
Mahal. Distance		0.011	19.576	1.995	2.020		410	
Cook's Distance		0.000	0.113	0.003	0.009		410	
Centered Leverage Value		0.000	0.048	0.005	0.005		410	
a. Dependent Variable: Attitude								

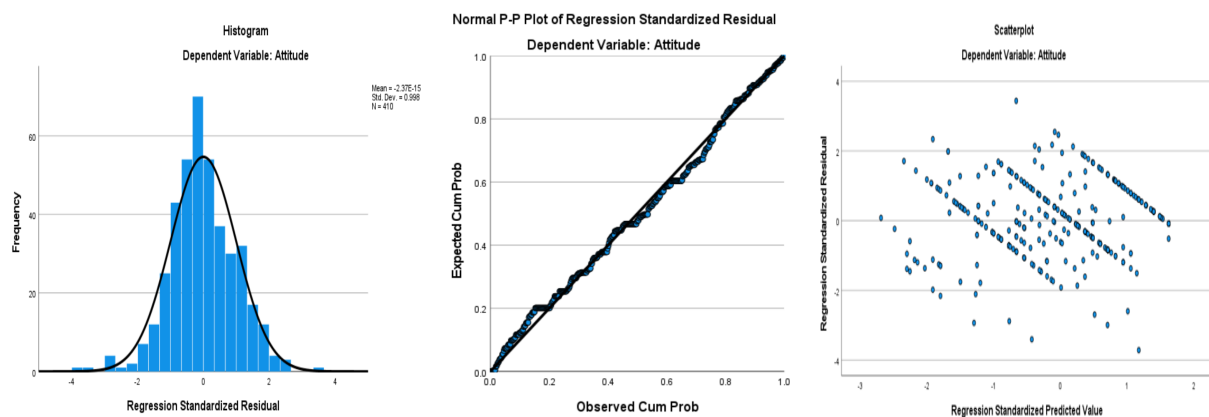


Figure 4.7 Histogram, normal p-p plot and scatterplot for individual factors

Organisational justice significantly predicts attitude towards use of AI technologies, $\beta = .16$, $t = 4.08$, $p < .001$. However, employee wellbeing is the most significant individual factor when predicting attitude towards use of AI technologies, $\beta = .72$, $t = 19.04$, $p < .001$.

4.7.3 Organisational factors on attitude towards use of AI technologies

The effect of organisational factors which include management support, training, and innovative culture on attitude towards use of AI technologies is also investigated using multiple regression. Table 4.16 provides the model summary, ANOVA table and coefficients used to interpret the results.

The overall regression model is statistically significant, $R^2 = .57$, $F(3, 406) = 181.024$, $p < .001$. The three independent variables explain 57% of the variance in attitude towards use of AI technologies. There is no evidence of multicollinearity as the VIF values are not more than 2.2 for all variables and the collinearity tolerance values are above .4. The Durbin-Watson value of 1.8 is within the acceptable range. The residual statistics section indicates that the Cook's D is below 1 (min = .000 and max = .153), indicating that there is no significant influence of outliers on the regression analysis ($D < 1$). In addition, the centered leverage values are satisfactory (min = 0.000 and max = .103).

Figure 4.8 does not show serious deviation from normality as the residuals in the histogram present a reasonably symmetric histogram and the normal p-p plots present data points that are linear, grouped around the upward sloping curve and falling approximately on a straight line. In the scatterplot, the residuals indicate homoscedasticity as residuals are randomly scattered.

Table 4.16 Multiple regression with organisational factors

Model Summary ^b						
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson	
1	.756 ^a	.572	.569	.55785	1.794	
a. Predictors: (Constant), Innovative Culture, Training Support, Management Support						
b. Dependent Variable: Attitude						
ANOVA ^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	169.004	3	56.335	181.024	<.001 ^b
	Residual	126.347	406	.311		
	Total	295.351	409			
a. Dependent Variable: Attitude						

b. Predictors: (Constant), Innovative Culture, Training Support, Management Support								
Coefficients ^a								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.934	.231		4.050	<.001		
	Management Support	.444	.047	.457	9.485	<.001	.454	2.203
	Training Support	.283	.049	.258	5.728	<.001	.518	1.929
	Innovative Culture	.153	.046	.140	3.327	<.001	.595	1.681
a. Dependent Variable: Attitude								
Residuals Statistics								
		Minimum	Maximum	Mean	Std. Deviation		N	
Predicted Value		4.1236	7.0986	5.8785	.64282		410	
Std. Predicted Value		-2.730	1.898	.000	1.000		410	
Standard Error of Predicted Value		.028	.181	.052	.018		410	
Adjusted Predicted Value		4.1263	7.1121	5.8779	.64333		410	
Residual		-1.37664	2.47840	.00000	.55580		410	
Std. Residual		-2.468	4.443	.000	.996		410	
Stud. Residual		-2.474	4.494	.001	1.003		410	
Stud. Deleted Residual		-2.489	4.605	.001	1.006		410	
Mahal. Distance		.017	42.273	2.993	3.629		410	
Cook's Distance		.000	.153	.003	.011		410	
Centered Leverage Value		.000	.103	.007	.009		410	
a. Dependent Variable: Attitude								

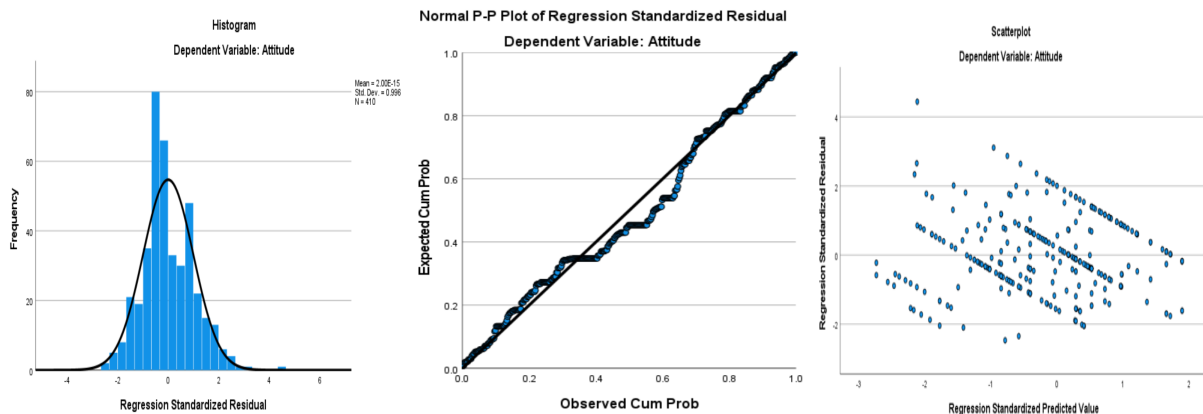


Figure 4.8 Histogram, normal p-p plot and scatterplot for organisational factors

All the organisational variables significantly predict attitude towards use of AI technologies. The results indicate that management support is the most significant organisational factor to predict attitude towards use of AI technologies, $\beta = .46$, $t = 9.49$, $p < .001$. Training support is

the second important predictor of attitude towards use of AI technologies, $\beta = .26$, $t = 5.73$, $p < .001$. The third variable, innovative culture is also a significant predictor of attitude towards use of AI technologies, $\beta = .14$, $t = 3.33$, $p < .001$.

4.7.4 Environmental factors on attitude towards use of AI technologies

Multiple regression analysis was conducted to investigate the effect of environmental factors on attitude towards use of AI technologies. The independent variables are social influence, customer pressure and competitor and pressure. Attitude towards use of AI technologies is the dependent variable. Table 4.17 provides the model summary, ANOVA table and coefficients used to interpret the results.

The overall regression model is statistically significant, $R^2 = .68$, $F(3, 406) = 289.25$, $p < .001$. The independent variables explain 68% of the variance in attitude towards use of AI technologies. There was no evidence of multicollinearity as the VIF are all below 3 for each of the variables and the collinearity tolerance values are above .3. The Durbin-Watson value of 1.5 is within the acceptable range. The residual statistics section indicates that the Cook's D is below 1 (min = .000 and max = .134), indicating that there is no significant influence of outliers on the regression analysis ($D < 1$). In addition, the centered leverage values are satisfactory (min = 0.000 and max = .040).

Figure 4.9 does not show serious deviation from normality as the residuals in the histogram present a reasonably symmetric histogram and the normal p-p plots present data points that are linear, grouped around the upward sloping curve and fall approximately on a straight line. In the scatterplot, the residuals indicate homoscedasticity as residuals are randomly scattered.

Table 4.17 Multiple regression with environmental factors

Model Summary ^b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.825 ^a	.681	.679	.48154	1.477
a. Predictors: (Constant), Competitive Pressure, Social Influence, Customer Pressure					
b. Dependent Variable: Attitude					
ANOVA ^a					

Model		Sum of Squares	df	Mean Square	F	Sig.		
1	Regression	201.209	3	67.070	289.248	<.001 ^b		
	Residual	94.142	406	.232				
	Total	295.351	409					
a. Dependent Variable: Attitude								
b. Predictors: (Constant), Competitive Pressure, Social Influence, Customer Pressure								
Coefficients ^a								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.397	.188		2.111	.035		
	Social Influence	.116	.038	.188	3.408	.002	.527	1.898
	Customer Pressure	.249	.045	.245	5.511	<.001	.396	2.524
	Competitive Pressure	.581	.048	.540	12.173	<.001	.400	2.503
a. Dependent Variable: Attitude								
Residuals Statistics								
		Minimum	Maximum	Mean	Std. Deviation		N	
Predicted Value		3.6483	7.0158	5.8785	.70139		410	
Std. Predicted Value		-3.180	1.621	.000	1.000		410	
Standard Error of Predicted Value		.024	.099	.045	.014		410	
Adjusted Predicted Value		3.6382	7.0281	5.8780	.70127		410	
Residual		-1.49991	2.05066	.00000	.47977		410	
Std. Residual		-3.115	4.259	.000	.996		410	
Stud. Residual		-3.128	4.320	.001	1.002		410	
Stud. Deleted Residual		-3.163	4.417	.001	1.005		410	
Mahal. Distance		.022	16.210	2.993	2.672		410	
Cook's Distance		.000	.134	.003	.008		410	
Centered Leverage Value		.000	.040	.007	.007		410	
a Dependent Variable: Attitude								

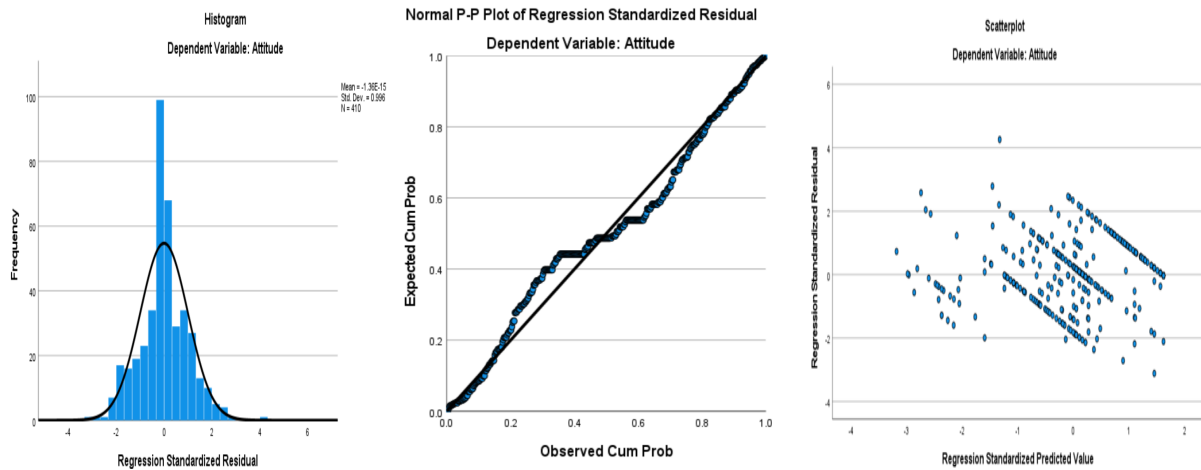


Figure 4.9 Histogram, normal p-p plot and scatterplot for environmental factors

All environmental factors are significant predictors of attitude towards use of AI technologies. Competitive pressure is the most significant environmental predictor of attitude towards use of AI technologies, $\beta = .54$, $t(406) = 12.17$, $p < .001$. Customer pressure is also a significant predictor of attitude towards use of AI technologies, $\beta = .25$, $t = 5.51$, $p < .001$. Social influence indicates the least influence on attitude towards use of AI technologies, $\beta = .19$, $t = 3.05$, $p = .002$.

4.7.5 Key determinants of attitude towards use of AI technologies

To select the most influential explanatory variables for attitude towards the use of AI technologies from all the technological, individual, organisational and environmental factors, multiple regression and stepwise regression is conducted on all the independent variables identified to be influencing attitude towards use of AI technologies. To begin with, a standard multiple regression analysis with all the 11 independent variable is conducted. Further regression analysis with only factors statistically significant in this model is be carried out to determine the best fit regression model.

The initial results are included in Table 4.18 which provide the model summary, ANOVA table and coefficients used to interpret the results. The multiple regression is statistically significant, $R^2 = .84$, $F(11, 406) = 182.80$, $p < .001$. All the independent variables explain 84% of the variance in attitude towards use of AI technologies. The multiple linear regression with all the independent variables explains much more variance than the technological (70%), individual (71%), organisational (57%) and environmental factors (68%) separately.

There is no evidence of serial multicollinearity as the VIF is less than 5 for each of the variables and the collinearity tolerance is above .2. The Durbin-Watson value of 1.8 is within the acceptable range. The residual statistics section indicates that the Cook's D is below 1 (min = .000 and max .124), indicating no significant influence of outliers on the regression analysis ($D < 1$). In addition, the centered leverage values are satisfactory (min = 0.05 and max = .155).

Table 4.18 Initial multiple regression with all independent variable

Model Summary ^b								
Model		R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson		
1		.914 ^a	.835	.830	.35016	1.792		
a. Predictors: (Constant), Organisational Culture, Innovative culture, Competitive pressure, Training support, Social Influence, Training Support, Perceived ease of use, Customer Pressure, Management Support, Perceived usefulness, Employee Wellbeing, Relative advantage								
b. Dependent Variable: Attitude								
ANOVA ^a								
Model		Sum of Squares		Df	Mean Square	F	Sig.	
1	Regression	246.552		11	22.414	182.804	<.001 ^b	
	Residual	48.799		398	.123			
	Total	295.351		409				
a. Dependent Variable: Attitude								
b. Predictors: (Constant), Competitive Pressure, Organisational Culture, Social Influence, Relative advantage, Training Support, Management Support, Subjective Wellbeing, Organisational Justice, Customer Pressure, Perceived usefulness, Perceived ease of use								
Coefficients ^a								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.401	.186		2.158	.031		
	Perceived usefulness	.186	.045	.178	4.159	<.001	.226	4.433
	Perceived ease of use	.152	.035	.166	4.299	<.001	.277	3.611
	Relative advantage	.023	.046	.022	.492	.623	.205	4.874
	Employee wellbeing	.182	.028	.269	6.497	<.001	.243	4.119
	Management support	.134	.034	.138	3.944	<.001	.341	2.934
	Training support	.034	.034	.031	1.012	.312	.442	2.262
	Innovative culture	-.018	.031	-.016	-.568	.570	.513	1.950
	Social influence	.015	.030	.015	.496	.620	.436	2.295
	Customer pressure	.069	.035	.068	1.974	.049	.348	2.874
	Competitive pressure	.286	.038	.266	7.477	<.001	.329	3.044
	Organisational justice	-.101	.036	-.098	-2.784	.006	.333	2.999

a. Dependent Variable: Attitude					
Residuals Statistics					
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	3.6061	7.3275	5.8785	.77641	410
Std. Predicted Value	-2.927	1.866	.000	1.000	410
Standard Error of Predicted Value	.031	.139	.058	.016	410
Adjusted Predicted Value	3.5981	7.3462	5.8773	.77598	410
Residual	-.99017	1.27470	.00000	.34542	410
Std. Residual	-2.828	3.640	.000	.986	410
Stud. Residual	-2.935	3.706	.002	1.005	410
Stud. Deleted Residual	-2.964	3.767	.002	1.008	410
Mahal. Distance	2.174	63.264	10.973	7.205	410
Cook's Distance	.000	.124	.003	.009	410
Centered Leverage Value	.005	.155	.027	.018	410
a Dependent Variable: Attitude					

The results show that relative advantage ($\beta = .02$, $t = .49$, $p = .62$), training support, ($\beta = .31$, $t = 1.01$, $p = .31$), innovative culture ($\beta = -.16$, $t = -.57$, $p = .57$) and social influence ($\beta = .15$, $t = .496$, $p = .62$), are insignificant predictors of attitude towards the use of AI technologies in the model. These are removed from further analysis.

Although organisational justice ($\beta = -.098$, $t = -2.784$, $p = .006$) is a significant predictor of attitude towards use of AI technologies and previously indicated a positive effect on attitude towards use of AI technologies, upon inclusion into the multiple regression with all the other independent variables, it indicates a negative coefficient beta. This is surprising as organisational justice is expected to have a positive effect on attitude towards use of AI technologies.

Given these results, organisational justice can be identified as negative suppressors because despite being positively correlated with attitude towards use of AI technologies, it received a negative coefficient beta weight when entered into the multiple regression with other factors. A negative suppressor is a variables that despite demonstrating a positive and strong correlation with the dependent variable in the bivariate analysis, reflects a negative beta once entered in the multiple regression with other variables (Krus & Wilkinson, 1986). This is the case for organisational justice which has a positive correlation with attitude towards use of AI technologies, $r = .66$.

Multicollinearity amongst the independent variables was investigated and it was evident that organisational justice has a strong correlation with the other factors in the model, such as

employee wellbeing ($r=.69$), management support ($r=.72$). To test the effect of removing organisational justice from the model, the regression was run without this variables and the R^2 dropped slightly by .003 (from .835 to .832), indicating that removing this variable does not have a significant impact on the model. In addition, the VIFs and collinearity tolerance reported above also indicate that multicollinearity is not a problem in this regression model.

Given that organisational justice indicates a coefficient beta of less than 0 and has a very low effect size, based on Cohen's (1988) guidelines that 0.10–0.29 indicates a small effect, 0.30–0.49 indicates a medium effect, and effect sizes of 0.50 or more indicate a large effect, the chances of an inverse relationship between organisational justice and attitude towards use of AI technologies is possible but also highly unlikely. Therefore, taking all the above into consideration, organisational justice is left in the regression model for further analysis.

Upon removing relative advantage, training support, innovative culture and social influence and repeating the multiple regression with the 7 remaining significant variables in the model, Table 4.19 shows the final regression model. The regression model is statistically significant, $R^2 = .83$, $F(7, 402) = 288.567$, $p < .001$. All the independent variables explain 83% of the variance of attitude towards use of AI technologies. There is no evidence of serial multicollinearity as the VIF is below 4 for each of the variables and the collinearity tolerance is above .2. An insignificant drop in the R^2 value of 0.001 from 0.835 in the initial model to 0.834 in the final model is noted, however, this final regression model includes only relevant factors to enable more reliability and precision of the model.

Figure 4.10 shows the normal p-p plot and the histogram which also indicates conformity to normality. In the scatterplot, the residuals indicate homoscedasticity as residuals are randomly scattered. The Durbin-Watson value of 1.8 is within the acceptable range. The residual statistics section indicates that the Cook's D is below 1 (min = .000 and max .098), indicating no significant influence of outliers on the regression analysis ($D < 1$). In addition, the centered leverage values are satisfactory (min = 0.03 and max = .096).

Table 4.19 Final multiple regression model with all independent variable

Model Summary ^b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.913 ^a	.834	.831	.34921	1.787

a. Predictors: (Constant), Organisational justice, Competitive pressure, Perceived ease of use, Management support, Customer pressure, Perceived usefulness, Employee wellbeing								
b. Dependent Variable: Attitude								
ANOVA ^a								
Model		Sum of Squares		df	Mean Square	F	Sig.	
1	Regression	246.329		7	35.190	288.587	<.001 ^b	
	Residual	49.023		402	.122			
	Total	295.351		409				
a. Dependent Variable: Attitude								
b. Predictors: (Constant), Organisational justice, Competitive pressure, Perceived ease of use, Management support, Customer pressure, Perceived usefulness, Employee wellbeing								
Coefficients ^a								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.455	.167		2.732	.007		
	Perceived usefulness	.195	.040	.187	4.823	<.001	.274	3.645
	Perceived ease of use	.155	.035	.170	4.485	<.001	.289	3.465
	Employee wellbeing	.187	.027	.276	6.973	<.001	.263	3.803
	Management support	.142	.032	.146	4.472	<.001	.385	2.597
	Customer pressure	.072	.034	.071	2.110	.035	.367	2.723
	Competitive pressure	.296	.037	.275	7.988	<.001	.348	2.871
	Organisational justice	-.092	.035	-.090	-2.667	.008	.366	2.730
a. Dependent Variable: Attitude								
Residuals Statistics								
		Minimum	Maximum	Mean	Std. Deviation		N	
Predicted Value		3.6019	7.3223	5.8785	.77606		410	
Std. Predicted Value		-2.934	1.860	.000	1.000		410	
Standard Error of Predicted Value		.026	.109	.047	.013		410	
Adjusted Predicted Value		3.5953	7.3350	5.8778	.77578		410	
Residual		-.95942	1.28952	.00000	.34621		410	
Std. Residual		-2.747	3.693	.000	.991		410	
Stud. Residual		-2.834	3.746	.001	1.004		410	
Deleted Residual		-1.02072	1.32694	.00075	.35483		410	
Stud. Deleted Residual		-2.859	3.808	.001	1.007		410	
Mahal. Distance		1.284	39.169	6.983	4.960		410	
Cook's Distance		.000	.098	.003	.008		410	
Centered Leverage Value		.003	.096	.017	.012		410	
a Dependent Variable: Attitude								

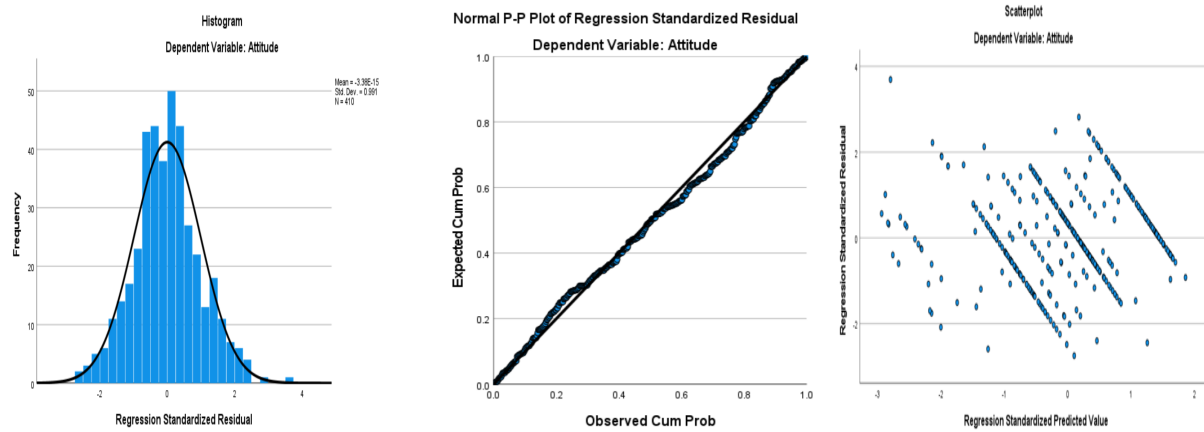


Figure 4.10 Final histogram and normal p-p plot for all independent variables

A stepwise regression is performed on all the independent variables. The results on the stepwise regression are shown in table 4.20 below. In model 1 employee wellbeing is selected as the most important variable, which explains the highest variance of ($R^2 = .69$) in attitude towards the use of AI technologies. In model 7, important variables are selected based on their rank and significance in predicting attitude towards use of AI technologies as follows, employee wellbeing, competitive pressure, perceived usefulness, perceived ease of use, management support, organisational justice and customer pressure. In model 7, the $R^2 = .83$, which means that all significant variables explain 83% of the variance in attitude towards use of AI technologies. Relative advantage, training support, innovative culture and social influence are rejected by the stepwise method as they also insignificant predictors in the stepwise regression.

This result is the same as the outcome of the final multiple regression results above, which indicate that 83% of the variance in attitude towards use of AI technologies is explained by the same variables. These results validate the outcome of both methods. The ANOVA statistics presented in table 4.20 for the stepwise method indicate that all the scenarios are significant, ($p < .001$), which confirms that all the model scenarios show a good fit for the data. There is no evidence of serial multicollinearity as the VIF is below 4 for each of the variables and the collinearity tolerance is above .2. The Durbin-Watson value is 1.8 which is within the acceptable range.

Figure 4.11 shows the normal p-p plot and the histogram which also indicates conformity to normality. In the scatterplot, the residuals indicate homoscedasticity as residuals are randomly scattered. The residual statistics section indicates similar results to the final regression model

above. The Cook's D is below 1 (min = .000 and max .098), indicating no significant influence of outliers on the regression analysis ($D < 1$). In addition, the centered leverage values are satisfactory (min = 0.03 and max = .096).

Table 4.20 Stepwise regression with all independent variable

Model Summary^h					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.832a	.693	.692	.47166	
2	.888b	.789	.788	.39146	
3	.903c	.815	.813	.36706	
4	.908d	.824	.822	.35849	
5	.911e	.830	.828	.35258	
6	.912f	.832	.830	.35070	
7	.913g	.834	.831	.34921	1.787
a Predictors: (Constant), Employee wellbeing					
b Predictors: (Constant), Employee wellbeing, Competitive pressure					
c Predictors: (Constant), Employee wellbeing, Competitive pressure, Perceived usefulness					
d Predictors: (Constant), Employee wellbeing, Competitive pressure, Perceived usefulness, Perceived ease of use					
e Predictors: (Constant), Employee wellbeing, Competitive pressure, Perceived usefulness, Perceived ease of use, Management support					
f Predictors: (Constant), Employee wellbeing, Competitive pressure, Perceived usefulness, Perceived ease of use, Management support, Organisational justice					
g Predictors: (Constant), Employee wellbeing, Competitive pressure, Perceived usefulness, Perceived ease of use, Management support, Organisational justice, Customer pressure					
h. Dependent Variable: Attitude					
ANOVA^a					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	204.586	1	204.586	919.635	<.001b
Residual	90.765	408	.222		
Total	295.351	409			
Regression	232.981	2	116.490	760.162	<.001c
Residual	62.370	407	.153		
Total	295.351	409			
Regression	240.649	3	80.216	595.372	<.001d
Residual	54.702	406	.135		
Total	295.351	409			
Regression	243.302	4	60.826	473.290	<.001e
Residual	52.049	405	.129		
Total	295.351	409			
Regression	245.130	5	49.026	394.387	<.001f
Residual	50.221	404	.124		

Total		295.351	409					
Regression		245.785	6		40.964	333.065	<.001g	
Residual		49.566	403		.123			
Total		295.351	409					
Regression		246.329	7		35.190	288.567	<.001h	
Residual		49.023	402		.122			
Total		295.351	409					
a Dependent Variable: Attitude								
b Predictors: (Constant), Employee wellbeing								
c Predictors: (Constant), Employee wellbeing, Competitive pressure								
d Predictors: (Constant), Employee wellbeing, Competitive pressure, Perceived usefulness								
e Predictors: (Constant), Employee wellbeing, Competitive pressure, Perceived usefulness, Perceived ease of use								
f Predictors: (Constant), Employee wellbeing, Competitive pressure, Perceived usefulness, Perceived ease of use, Management support								
g Predictors: (Constant), Employee wellbeing, Competitive pressure, Perceived usefulness, Perceived ease of use, Management support, Organisational justice								
h Predictors: (Constant), Employee wellbeing, Competitive pressure, Perceived usefulness, Perceived ease of use, Management support, Organisational justice, Customer pressure								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
7	(Constant)	.455	.167		2.732	.007		
	Employee wellbeing	.187	.027	.276	6.973	<.001	.263	3.803
	Competitive pressure	.296	.037	.275	7.988	<.001	.348	2.871
	Perceived usefulness	.195	.040	.187	4.823	<.001	.274	3.645
	Perceived ease of use	.155	.035	.170	4.485	<.001	.289	3.465
	Management support	.142	.032	.146	4.472	<.001	.385	2.597
	Organisational justice	-.092	.035	-.090	-2.667	.008	.366	2.730
	Customer pressure	.072	.034	.071	2.110	.035	.367	2.723
Residuals Statistics								
		Minimum	Maximum	Mean	Std. Deviation	N		
Predicted Value		3.6019	7.3223	5.8785	.77606	410		
Std. Predicted Value		-2.934	1.860	.000	1.000	410		
Standard Error of Predicted Value		.026	.109	.047	.013	410		
Adjusted Predicted Value		3.5953	7.3350	5.8778	.77578	410		
Residual		-.95942	1.28952	.00000	.34621	410		
Std. Residual		-2.747	3.693	.000	.991	410		
Stud. Residual		-2.834	3.746	.001	1.004	410		
Stud. Deleted Residual		-2.859	3.808	.001	1.007	410		
Mahal. Distance		1.284	39.169	6.983	4.960	410		
Cook's Distance		.000	.098	.003	.008	410		
Centered Leverage Value		.003	.096	.017	.012	410		
a Dependent Variable: Attitude								

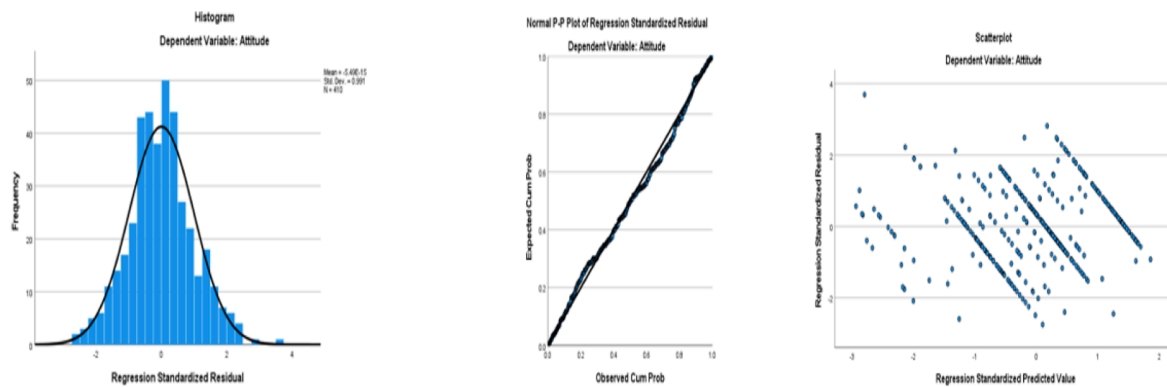


Figure 4.11 Histogram and normal p-p plot stepwise regression

4.8 Attitude and acceptance of AI technologies

The following section presents the research results regarding attitude towards use of AI technologies as well as acceptance towards use of AI technologies. Mean scores of attitude towards use of AI technologies and acceptance of AI technologies are converted into categorical data and used to analyse the relationship between each of these two variables and gender, age, experience and employees' job role. The attitude-acceptance relationship is then investigated in order to test hypothesis 12 which states that employees' attitude towards use of AI technologies positively influences AI acceptance of AI technologies.

4.8.1 Attitude towards use of AI technologies

Figure 4.12 shows that the employees' attitude towards use of AI technologies is positive as 61% of participants have a mean score which indicate that they mostly agreed or strongly agreed with statements that represent a positive attitude towards the use of AI technologies. 32% of participants have a mean score that indicates that they somewhat agree with statements that reflect a positive attitude towards the use of AI technologies. 5% of participants have a mean score that indicates a neutral response to most of the statements regarding their attitude towards the use of AI technologies. 2% of participants either selected the 'somewhat disagree' or 'disagree' responses to items measuring attitude towards the use of AI technologies, as their mean scores indicates that overall, they 'somewhat disagreed' with statements that demonstrate a positive attitude towards the use of AI technologies. None of the participants selected the 'strongly disagree' response.

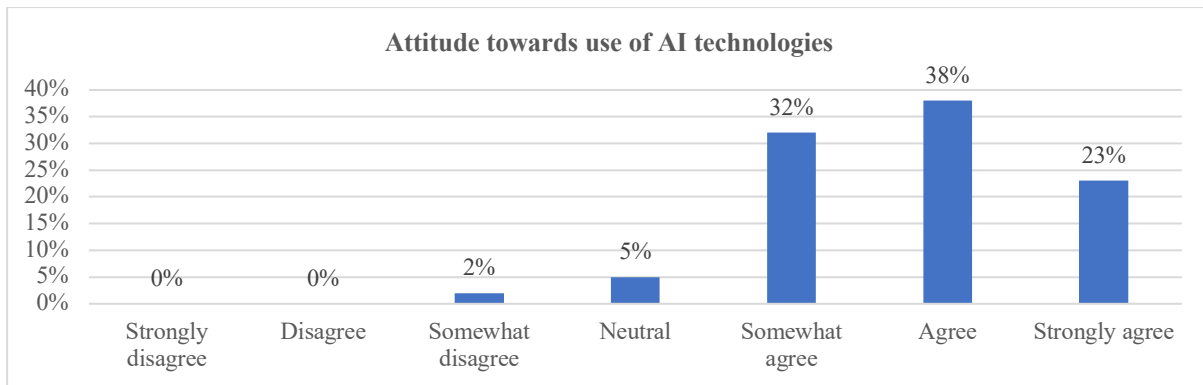


Figure 4.12 Responses to statements indicating attitude towards use of AI technologies

4.8.1.1 Attitude towards use of AI technologies and gender

Table 4.21 provides a cross tabulation of employees' responses to attitude towards use of AI technologies based on the gender indicated by participants. The chi-square test of independence indicates that there is a significant relationship between gender and attitude towards use of AI technologies, $X^2 (4, N = 410) = 32.311, p < .001$. The Mann–Whitney U test indicates that males (Median=6, n=191) are significantly more positive than females (Median=6, n=219), in terms of their attitude towards the use of AI technologies ($U=14567, p < .001$).

Table 4.21 Cross tabulation of attitude and gender

Gender	Attitude Scale						
	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
Male	0%	0%	0%	2%	11%	19%	15%
Female	0%	0%	2%	3%	21%	19%	8%
% of Total	0%	0%	2%	5%	32%	38%	23%

4.8.1.2 Attitude towards use of AI technologies and age

Table 4.22 provides a cross tabulation of employees' responses to attitude towards use of AI technologies based on the participants' age group. The chi-square test of independence indicates that there is no significant association between employees' age group and attitude towards use of AI technologies, $X^2 (16, N = 410) = 11.624, p = .769$. Employees' attitude towards use of AI technologies is not related to their age group. The independent samples Kruskal-Wallis tests also indicates similar results, $H(4)=3.5, P=.481$, and the post hoc test and pairwise comparison also confirms that there is no significant difference with regards to employees' attitude towards use of AI technologies and age group.

Table 4.22 Cross tabulation of attitude and age

Age group		Attitude Scale					
	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
18 - 30 years	0%	0%	0%	1%	4%	7%	4%
31 - 40 years	0%	0%	0%	1%	14%	15%	10%
41 - 50 years	0%	0%	1%	1%	10%	13%	7%
51 - 60 years	0%	0%	1%	1%	3%	2%	2%
> 60	0%	0%	0%	1%	1%	1%	0%
% of Total	0%	0%	2%	5%	32%	38%	23%

4.8.1.3 Attitude towards use of AI technologies and job role

Table 4.23 provides a cross tabulation of employees' responses to attitude towards use of AI technologies based on employees' job roles. Employees in professional IT roles are the most positive group of all the individuals. Those in administrative roles indicate uncertainty or less positive attitude towards the use of AI technologies. The chi-square test of independence indicates that there is a significant relationship between employees' job roles and their attitude towards use of AI technologies, $X^2(20, N = 410) = 160.81, p < .001$.

The independent samples Kruskal-Wallis test is performed, and the results indicate that there is a significant difference between employees' job roles and attitude towards use of AI technologies, $H(5) = 123, P < .001$. The post hoc test and pairwise comparison of employees' job roles indicate that employees in top management/executive roles and those in Professional IT roles are similar in terms of their attitude towards the use of AI technologies while those in middle management, first line management and professional non-IT roles also share similar attitudes toward the use of AI technologies. Employees in administrative roles differ the most from employees in other roles and are more likely to be less positive about the use of AI technologies.

Table 4.23 Cross tabulation of attitude and job role

Job role		Attitude Scale					
	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
Top management/Executive	0%	0%	0%	0%	1%	4%	3%
Middle management	0%	0%	0%	0%	9%	12%	4%

First-line management	0%	0%	0%	1%	5%	5%	2%
Professional IT	0%	0%	0%	0%	3%	9%	12%
Professional non-IT	0%	0%	1%	2%	8%	7%	2%
Administrative	0%	0%	1%	2%	6%	1%	0%
% of Total	0%	0%	2%	5%	32%	38%	23%

4.8.1.4 Attitude towards AI technologies and experience using AI technologies

Table 4.24 provide a cross tabulation of employees' responses to attitude towards use of AI technologies based on experience with using AI technologies. The chi-square tests of independence shows that employees' experience with using AI technologies and their attitude towards the use of AI technologies are significant, $X^2(4, N=410) = 142.71, p < .001$. Employees' experience with using AI technologies are more likely than those with no experience with using AI technologies to be more positive than negative towards the use of AI technologies. The Mann–Whitney U test indicates that those with experience using AI technologies (Median=6, $n=167$) are significantly more positive than those without experience using AI technologies (Median=5, $n=243$), in terms of their attitude towards the use of AI technologies ($U=6693.5, p < .001$).

Table 4.24 Cross tabulation of attitude and experience with use of AI technologies

Experience using AI technologies	Attitude Scale						
	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
Yes	0%	0%	0%	0%	3%	19%	19%
No	0%	0%	2%	5%	29%	19%	4%
% of Total	0%	0%	2%	5%	32%	38%	23%

4.8.2 Acceptance towards use of AI technologies

Figure 4.13 shows that employees' acceptance AI technologies is mostly positive and high. 71% of participants have a mean score that indicates that they either 'agree' or 'strongly agree' with statements that indicate a positive and high level of acceptance of AI technologies. 24% of employees' responses indicate that they 'somewhat agree' with statements that reflect the acceptance of AI technologies. 4% of participants mean scores indicate neutrality towards statements reflecting the acceptance of AI technologies. Only 1% of participants' responses indicate some disagreements to statements that represent the acceptance of AI technologies. None of the participants selected the "strongly disagree" response.

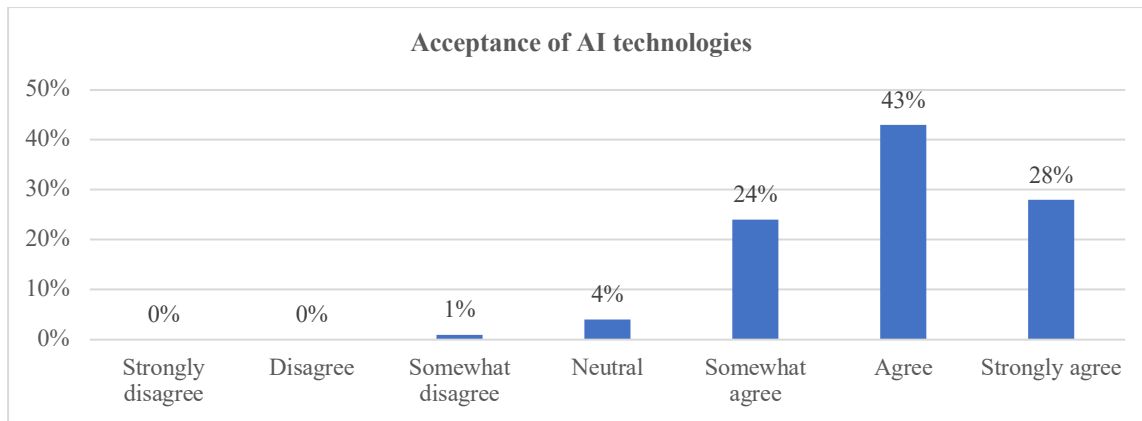


Figure 4.13 Responses to statements indicating acceptance of AI technologies

4.8.2.1 Acceptance towards use of AI technologies and gender

Table 4.25 provides a cross tabulation of employees' responses to acceptance of AI technologies based on their gender. The chi-square tests of independence shows that there is a significant relationship between gender and acceptance of AI technologies, $X^2 (4, N = 410) = 27.946, p < .001$. The Mann–Whitney U test indicates that males (Median=6, n=191) are significantly more positive than females (Median=6, n=219), in terms of their acceptance of the use of AI technologies ($U=14567, p < .001$).

Table 4.25 Cross tabulation of acceptance of AI and gender

Gender	Acceptance Scale						
	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
Male	0%	0%	0%	1%	8%	21%	17%
Female	0%	0%	1%	3%	16%	22%	11%
% of Total	0%	0%	1%	4%	24%	43%	28%

4.8.2.2 Acceptance towards use of AI technologies and age

Table 4.26 provide a cross tabulation of employees' responses to acceptance of AI technologies based on their age group. The chi-square test of independence indicates that there is no significant association between employees' age group and acceptance of AI technologies, $X^2 (16, N = 410) = 14.5, p = .56$. Employees' acceptance of AI technologies is not related to their age group. The independent samples Kruskal-Wallis test is also performed which also confirms the insignificant relationship between employees' age group and acceptance of AI technologies, $H(4)=3.2, P=523$. The post hoc test and pairwise comparison of age group also

indicates that there is no significant difference between employee's age group and their acceptance of AI technologies.

Table 4.26 Cross tabulation of acceptance of AI and age

Age group	Acceptance Scale						
	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
18 - 30 years	0%	0%	0%	1%	3%	7%	5%
31 - 40 years	0%	0%	0%	1%	11%	19%	10%
41 - 50 years	0%	0%	1%	2%	7%	13%	9%
51 - 60 years	0%	0%	0%	0%	3%	3%	3%
> 60 years	0%	0%	0%	0%	0%	1%	1%
% of Total	0%	0%	1%	4%	24%	43%	28%

4.8.2.3 Acceptance towards use of AI technologies and job role

Table 4.27 provides a cross tabulation of employees' responses to acceptance of AI technologies based on their job role. As with attitude towards use of AI technologies, employees in top management roles and professional-IT roles indicate a high level of acceptance of AI technologies. The chi-square test of independence indicates that there is a significant relationship between participants' job role and acceptance of AI technologies, $X^2(20, N = 410) 126.3, p < .001$. An association between employees' job role and their acceptance of AI technologies is evident.

The independent samples Kruskal-Wallis test results also indicates that there is a significant difference between employees' job role and their acceptance of AI technologies, $H(5)=100.2, P < .001$. The post hoc test and pairwise comparison of employees' job roles indicates that employees in top management/executive roles and those in Professional IT roles have similar high levels of acceptance of AI technologies, while participants in other roles all differ in terms of their level of acceptance of AI technologies. The lowest level of acceptance of AI technologies is amongst employees in administrative roles.

Table 4.27 Cross tabulation of acceptance of AI and job role

Job role	Acceptance Scale						
	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
Top management/Executive	0%	0%	0%	0%	1%	3%	4%
Middle management	0%	0%	0%	0%	7%	13%	5%
First-line management	0%	0%	0%	1%	3%	6%	3%
Professional IT	0%	0%	0%	0%	2%	8%	14%
Professional non-IT	0%	0%	0%	1%	6%	11%	2%
Administrative	0%	0%	1%	2%	5%	2%	0%
% of Total	0%	0%	1%	4%	24%	43%	28%

4.8.2.4 Acceptance of AI technologies and experience using AI technologies

Table 4.28 provides a cross tabulation employees' responses to acceptance of AI technologies based on their experience with using AI technologies. The chi-square tests of independence results shows that employees' experience with using AI technologies and their acceptance of AI technologies have a significant relationship, $X^2(4, N = 410) = 123.4, p < .001$. Individuals with experience using AI technologies in their work are more likely than those with no experience with using AI technologies to accept the use of AI technologies. The results of the Mann–Whitney U test ($U=7121.5, p < .001$), also indicate that those with experience with using AI technologies (Median=7, $n=167$) have significantly higher levels of acceptance of AI technologies compared to those without experience with using AI technologies (Median=6, $n=243$).

Table 4.28 Cross tabulation of acceptance and experience with use of AI technologies

Experience with using AI	Acceptance Scale						
	Strongly disagree	Disagree	Somewhat disagree	Neutral	Somewhat agree	Agree	Strongly agree
Yes	0%	0%	0%	0%	2%	17%	22%
No	0%	0%	1%	4%	22%	26%	6%
% Total	0%	0%	1%	4%	24%	43%	28%

4.8.3 Analysis of the attitude-acceptance relationship

According to the Spearman rank correlation coefficient, employees' attitude towards use of AI technologies and acceptance of AI technologies have a strong and positive correlation,

$r(408) = .88, p < .01$. Similar results are noted with the Pearson correlation are also indicated in Table 4.29 below.

Table 4.29 Correlation between attitude and acceptance of AI technologies

Variables	Spearman correlation	Pearson correlation
Attitude and Acceptance of AI technologies	0.875	0.897

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

Further analysis of the relationship between employees' attitude towards use of AI technologies and their acceptance of AI technologies in order to determine the extent to which attitude towards use of AI technologies influences acceptance of AI technologies is conducted using linear regression analysis, with acceptance as the dependent variable and attitude as the independent variable. Table 4.30 provides the results of the regression analysis.

The overall regression is statistically significant, $R^2 = .80, F(1, 406) = 1675.3, p < .001$. Attitude towards use of AI technologies explains 80% of the variance in acceptance of AI technologies. Attitude towards use of AI technologies significantly predicts acceptance of AI technologies, ($\beta = .90, p < .001$).

No issues of multicollinearity are found as VIF is 1 and the collinearity is also 1. The Durbin-Watson value of 1.7 is within the acceptable range. The residual statistics section indicates that the Cook's D is below 1 (min = .000 and max .044), indicating no significant influence of outliers on the regression analysis ($D < 1$). In addition, the centered leverage values are satisfactory (min = 0.000 and max = .018). In Figure 4.14, the histogram presents a reasonably symmetric histogram and the normal p-p plots present data points that have an upward gradient. In the scatterplot, the residuals indicate homoscedasticity as residuals are randomly scattered.

Table 4.30 Linear regression for attitude and acceptance of AI technologies

Model Summary ^b					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.897 ^a	.804	.804	.34718	1.690
a. Predictors: (Constant), Attitude					
b. Dependent Variable: Acceptance					
ANOVA ^a					

Model		Sum of Squares		df	Mean Square	F	Sig.	
1	Regression	201.924		1	201.924	1675.282	<.001 ^b	
	Residual	49.177		408	.121			
	Total	251.100		409				
a. Dependent Variable: Acceptance								
b. Predictors: (Constant), Attitude								
Coefficients ^a								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	1.22	.120		10.187	<.001		
	Attitude	.827	.020	.897	40.930	<.001	1.000	1.000
a. Dependent Variable: Acceptance								
Residuals Statistics								
		Minimum		Maximum	Mean		Std. Deviation	N
Predicted Value		4.1989		7.0102	6.0829		.70264	410
Std. Predicted Value		-2.681		1.320	.000		1.000	410
Standard Error of Predicted Value		.017		.049	.023		.007	410
Adjusted Predicted Value		4.1989		7.0130	6.0830		.70244	410
Residual		-.85262		1.44349	.00000		.34675	410
Std. Residual		-2.456		4.158	.000		.999	410
Stud. Residual		-2.459		4.168	.000		1.001	410
Stud. Deleted Residual		-2.475		4.255	.001		1.005	410
Mahal. Distance		.009		7.189	.998		1.315	410
Cook's Distance		.000		.044	.002		.005	410
Centered Leverage Value		.000		.018	.002		.003	410
a. Dependent Variable: Acceptance								

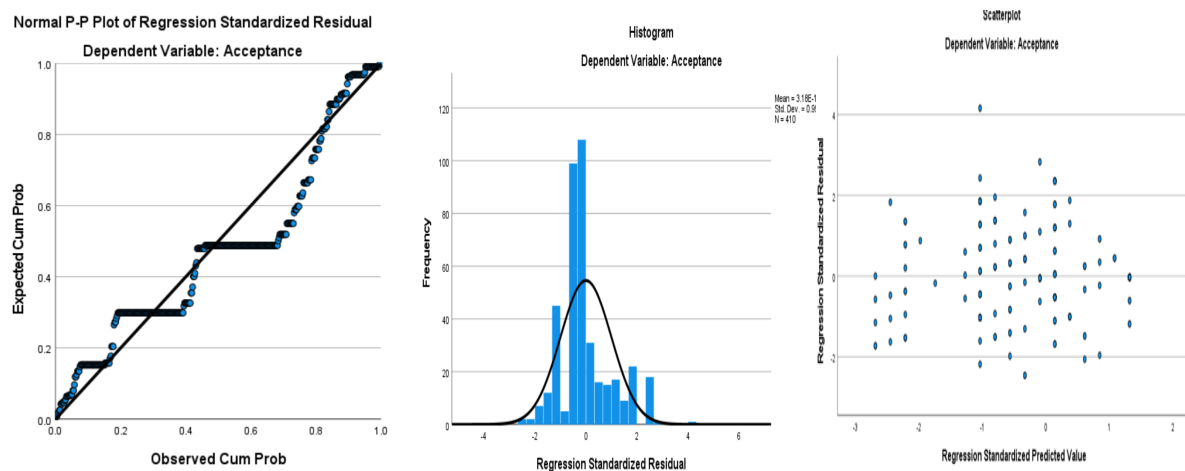


Figure 4.14 Histogram, normal p-p plot and scatterplot for attitude and acceptance

4.8.4 Effect of experience and job role on the attitude-acceptance relationship

Before analysing the moderating effect of experience and job role on the attitude and acceptance relationship, the moderating role of demographic variables such as of gender and age on the attitude and acceptance relationship was investigated. The moderation effect of gender is significant but small, $\beta = .06$, $p = .009$, and insignificant for age $\beta = .026$, $p = .257$. The focus however of this research is to investigate the moderating role of employees' experience with using AI technologies or employees' job role on the attitude and acceptance relationship.

The above indicated that attitude has a significant positive effect on acceptance, ($\beta = .90$, $p < .001$). Linear regression is used to test the interaction effect of employees' experience with using AI technologies, as well as the interaction effect of employees' job roles on the attitude and acceptance relationship.

4.8.4.1 Moderating effect of experience with using AI technologies

Multiple regression is conducted to determine whether attitude towards use of AI technologies and experience with using AI have a significant effect on acceptance. Attitude towards use of AI technologies ($\beta = .86$, $p < .001$) and experience with using AI technologies ($\beta = -.066$, $p < .001$) both have a significant effect on the acceptance of AI technologies. The overall regression is statistically significant, $R^2 = .807$, $F(2, 406) = 851.612$, $p < .001$.

Upon introducing the interaction effect (moderator_ex) into the model, the regression analysis is conducted again. Table 4.31 indicates that the overall regression is statistically significant, $R^2 = .81$, $F(3, 406) = 581.364$, $p < .001$. The interaction effect is significant ($\beta = .07$, $p = .003$) and increases the R^2 from .807 to .811. The results therefore indicate that although it's a small effect, experience with using AI technologies does have some effect on the attitude-acceptance relationship. As such, hypothesis 13 is supported.

Table 4.31 Linear regression of moderator_experience

Model Summary					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.901 ^a	.811	.850	.43614729	1.725
a. Predictors: (Constant), Moderator_Ex, Attitude, Experience with AI					

ANOVA ^a								
Model		Sum of Squares	df	Mean Square	F	Sig.		
1	Regression	331.769	3	110.590	581.364	<.001 ^b		
	Residual	77.231	406	.190				
	Total	409.00	409					
a. Dependent Variable: Acceptance								
b. Predictors: (Constant), Moderator_Ex, Attitude, Experience with AI								
Coefficients ^a								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Tolerance	VIF
		B	Std. Error	Beta				
1	(Constant)	.049	.027		1.791	.074		
	Zscore:Attitude	.835	.027	.835	30.398	<.001	.617	1.622
	Zscore: Experience	-.098	.028	-.098	-3.467	<.001	.578	1.731
	Moderator_Ex	.086	.029	.069	2.948	0.003	.846	1.182
a. Dependent Variable: Acceptance								

4.8.4.2 Moderating effect of employees' job role

Firstly, multiple regression is conducted to determine whether employees' attitude towards use of AI technologies and employees' job roles have a significant effect on acceptance. The overall regression is statistically significant, $R^2 = .804$, $F(2, 406) = 836.398$, $p < .001$. Attitude towards use of AI technologies ($\beta = .89$, $p < .001$) has a significant effect, while employees' job roles does not ($\beta = -.013$, $p = .573$). So when the interaction effect (moderator_role) is introduced into the model, both the job role ($\beta = -.008$, $p = .727$) and the moderator_job role ($\beta = .030$, $p = .208$), have an insignificant effect on acceptance of AI technologies. This indicates that employees' job roles do not have an effect on the attitude-acceptance relationship. As such, hypothesis 14 is not supported.

Table 4.32 Linear regression of moderator_job role

Model Summary					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	.897 ^a	.805	.804	.44313506	1.694

a. Predictors: (Constant), Moderator_Role, Job role, Attitude						
ANOVA^a						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	329.274	3	109.758	558.939	<.001 ^b
	Residual	79.726	406	.196		
	Total	409.000	409			
a. Dependent Variable: Acceptance						
b. Predictors: (Constant), Moderator_Role, Job role, Attitude						
Coefficients^a						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.008	.023		.369	.713
	Attitude	.885	.024	.885	37.047	<.001
	Job role	-.008	.023	-.008	-.349	.727
	Moderator Role	.028	.022	.030	1.261	.208
a. Dependent Variable: Acceptance						

4.9 Summary of hypothesis testing

The research hypotheses were tested and the results are shown in Table 4.33 below. A positive and linear relationship was evident between each of the technological, individual, organisational, environmental factors and attitude towards use of AI technologies. Separate multiple regression analysis was conducted to assess the influence of each of the technological, individual, organisational and environmental factors on attitude towards use of AI technologies, and this indicated that each of the 11 factors has a significant and positive influence on attitude towards use of AI technologies.

To determine the combined effect of these 11 factors on attitude towards use of AI technologies, and identify the key determinants of attitudes towards use of AI technologies from factors included in the research model, a multiple regression analysis was carried out with all the factors, as well as a stepwise regression analysis to validate the results. 7 of the 11 factors indicate a significant relationship with attitude towards use of AI technologies and are identified as key determinants of attitude towards use of AI technologies. The attitude-acceptance relationship is significant and positive. Experience with using AI technologies moderates the attitude-acceptance relationship while employees' job roles do not.

Table 4.33 Results of hypotheses testing and analysis of final model

Hypotheses	Linear and multiple regression to determine the independent influence of each variable	Multiple regression with all variables to determine the combined effect and key determinants	Stepwise regression with all variables to determine the combined effect and key determinants
H1: Perceived usefulness has a significant positive influence on attitude towards use of AI technologies.	Supported	Supported	Supported
H2: Perceived ease of use has a significant positive influence on attitude towards use of AI technologies.	Supported	Supported	Supported
H3: The relative advantage of AI technologies has a significant positive influence on attitude towards use of AI technologies.	Supported	Not supported	Not supported
H4: Organisational justice has a significant positive influence on attitude towards use of AI technologies.	Supported	Not supported	Not supported
H5: Subjective wellbeing has a significant positive influence on attitude towards use of AI technologies.	Supported	Supported	Supported
H6: Management support has a significant positive influence on attitude towards the use of AI technologies.	Supported	Supported	Supported
H7: Training support on the use of AI technologies has a significant positive influence on attitude towards use of AI technologies.	Supported	Not supported	Not supported
H8: An innovative organisational culture has a significant positive influence on attitude towards the use of AI technologies	Supported	Not supported	Not supported
H9: Social influence has a significant and positive influence on attitude towards use of AI technologies.	Supported	Not supported	Not supported
H10: Customer pressure has a significant positive influence on attitude towards the use of AI technologies.	Supported	Supported	Supported
H11: Competitive pressure has a significant positive influence on attitude towards the use of AI technologies.	Supported	Supported	Supported
H12: Attitude towards the use of AI technologies has a significant and positive influence on the acceptance of AI technologies.	Supported	N/A	N/A
H13: Employees' experience with using AI technologies moderates the relationship between attitude and acceptance of AI technologies.	Supported	N/A	N/A
H14: The relationship between attitude towards use of AI technologies and acceptance of AI technologies is moderated by employees' job roles.	Not Supported	N/A	N/A

4.10 Presentation of qualitative data

Of the 410 survey participants, 169 (41%) provided at least one textual response to the three open-ended questions included at the end of the questionnaire. This data was reviewed, analysed and coded and categorised into themes or key words or phrases before being entered into a textual analysis and visualisation tool called WordItOut, where the results were

processed and presented in a visual form of word clouds, with the size of the word reflecting frequency of words that were coded.

4.10.1 Overall attitude and views towards the use of AI technologies

Comments provided by participants indicate that although participants are positive, optimistic, excited, and curious to use and experience the potential of AI technologies, there are also anxious, uncertain and have mixed views regarding the use of AI technologies. Figure 4.15 provides a visual presentation of key words deduced from participants' responses regarding their attitude and views towards the use of AI technologies.

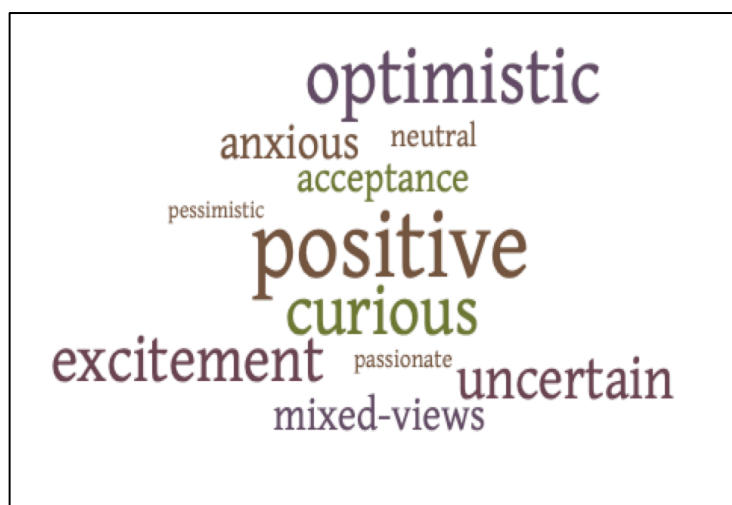


Figure 4.15 Word cloud of employees' attitude towards the use of AI technologies

4.10.2 Considerations to be given to employees' work

Participants were asked to comment on the factors they would like to be considered when AI is implemented in doing their work. Figure 4.16 provides a visual presentation of the common themes/factors that are identified. The impact on employees' work and/or their roles is a prominent factor. Education on what AI is and what it can do to gain or improve understanding on AI technologies, training on AI technologies, as well as the ability to experiment with AI were also some of the key themes that were noted.

Additional factors to be considered include factors that influence the design and use of AI technologies, ensuring that AI technologies implemented are user-friendly, the type of AI tools and software implemented, the accuracy and security of data used, the usefulness of the AI technologies implemented and the support available through the process. Further, other factors noted which participants feel should be considered when implementing and using AI in their

work include consideration of the impact of using AI on employees, their work, processes, customers. A few participants also note that the human element, “human-touch”, in terms of the way employees work and interact with each other and especially customer should not be lost.



Figure 4.16 Word cloud considerations to be given to employees’ work

4.10.3 Consideration to be given to the organisation

Participants note several factors to be considered when implementing AI technologies within organisations. Figure 4.17 provides a visual presentation of the common themes/factors that are identified. The most prominent factors are training on AI, a clear and effective implementation process, the cost of AI, fairness in working with AI, understanding of AI, job security and having a clear AI strategy. It is also evident that most of the factors raised are factors that affect the effective implementation process of AI, for example, data used to develop algorithms, proper testing of AI systems, experimentation with AI, communication, collaboration and employee buy-in. The ethical and fair use of AI is also highlighted, together with the need to regulate the use of AI technologies.



Figure 4.17 Word cloud of consideration to be given to the organisation

4.11 Summary

In this chapter, the research results are presented. Although 432 survey responses were collected, 410 valid responses were retained after preliminary analysis. The measurement instrument was found to be valid and reliable. A profile of the respondents, their experience with using AI technologies as well as an overview of the business applications of AI as indicated by participants in this research was presented. The results of the univariate analysis, bivariate analysis and multivariate analysis carried out to test the hypotheses were presented. In addition, the findings of the analysis to determine key determinant of employees' attitudes towards the use of AI, as well as the results of the analysis of the attitude-acceptance relationship as well as the effect of the proposed moderators on this relationship was presented. Responses from open-ended responses are analysed and illustrated in the form of word clouds. A discussion of these research results is provided in the following chapter, Chapter 5, where each research question is addressed. In addition, based on the research findings, a model that provides guidelines to the successful implementation, integration, and use of AI technologies is presented.

CHAPTER 5: DISCUSSION

5.1 Introduction

This chapter provides a discussion of the research results, linking current results to literature and previous research related to the attitude and acceptance of AI technologies. To begin with, a discussion of the demographic information provided by the research participants is provided. This is followed by a discussion of research findings on factors influencing employees' attitude and acceptance of AI technologies. In doing so, the research findings are interpreted in the context of the research questions and objectives for this research. A proposed model to be considered when implementing and using AI technologies within the context of this research is proposed.

5.2 Demographic information

The following section provides a discussion of the research sample, from which the research findings will be generalised to the population of employees within the South African financial services industry. The profile of employees that participated in this research, specifically in terms of the gender selected by employees, the age of the employees, the employees' experience with using AI technologies and their job roles is analysed and discussed by considering the context of this research and relevant previous studies.

5.2.1 Gender

The 2023 Q3 labour force survey published by Statistics South Africa (2023) indicates that more males (1 597 000) than females (1 239 000) are employed in the financial services industry across the country. Of the 410 valid survey participants in this research survey, 53% are females while 47% are males. Although the sample is not necessarily representative of the industry's demographics in this regard, the difference in the total number of participants based on their gender is marginal, only 6%.

The sample is however representative of the gender disparity within the South African population and across the world, in terms of women's occupation in IT roles and in top management and executive roles. A research report by Hupfer et al. (2021) on women in the tech industry as well as the Women in Tech SA (2022) report indicates that on average, women occupy below a quarter (23%) of IT related roles. Although there is a projected increase in the number of women in IT roles, the projected increase is only about 2%, due to challenges related

to education, recruitment, retention, pay and promotion of women (Hupfer et al., 2021). The 2023 Women in business report by SNG Grant Thornton (2023) indicates that in South Africa, women occupy less than half of the positions in senior management compared to men, 41%, and that this higher than the global average of 32%.

The research sample indicates that there are more males (72%) than females in IT roles (28%). This confirms past research that indicates that men have historically been more likely than women to work in the technical jobs such as IT roles, while women have been more likely to work in roles requiring more interpersonal skills (Webb, 2019). In addition, there were more males (73%) than females (27%) that indicated their occupation to be top management and executive positions.

In this research, more males (60%) than females (40%) indicated that they have experience with using AI technologies. The research results also indicate that exposure and experience with using AI technologies results in males being more likely to have positive attitudes towards the use of AI as well as a higher level of acceptance of AI technologies than females. Females in this research were more likely than males to be uncertain or negative towards use of AI technologies.

Various studies have reported on gender similarities and differences in research on the implementation and use of automation and AI-related technologies. Ivanov et al.'s (2020) research on automation fears drivers and solutions concludes that there is no significant evidence that indicates that gender influences automation fears. Roberts et al.'s (2021) research on South African attitudes towards the automation and AI related technologies find that women are only slightly less accepting of automation and AI technologies than men. However, the findings of this research concur with Gnambs et al.'s (2019) research on attitudes towards robots which indicates that males are more positive towards robots than females.

5.2.2 Age

The working population in South Africa is between 15 years and 64 years old, according to Statistics South Africa (2023). The 2023 Q3 labour force survey published by Statistics South Africa (2023) indicates that highest employment rate is within the 25 years to 34 years age group, followed by the 15 years to 24 years, 35 years to 44 years to 54 years and 55 years to 64 years respectively. Given the target population for this research discussed in chapter 3,

employees working in the financial services industry within the specified roles are expected to be at least 18 years of age (given the average age of matriculation as the minimum requirement for entry into formal employment). The majority of participants in this research were between 18 years and 50 years old, (89%) of the total participants.

The findings of the research are that employees' age and their attitude towards the use of AI technologies are not related. Similarly, employees' age is not related to their acceptance of AI technologies. This means that neither attitude towards use of AI technologies nor the acceptance of AI technologies is influenced by the age of employees. This research finding contradicts previous research, for example research by Roberts et al. (2021) that find a significant relationship between age and attitude towards automation technologies, and concludes that young South Africans tend to be more accepting of automation than older South Africans.

5.2.3 Experience with using AI technologies

Less than half of the participants indicate that they have experience with using AI technologies 41%. A significant relationship between employees' job role and experience with using AI technologies is noted (see p.113). Professionals in IT roles indicate to have the most experience using AI technologies, about 19% of the 41% that indicated to have experience using AI technologies. The proportion of employees in middle management role, first-line management roles, non-IT professional roles, top management/executive roles and in administrative roles that indicate to have experience with using AI technologies is 9%, 5%, 3%, 2% and 1% respectively. Compared to employees in other roles, professionals in IT roles had more employees with experience using AI technologies than those that did not (77% vs 23%).

This is not surprising, given that AI is still in its early stages (Füller et al., 2022; Tjebane et al., 2022) and the people likely to be exploring or working with AI technologies and/or make decisions about the implementation and use of AI technologies are likely to be those in management or IT-related roles. This could be the reason why most research on the adoption, attitude, and acceptance of AI technologies within South African organisations has focused mainly on sampling these employees in these roles and collecting views from management and IT experts, for example research by Ndoro et al. (2020) in the financial services industry and research by Tjebane et al. (2022) in the construction industry.

A significant relationship between experience with using AI technologies and attitude towards use of AI technologies is evident. Those with experience using AI technologies indicate a more positive attitude towards the use of AI technologies than those that do not have experience with using AI technologies (see p.146). Similarly, those with experience using AI technologies have a significantly higher level of acceptance of AI technologies compared to those without experience using AI technologies (see p.149). These results align with research findings by Vasilyeva et al. (2021) which indicate a significant difference in attitudes between employees working in organisations that have implemented AI technologies and those that have not yet implemented AI technologies. Those working in organisations that have implemented AI-related technologies were more positive than those working in organisations that had not yet implemented AI technologies (Vasiljeva et al., 2021). These findings highlight the positive role that experience has on the adoption, attitude and acceptance of AI technologies (Horowitz & Kahn, 2021).

5.2.4 Job role

Although the use of AI technologies will impact all jobs in one way or the other, there is currently a lot of debate with regards to how the AI technologies will impact job roles differently (Ivanov et al., 2020; Lane & Saint-Martin, 2021). As such, research on employees' attitudes and acceptance of AI technologies across the different job levels and job roles within organisations is encouraged (Kar & Kushwaha, 2021; Siderska et al., 2023). For this reason this research aimed to obtain participation from employees working across the different levels of the organisation.

Most of the research participants, 69%, are in middle management (25%), professional IT roles (24%) and professional non-IT roles (20%). The lowest participation is from those in top/management/executive (8%) and administrative role (10%). The research results show that there is a significant relationship between employees' job roles and attitude towards use of AI technologies (see p.145). Acceptance of AI technologies also varied depending on the employees' job roles (see p.148).

Employees in top management/executive roles and those in professional IT roles have similar responses to their attitude towards the use of AI technologies and their acceptance of AI technologies. Those in middle management, first line management and professional non-IT

roles share similar views in terms of their attitude toward the use of AI technologies but have different and varying responses in terms of their acceptance of AI technologies. Employees in administrative roles differ the most from employees in other job roles and are more likely to be less enthusiastic and less positive about the use of AI technologies, as well as having low levels of acceptance of AI technologies.

The positive attitude and high levels of acceptance portrayed by individuals in top management executives roles as well as those in professional IT roles can be explained by the fact that they are likely to have had more experience and exposure to using AI, as discussed above, compared to those in other roles. Research notes that AI adoption is one of the top priorities for top management/executives, as organisations are trying to find ways of leveraging the potential of AI and gaining competitive advantage (Noponen, 2019; Schoeman et al., 2021). This may explain the positive attitude, as well as high level of acceptance of AI for those in the top management/executives. In addition, given that IT professionals are likely to be the ones to develop and work with AI technologies first-hand, they are likely to be in a position where they have a better view of the potential of AI technologies based on their experience and therefore be more positive and accepting AI technologies.

Employees in middle management, first line management and non-IT professional roles were generally positive about the use of AI technologies. However, their acceptance of AI technologies differs. This could be because although individuals in these roles may be positive about the use of AI technologies, they may be unclear about how the use of AI technologies may impact them, their way of working and jobs. This is based on responses to the open-ended questions provided by some of the employees which highlight factors such as limited understanding of AI and uncertainty with the impact and/or perceived impact of AI technologies on their work and job roles, which may contribute to uneasiness towards accepting AI technologies.

Further, the less positive attitudes and low levels of acceptance of AI technologies portrayed by those in administrative positions may be due to limited understanding and exposure of AI technologies, as well as fear of losing jobs. Since AI technologies also aim to automate and replace repetitive and mundane tasks (Baggio & Omana, 2019; Davenport & Ronanki, 2018; Ivanov et al., 2020), tasks occupied by employees in administrative roles are likely to be at a

higher risk of being automated, which may pose a threat to the professional identity and job security of employees in these roles (Strich et al., 2021).

5.3 Factors influencing attitude towards use of AI technologies

The first objective of this research was to analyse factors impacting attitudes towards the use of AI technologies, using an extended TAM-TOE framework. Given the complex nature of AI technologies, an analysis of broad factors that could influence the attitude and acceptance of AI technologies and impact the successful implementation and use of AI technologies was undertaken. Potential technological, individual, organisational, and environmental factors proposed to influence attitude towards the use of AI technologies were identified from the literature review. In line with the first objective, eleven hypotheses were formulated to answer the first research question.

RQ1: To what extent do the technological, individual, organisational, and environmental factors independently influence employees' attitude towards the use of AI technologies in the financial services industry in South Africa?

The following provides a discussion of the hypotheses testing used to identify technological, individual, organisational, and environmental factors influencing employees' attitude towards the use of AI technologies to answer the first research question.

5.3.1 Effect of technological factors on attitude towards use of AI technologies

Technological factors included in this research when investigating employees' attitude and acceptance of AI technologies include perceived usefulness, perceived ease of use and relative advantage. Correlation and multiple regression analysis was conducted to investigate the relationship between each of these three technological factors and attitude towards use of AI technologies. The multiple regression model with all the three predictors (technological factors) is statistically significant. The regression model indicates that technological factors explain 74% of the variance in attitude towards use of AI technologies (see Table 4.14, p.127). A discussion of the effect of each on these factors on attitude towards use of AI technologies follows.

5.3.1.1 Perceived usefulness

For this research, it was hypothesised that perceived usefulness has a significant positive influence on attitude towards the use of AI technologies. The results show that perceived usefulness is positively and significantly correlated with attitude towards use of AI technologies (see Table 4.13, p.124). The multiple regression model with all the three technological factors indicates that perceived usefulness has a significant positive effect on attitude towards the use of AI technologies and is the strongest predictor of attitude towards use of AI technologies amongst the three technological factors (see Table 4.14, p.128). This implies that the more employees perceive the use of AI technologies to be useful in their work, the more positive their attitudes towards the use of AI technologies are.

These results are consistent with literature that note the consistent role of perceived usefulness in technology acceptance research (Brown et al., 2002; Karunaratne & Abeyratne, 2020; Sun & Zhang, 2006). as well as in influencing attitude towards use of AI technologies (Bhargava et al., 2020; Na et al., 2022). In addition, these research findings also support Brown et al.'s (2002) argument that the perceived usefulness of a new technology is very important in mandatory settings in terms of enabling usage and acceptance of a new technology.

Responses to open-ended questions indicate that although perceived usefulness is not a dominant factor that employees highlight to be considered when using AI technologies in doing their work, the usefulness of using AI in order to improve their performance is noted (see Figure 4.16, p.169).

Overall, the hypothesis that perceived usefulness has a significant positive influence on attitude towards the use of AI technologies is supported. This research findings highlights the importance of ensuring the AI technologies implemented in organisations are purposeful and are directed at providing a specific need or solving a specific problem (Chen et al., 2020; Rzepka & Berger, 2018). In doing so, employees are likely to perceive the AI technologies implemented to be useful in doing their work and capable of improving their performance, and therefore be positive towards the use of AI technologies.

5.3.1.2 Perceived ease of use

With regards to perceived ease of use, the hypothesis was that perceived ease of use has a significant positive influence on attitude towards use of AI technologies. Perceived ease of use has previously been noted as being inconsistent with regards to its role in influencing attitude or adoption of new technologies (Sun & Zhang, 2006). However, according to Van den Berg and Van der Lingen (2019), the ease of use of new technologies is a key determinant of employees' attitude towards use of new technologies in mandatory settings, as they consider this to outweigh the perceived usefulness of a new technology in mandatory settings given that if a technology is perceived to be easy to use, this would outweigh the perceived usefulness of the technology, since the usefulness of the technology is not always clear and evident in mandatory settings.

The research findings indicate that perceived ease of use is positively and significantly correlated with attitude towards use of AI technologies (see Table 4.13, p.124). The multiple regression model with all the three technological factors indicates that perceived ease of use has a significant positive effect on attitude towards the use of AI technologies and is the second strongest predictor of attitude towards use of AI technologies (see Table 4.14, p.128). This confirms that the more employees perceive AI technologies to be user-friendly, the more positive their attitude towards its use are.

The results are consistent with past research that has shown that the perceived ease of use of AI related technologies significantly influences attitude and/or behavioural intention to use AI technologies in various settings, such as manufacturing and production (Bröhl et al., 2016), construction (Na et al., 2022), accounting and auditing (Damerji & Salimi, 2021), banking (Rahman et al., 2021) and the healthcare sector (Alhashmi, Salloum, & Mhamdi, 2019). Analysis of the responses to the open-ended questions also indicate that the user-friendliness of AI technologies is one of the common key factors respondents highlight as a consideration in using AI technologies in doing their work (see Figure 4.16, p.157).

The hypothesis that perceived ease has a significant positive influence on attitude towards use of AI technologies is therefore supported. The research findings indicate that AI technologies should be easy to use, easy to learn, clear and understandable, especially since AI technologies are often regarded to be very complex technologies (Füller et al., 2022; O'Shaughnessy et al.,

2023). Finding ways to simplify employees' engagement with AI technologies is crucial, as this will influence their attitude and acceptance of AI technologies. This is why Rzepka & Berger (2018) recommend that system designers and IT providers of AI technologies adequately assess the capability and functionality of AI technologies, consider the experience of users and focus on improving user interactions with AI technologies when implementing AI technologies to ensure that they are user-friendly.

5.3.1.3 Relative advantage

In line with Roger's (1983) definition, relative advantage in this research is defined as the extent to which employees would perceive the use of AI technologies to be beneficial and better than using alternative, previous or current technologies. The use of AI technologies in the financial services industry is argued to be capable of making work easier by taking over mundane tasks, cutting costs, increasing efficiency and positively influencing the top and the bottom line (Davenport & Ronanki, 2018; Phuoc, 2022).

The research results indicate that relative advantage is positively and significantly correlated with attitude towards use of AI technologies (see Table 4.13, p.124). The multiple regression model with all the three technological factors indicates that although relative advantage is the least strongest predictor in this regression model, relative advantage also has a significant positive effect on attitude towards the use of AI technologies (see Table 4.14, p.128). The results therefore indicate that the more employees perceive the use of AI technologies to be beneficial and better than other technologies, the more positive their attitudes towards the use of AI technologies are. The hypothesis that the relative advantage of AI technologies has a significant positive influence on attitude towards use of AI technologies is supported.

The research results are consistent with research findings by Vasiljeva et al.'s (2021) and Phouc's (2022) research on the public's attitudes towards AI technologies in Latvia and factors influencing AI adoption in Vietnam respectively, which also find relative advantage to be a significant factor in influencing attitude and adoption of AI technologies. Chiu et al.'s (2021) research on employees' pre-adoptive perceptions of AI also highlights that the perceived benefits of the AI's capabilities in terms of increased performance, flexibility, reliability, efficiency and successful integration with other systems is positively related to attitude towards the use of AI technologies. Research by Gupta et al. (2022) on employees' adoption of AI

technologies within the insurance industry in India also indicate that relative advantage has a significant positive effect on AI adoption. Ahn and Chen's (2022) research on employees' willingness to use AI technologies within government sectors also find that employee's perception of AI enhancing the efficiency and effectiveness in their work positively influenced their willingness to implement and use AI technologies.

Comments provided by employees to the open-ended questions also highlight the need for employees to understand the benefit and efficiency gains from using AI technologies as well as the need to be comfortable with the accuracy of using AI technologies compared to humans or other systems, all of which influence employees perceptions of the relative advantage of using AI technologies (see Figure 4.17, p.134).

5.3.2 Effect of individual factors on attitude towards use of AI technologies

Literature notes the mixed views regarding individuals perceptions of how AI technologies will be implemented and used fairly, and how the use of AI technologies will impact individuals jobs, way of working, work relationships, job satisfaction and their overall well-being (Ivanov et al., 2020). These mixed views and concerns are argued to influence the attitude and acceptance of AI technologies (Flavián et al., 2021).

In a country like South Africa where concerns of inequality and high levels of unemployment are prevalent, investigating how these concerns influence employees attitudes towards the use of AI technologies is crucial as this would impact the successful implementation and use of AI technologies within organisations. For this reason, employees' perceptions of organisational justice and employee wellbeing, and their effect on attitude towards the use of AI technologies is investigated. The multiple regression model with both these individuals is statistically significant. The regression model indicates that these individual factors explain 71% of the variance in attitude towards use of AI technologies (see Table 4.15, p.129).

5.3.2.1 Perceptions of organisational justice

The research hypothesised that organisational justice has a significant positive influence on attitude towards use of AI technologies. In this research, organisational justice refers to the extent to which employees perceive fairness in the communication, transparency, consistency

of process followed, and overall implementation and use of AI technologies within the organisation.

The results show that organisational justice is positively and significantly correlated with attitude towards use of AI technologies (see Table 4.13, p.124). The multiple regression model with the two individual factors indicates that despite organisational justice having a lesser effect on attitude towards the use of AI technologies compared to employee wellbeing, organisational justice has a significant positive effect on attitude towards the use of AI technologies (see Table 4.15, p.130). Therefore, the hypothesis that organisational justice has a significant positive influence on attitude towards use of AI technologies is supported. This confirms that the more employees perceive fairness with regards to the processes and communication regarding the implementation and use of AI technologies, the more positive they are in terms of their attitude toward the use of AI technologies.

The research findings support previous literature on the importance of communication, transparency and fairness when using AI technologies. Rzepka and Berger (2018) emphasise the need to ensure that there is communication and explanation of AI systems, as well as transparency when implementing AI technologies as this influences users' behaviour, trust and perceptions of the AI technologies implemented. Given the concerns, fears, anxiety, and limited knowledge and understanding of AI (Kelly et al., 2023; Ndoro et al., 2020), Chen et al. (2020) state that it is important that individuals are involved and kept informed throughout the implementation and use of AI technologies. Research findings by Smit and Eybers (2022) on AI adoption in the South African automotive manufacturing industry also highlight the need for organisations to ensure fairness, accountability, transparency and explainability as part of their AI adoption process and initiatives to be able to ensure the successful implementation and use of AI technologies.

Employees' textual responses indicate that employees highlight factors such as trust, fairness, ethics, communication, employees' buy-in, implementation of AI and AI's impact on processes as factors they would want to be considered when implementing AI technologies within the organisations (see Figure 4.17, p.158), which impact perceptions of organisational justice.

It is therefore imperative that organisational justice is promoted within organisations. Employees should be encouraged and supported to express their specific concerns and fears,

and management should make an effort to understand and address issues raised. This is likely to promote buy-in from employees and promote positive attitudes towards the use of AI technologies. In addition, this is likely to lessen the impact of the unfavourable outcomes of using AI technologies, because as noted by Ötting and Maier (2018) and Saunders (2021), perceptions of procedural or interactional justice mitigate the negative effect of the unfavourable outcomes of decisions and changes made within the organisation.

5.3.2.2 Employee wellbeing

For the purposes of this research, employee wellbeing refers to the extent to which employees think or feel that using AI technologies will contribute more to their job satisfaction, career development, engagement with others and autonomy, and less to their work-related stress, anxiety and feelings of job insecurity. This research hypothesised that employee wellbeing has a significant positive influence on attitude towards use of AI technologies.

Employee wellbeing has the lowest mean and highest standard deviation ($M = 5.14$, $SD = 1.25$), indicating that participants' views of the impact of AI technologies on their employee wellbeing vary substantially. This is not surprising given the mixed views and varying perceptions and concerns towards the impact of AI technologies.

Employee wellbeing is positively and significantly correlated with attitude towards use of AI technologies (see Table 4.13, p.124). The multiple regression model with the two individual factors (organisational justice and employee wellbeing) indicates that employee wellbeing has a significant and large positive effect on attitude towards use of AI technologies (see table 4.15, p.130). The hypothesis that employee wellbeing has a significant positive influence on attitude towards use of AI technologies is supported. The more employees perceive the use of AI technologies to contribute positively to their wellbeing, the more positive their attitude towards the use of AI technologies are.

Literature shows that the impact of the use of AI technologies is debatable and unclear. As a result, there are contradictory views on how the use of AI technologies will impact employees' wellbeing. For example, Nazareno and Schiff (2021) find that the automation and use of AI technologies has a negative impact on employees' stress and health, while Parker and Appel

(2021) find that the use of robotic process automation enhances employee engagement and job satisfaction and also reduces stress.

Given that employee wellbeing is shown to have a significant and large effect on attitude towards the use of AI technologies, the research findings highlight the need for management and organisations to prioritise factors impacting employee's wellbeing when implementing and using AI technologies. Similar research findings and recommendations are made by Cao et al. (2021) whose research indicate that personal wellbeing concerns have a significant impact on the attitude towards using AI technologies.

Employees responses to the open-ended questions also highlight concerns to their wellbeing, which include concerns regarding the impact of AI technologies on their roles, concerns regarding job security and autonomy, as well as the potential loss of the human-touch when it comes to interacting and engaging with others (see Figure 4.16, p.157). For this reason, it is recommended that management is aware of and address concerns employees' concerns which may impact employees' employee wellbeing and their attitude towards use of AI technologies.

5.3.3 Effect of organisational factors on attitude towards use of AI technologies

Management support, training support and an innovative culture were identified and examined as key determinants of attitude towards use of AI technologies. The individual effect that these variables have on attitude towards use of AI technologies is discussed below. Correlation and multiple regression analysis was conducted to investigate the relationship between each of these three organisational factors and attitude towards use of AI technologies. The multiple regression model with all the three predictors (organisational factors) is statistically significant. The regression model indicates that organisational factors explain 57% of the variance in attitude towards use of AI technologies (see Table 4.16, p.131). A discussion of the effect of each of these factors on attitude towards use of AI technologies follows.

5.3.3.1 Management support

Management support in this research is defined as the extent to which employees feel that management provide sufficient guidelines on the use of AI technologies, access to training, resources and software as well opportunities for employees to give feedback on the use of AI

technologies. It was hypothesised that management support has a significant positive influence on attitude towards the use of AI technologies.

The results indicate that management support positively and significantly correlates with attitude towards use of AI technologies (see Table 4.13, p. 124). The multiple regression model with the three organisational factors indicates that management support has a significant positive effect on attitude towards the use of AI technologies and has a greater effect on attitude towards the use of AI technologies than the other two organisational factors, training support and innovative culture (see Table 4.16, p.132). The results indicate that the more employees perceive the presence of management's ability to provide adequate support and guidance through the implementation and use of AI technologies, the more positive their attitudes are. The hypothesis that management support has a significant positive influence on attitude towards the use of AI technologies.

These research results concur with previous research findings on the adoption and attitudes towards AI technologies by for example, Chen et al. (2020) in the telecommunication industry, Chatterjee et al. (2021) in the manufacturing industry, and Gupta et al. (2022) in the insurance industry, that find management support to be a significant and key determinant of attitude and/or adoption of AI technologies. Therefore the role of effective leadership and management support throughout the implementation and use of AI technologies is supported by current research findings.

Employees in their textual responses note the need for better education and understanding of AI technologies and opportunities to learn and experiment with AI (see Figure 4.16, p.157 and Figure 4.17, p.158). In mandatory settings where management make decisions regarding the use of AI technologies, providing employees with the resources and opportunities required to facilitate education, understanding and exposure to the use of AI technologies is key to the successful implementation and use of AI technologies throughout the process of engaging and working with AI technologies.

Although the use of AI technologies is in its early stages (Mikalef et al., 2019; Tjebane et al., 2022), and a lot that is still unknown, management's support in terms of being proactive about the communication, translation and implementation of the AI strategy is key. In addition, acknowledging and addressing employees concerns from the onset, even if they may not have

all the answers enhances transparency, trust and better collaboration with employees through the process. Li et al. (2019) and Tjebane et al. (2022) note that management's support in the form of providing guidance, direction, and motivation to employees to use the new technologies can help minimise stress and anxiety that employees experience while dealing with AI technologies.

5.3.3.2 Training support

Training support refers to the extent to which employees feel that there is sufficient training provided to enable them to understand AI, be more comfortable and confident when using AI technologies, as well as be more receptive towards the use of AI technologies. It was hypothesised that training support on the use of AI technologies has a significant positive influence on attitude towards use of AI technologies.

The results indicate that training support positively and significantly correlates with attitude towards use of AI technologies (see Table 4.13, p.124). The multiple regression model with the three organisational factors indicates that training support has a significant positive effect on attitude towards the use of AI technologies and is the second strongest predictor of attitude towards the use of AI technologies (see Table 4.16, p.132). The results indicate that the more employees perceive the availability of training support in order to learn and upskill on AI technologies, the more positive their attitudes towards the use of AI technologies are. Therefore, the hypothesis that training support on the use of AI technologies has a significant positive influence on attitude towards use of AI technologies is supported.

The research findings support previous research that indicate that training opportunities are an important element in facilitating readiness and successful implementation of AI related technologies (Ghaleb et al., 2021; Kolbjørnsrud et al., 2017). In addition, the availability and need for training was the most frequent factor noted by employees in their textual responses as a factor to be considered when implementing and using AI technologies in organisations (see Figure 4.16, p.157 and Figure 4.17, p.158).

Further, the findings of this research support previous research cited by Lane and Saint-Martin (2021) that urges management to not underestimate the willingness of employees to train and upskill on AI technologies. Instead, management should be prepared to and follow through in

making the investment to training their employees on the use of AI technologies as this is key to providing understanding, experience and appreciation of AI technologies which may lessen anxiety, stress and fear of AI technologies (Gu et al., 2022; Robb et al., 2020).

5.3.3.3 Innovative culture

An innovative organisational culture in this research refers to the extent to which employees perceive the culture of the organisation to be flexible, agile, innovative, collaborative, and capable of effectively integrating AI technologies in their way of working. It was hypothesised that an innovative culture has a significant positive influence on attitude towards the use of AI technologies.

The results of this research indicate that an innovative culture has a moderate, positive and significant correlation with attitude towards use of AI technologies (see Table 4.13, p.124). The multiple regression model with the three organisational factors indicates that innovative culture has a significant positive effect on attitude towards the use of AI technologies even though it is the least predictor of attitude towards the use of AI technologies compared to other organisational factors (see Table 4.16, p.132).

The research findings indicate that the more employees perceive their organisation to be agile, flexible, innovative, and capable of enabling effective collaboration to successfully integrate the use of AI technologies, the more positive their attitude towards the use of AI technologies are. Therefore, the hypothesis that an innovative organisational culture has a significant positive influence on attitude towards the use of AI technologies is supported.

Textual responses from employees also highlight the importance of considering processes or ways of working, communication, collaboration, availability of training, experimentation, trust alignment across different departments when implementing AI technologies within the organisation (see figure 4.17, p.158), which all influence and are influenced by an organisation's culture and its ability to be innovative.

These findings concur with past research and literature that highlight the significant role of an agile, digital, and innovative organisational culture in positively influencing the adoption, attitude, use and acceptance of new technologies (Martínez-Caro et al., 2020; Neumann et al.,

2022; Duana et al., 2019; Hameed & Arachchilage, 2017). According to Na et al. (2022) an organisation's culture is key in the implementation and use of a new technology such as AI technologies because it influences what technology is implemented, why it is implemented, how it will be implemented as well as the processes, policies, and expectations of the new technology.

Current research findings also complement the research findings by Siderska and Alsaqoor (2023) on employees attitudes towards robotic process automation (RPA), which indicates that employee's involvement in the design and implementation of RPA, which depends on the organisation's culture, is a key factor influencing attitude towards RPA. They conclude that cooperation between management and employees is reflective of an organisation's culture that is open to working constructively with innovative technologies and changes within an organisation (Siderska et al., 2023).

Important to note is that an organisation's culture is unique for each organisation, and difficult to change (Hubbard & Rogers, 2019). Therefore, organisations need to become aware of and understand the impact of their organisations' culture on their way of working when introducing AI technologies, and how this may impact employees' behaviours and attitudes. Where necessary, deliberate action can be taken to change specific aspects of the organisation's culture to facilitate the effective implementation and use of AI technologies.

5.3.4 Effect of environmental factors on attitude towards use of AI technologies

Social influence, customer pressure and competitive pressure were identified as factors influencing the attitude towards use of AI technologies. The individual effect of each of these factors on attitude towards use of AI technologies is discussed below. Correlation and multiple regression analysis was conducted to investigate the relationship between each of these three environmental factors and attitude towards use of AI technologies. The multiple regression model with all the three predictors is statistically significant. The regression model indicates that environmental factors explain 68% of the variance in attitude towards use of AI technologies (see Table 4.17, p.133).

5.3.4.1 Social influence

Social influence in this research refers to the extent to which others' positive beliefs about the use of AI technologies influences employees' attitude towards the use of AI technologies. Social influence can come from the employee's social network, the media, or the public. It was hypothesised that social influence has a significant and positive influence on attitude towards use of AI technologies.

The research results indicate that social influence has a moderate, positive and significant correlation with attitude towards use of AI technologies (see Table 4.13, p.124). The multiple regression model with the three environmental factors indicates that although social influence has the least effect on attitude towards the use of AI technologies compared to competitive pressure and customer pressure, it has a significant and positive effect on attitude towards use of AI technologies (see Table 4.17, p.134). The results indicate that the more positive social influence employees experience regarding the use AI technologies, the more positive they are in terms of their attitude towards the use of AI technologies. Therefore, the hypothesis that social influence has a significant and positive influence on attitude towards use of AI technologies is supported.

Literature on the significance of social influence in the adoption, attitude, acceptance, and usage of technology has been inconsistent (Kim & Crowston, 2011; Lee et al., 2003; Sun & Zhang, 2006). For example, Ye et al. (2019) find social influence to positively influence intention to use AI devices and Prastiawan et al. (2021) also share similar findings as social influence indicates a positive effect on attitude towards use of mobile banking. On the other hand, Na et al.'s (2022) TAM-TOE research on employees' acceptance of AI technologies in the construction industry find suggestions or influences from others to be disruptive to users' technology acceptance.

The presence of both positive and negative views and experiences regarding the use of AI technologies is noted in literature (Ahn & Chen, 2022; Lichtenthaler, 2020; Tussyadiah & Miller, 2019). These views, negative or positive, are shared by others at work, during various social interactions and via the media, and influence employees' views, perceptions and attitude towards AI technologies, especially those with limited knowledge and experience with AI, who rely on hearsay when it comes to understanding and forming opinions about AI technologies

and its impact. Therefore, it is not surprising that social influence would have an effect on attitude towards the use of AI technologies, given that more than half of the employees in this research did not have experience with using AI technologies (59%).

As more employees gain more knowledge and experience with using AI technologies, one would expect the effect of social influence on attitude toward use of AI technologies to lessen, in line with previous research findings. Venkatesh and Davis (2000) found that the effect of social influence on the acceptance of a new technology lessened over time, due to the fact that as individuals gained more experience with the new technology, they relied more on their experience and less of their social influence when deciding whether or not to accept a new technology.

Given that employees can be exposed to both negative and positive views and experiences regarding the use of AI technologies, it is imperative that management ensures that they provide consistent, credible explanations and better understanding of AI, while keeping employees informed regarding the implementation, use and impact of AI technologies, especially in terms of their jobs and ways of working. Leaving employees to form their own opinions based on narratives from others (internally through peers or externally through their social network and the media) may easily lead to misinformation or less credible and negative information being shared, resulting in employees potentially forming fewer positive attitudes towards the use of AI technologies. Management should therefore be proactive when it comes to controlling the narrative around AI within the organisation.

5.3.4.2 Customer pressure

Given the increased changing needs and demands of customers to have more efficient, quick, and easily accessible good quality and convenient service (Dwivedi et al., 2021; Guo & Polak, 2021; Hentzen et al., 2021), organisations and employees are experiencing pressure to adapt the way they engage with and service customers. Finding ways of using AI technologies to address this pressure can encourage employees to be more open to the use of AI technologies. Therefore, it was hypothesised that customer pressure has a significant positive influence on attitude towards the use of AI technologies.

The results indicate that customer pressure positively and significantly correlates with attitude towards use of AI technologies (see Table 4.13, p.124). The multiple regression model with the three environmental factors indicates that customer pressure has a significant positive effect on attitude towards the use of AI technologies and has the second greatest effect on attitude towards the use of AI technologies (see Table 4.17, p.134). Therefore, the hypothesis that customer pressure has a significant positive influence on attitude towards the use of AI technologies is supported.

These results are not surprising, given that the pressure from customers to provide digital and convenient services is increasing, employees and businesses are motivated to consider ways of meeting these demands through the use of AI technologies (Flavián et al., 2021; Khera et al., 2022). However, in the process of using AI technologies to services customers, employees highlight in their textual responses the need to be cognisant of the fact AI technologies will not completely replace humans in the process of dealing with and servicing customers and that maintaining the human-touch is key (see figure 4.16, p.157 and figure 4.17, p.158).

This is also in line with past research by Lui and Lamb (2018) and Lane and Saint-Martin (2021) that promote the idea of augmented intelligence which encourages collaboration and integration between AI technologies and human-skills. Literature continues to emphasise that the use of AI technologies should not be aimed at replacing employees, since employees are still required and have skills that AI technologies do not, for example, when it comes to being empathetic, and making use of their emotional intelligence when dealing with customers and solving customer problems (Georgieff & Hyee, 2022; Raisch & Krakowski, 2021).

5.3.4.3 Competitive pressure

Competitive pressure in this research refers to the extent to which employees perceive that the pressure to implement and use AI technologies within the organisation comes from competitors. Competitive pressure has been a common factor included in research on environmental factors influencing the attitudes, adoption, and use of new technologies. Financial services organisations continue to experience pressure to adopt new technologies such as AI to keep up with their competitors, be competitive in the market, and more importantly survive (Gupta et al., 2022; Noreen et al., 2023). Based on this, the research

hypothesised that competitive pressure has a significant positive influence on attitude towards the use of AI technologies.

The results indicate that competitive pressure positively and significantly correlates with attitude towards use of AI technologies (see Table 4.13, p.124). The multiple regression model with the three environmental factors indicates that competitive pressure has the greatest effect on attitude towards use of AI technologies amongst all the environmental factors (see Table 4.17, p.134). Therefore, the hypothesis that competitive pressure has a significant positive influence on attitude towards the use of AI technologies is supported.

These research findings are in support of previous research that also find the positive and significant role of competitive pressure in research on AI adoption, attitudes, and/or acceptance of new technology. For example, research by Nguyen et al. (2022) on factors affecting the adoption of artificial intelligence in Vietnam, as well as research by Gupta et al. (2022) on the adoption of AI in the insurance industries in India, find that competitive pressure has a significant positive effect on the adoption of AI technologies.

It can be deducted from these findings that as employees recognise the competitive pressure within their industry, they may view the use of AI technologies to be important for them and their organisation to adopt the use of AI technologies in order to remain relevant and/or be competitive. Employees also have a vested interest in seeing their organisations grow be successful. If their organisations are competitive and performing well in the market, they will also be able benefit through an increased sense of job security and opportunities of career growth within the organisation, for example.

5.4 Key determinants of attitude towards use of AI technologies

The second objective for this research was to determine which technological, individual, organisational, and environmental factors are the most influential determinants of employees' attitude towards the use of AI technologies. This multidimensional approach will enable the analysis and identification of comprehensive and crucial factors contributing to employees' attitudes towards the use of AI technologies, which need to be prioritised and addressed to ensure the successful implementation and use of AI technologies. This will also enable management to proactively put in place and apply relevant strategies and processes to

effectively manage these factors when implementing and using AI technologies. The following research question was stated:

RQ2: Which technological, individual, organisational and environmental factors are the most influential determinants of employees' attitude towards the use of AI technologies?

5.4.1 Identification of key determinants of attitude

Multiple regression was conducted with all the independent variables (technological, individuals, organisational and environmental factors) included in the research model to determine the most influential factors in determining attitude towards the use of AI technologies. The combined effect of all the significant technological, individual, organisational and environmental factors is shown in the final results of the multiple regression model shown on Table 4.19, p.138. The variance explained by these factors is 83%. This shows that the combined effect of all these factors increases the variance explained in attitude towards the use of AI technologies, when compared to the effect of each of these factors (technological factors, 74%; individual factors, 71%; organisational factors, 57% and environmental factors, 68%) on attitude towards use of AI technologies separately. The results support the need to consider broad and comprehensive factors when investigating factors influencing attitude towards the use of AI technologies.

Relative advantage (a technological factor), training support (an organisational factors) and innovative culture (an organisational factors) and social influence (an environmental factor) have an insignificant effect on attitude towards the use of AI technologies and are removed in this final regression model. The most influential technological factors include perceived usefulness and perceived ease of use. The two individual factors, employee wellbeing and organisational justice are influential factors in the model. Management support is the only key influential organisational factor. Competitive pressure and customer pressure are influential environmental factors in the model.

The results of the stepwise regression indicate similar results, as relative advantage, training support, innovative culture and social influence are rejected from the final model (see model 7, Table 20, p.141), due to them being insignificant predictors of attitude towards the use of AI technologies. The stepwise regression model also explains 83% of the variance in attitude towards use of AI technologies, which validated the outcome of both methods employed. From

both the multiple regression and stepwise regression, employee wellbeing ($\beta = .276$) and competitive pressure ($\beta = .275$) are the most influential factors and have strongest effect on attitude towards use of AI technologies. Perceived usefulness ($\beta = .187$), perceived ease of use ($\beta = .170$), management support ($\beta = .146$), organisational justice ($\beta = -.090$) and customer pressure ($\beta = .071$) are ranked respectively in order of their effect and importance in the model.

Although organisational justice has a significant effect on attitude towards use of AI technologies in the regression model with only individual factors ($\beta = .16$, $t = 4.08$, $p < .001$), when entered into the regression model with all the factors (technological, individual, organisational and environmental factors) proposed to be influencing attitude towards the use of AI technologies, organisational justice has a negative beta weight (an opposite sign from its correlation with attitude towards use of AI technologies which is positive), which indicates that organisational justice is a negative suppressor.

Given that organisational justice is also highly correlated with other variables (see correlation matrix in Appendix E) and that leaving it in the model would potentially cause challenges to the reliability of the regression model results, its impact in the regression model was investigated. Removing organisational justice from the regression model has a very small effect on the model in term of change in the variance explained (a decrease of only .003). In addition, organisational justice indicates a coefficient beta of less than 0.1, which means that it has a very small effect in the regression model. The chances of an inverse relationship between organisational justice and attitude towards use of AI technologies although possible, is therefore highly unlikely. For these reasons, organisational justice is left in the model.

It would also appear that when other factors that have a significant effect on attitude towards use of AI technologies are considered in the model, the more employees perceive the organisation to be fair in the implementation and use of AI technologies, the less importance they would place on their own feelings or attitude towards the use of AI technologies. This could be because employees may trust and expect their management to do what is right for them when implementing and using AI technologies, regardless of how they feel about the use of AI technologies.

5.4.2 Summary of key determinants of attitude towards use of AI technologies

The final multiple regression model (see table 4.19, p.138) and stepwise regression analysis (see table 4.20, p.141) indicate that seven out of the eleven factors included in the research model are key determinants of attitude towards use of AI technologies. Figure 5.1 depicts key determinants of attitude towards the use of AI technologies.

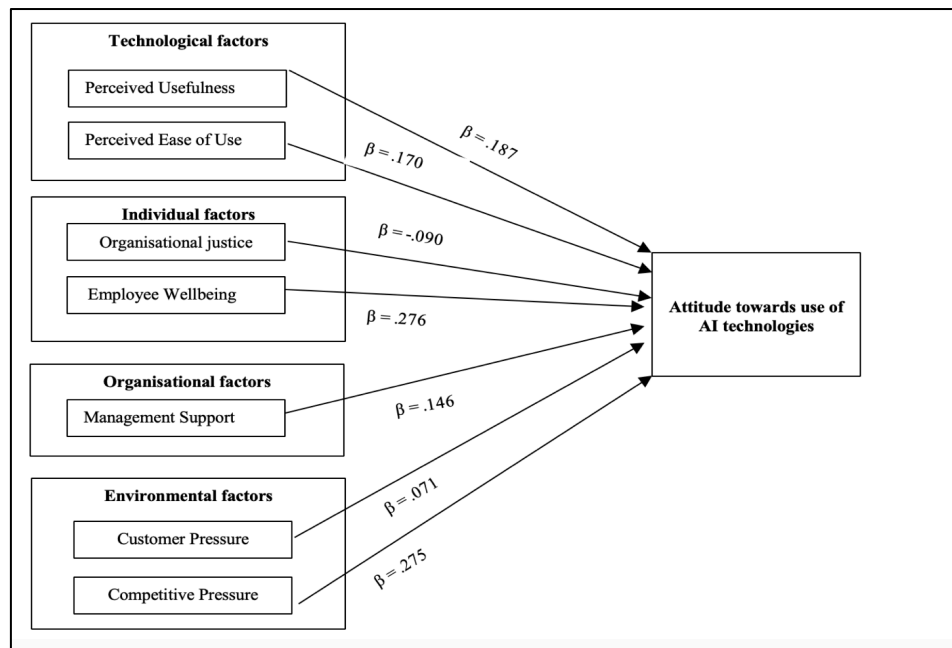


Figure 5.1 Key determinants of attitude towards use of AI technologies

5.5 Attitude and acceptance of AI technologies

The third objective of this research was to investigate the relationship between attitude towards use of AI technologies and acceptance of AI technologies, which despite being key determinants of the success of a new technologies implemented, their relationship has been widely contested. Therefore, the third research question was :

RQ3: To what extent do employees' attitude towards the use of AI technologies influence acceptance of use of AI technologies?

5.5.1 Attitude towards use of AI technologies

Employees attitude towards the use of AI technologies was mostly positive (see Figure 4.12, p.144). However, it is evident that about 38% of the employees have mixed views or uncertainties regarding the use of AI technologies as they mostly selected either the 'neutral' response or the 'somewhat agree' or 'somewhat disagree' response to statements regarding

their attitude towards the use of AI technologies. Despite being anxious and/or unsure about the actual impact of AI, most of the employees indicate excitement and a positive attitude towards the use of AI technologies in their textual responses as well (see Figure 4.15, p.156).

These research findings correspond with Bhattacharjee et al. (2018) who note that in most instances, employees may simultaneously have positive and negative attitudes towards a new technology. Wang et al.'s (2019) research on data scientists' perceptions of the use of AI indicates that although data scientists are concerned about the automation of their jobs, they acknowledge that this is inevitable, and are also positive about working and collaborating constructively with AI technologies. Chiu et al. (2021) also notes from their research that although employees may have concerns regarding the use of AI technologies and its impact, they may also be positive about its use because they expect the use of AI technologies to benefit them and their organisation. The results also reflect what Lichtenthaler (2020) refers to as the complexities of attitudes towards AI technologies, which create a paradox as individuals tend to have both positive and negative attitudes towards AI.

These research findings indicate that most of the employees have a positive attitude towards the use of AI technologies, despite previous research that has found employees' attitude towards the use of AI technologies to be negative. For example, Gnambs and Appel's (2019) research finds that employees' attitudes toward robots across Europe, although once positive, have started to become less positive. Lichtenthaler (2020) notes that negative attitudes towards the use of AI technologies are still dominant in the business environments. Further, given concerns raised in emerging market economies, such as South Africa, in terms of the potential negative impact of AI on job security, privacy, data security, fairness and ethics and the overall society (Arakpogun et al., 2021; Kheira, 2021), the current research findings provide a positive outlook on attitude towards the use of AI technologies, within the context of the research.

All the technological, individual, organisational and environmental factors explain 83% of the variance in attitude towards use of AI technologies (see Table 4.19, p.138). This is higher than previous studies that have investigated factors influencing attitude towards the use of AI technologies. Vasiljeva et al. (2021) and Cao et al. (2021) report that the factors included in

their research explain 56% and 64% of the variance in attitude towards use of AI technologies respectively.

5.5.2 Acceptance of AI technologies

Acceptance of AI technologies has the highest mean scores (see Table 4.12, p.122), which indicates that employees are mostly in agreement with statements indicating acceptance of AI technologies than there are about statements representing other factors in this research. Employees indicate a high level of acceptance of AI technologies, with only 1% indicating some form of resistance towards the acceptance of AI technologies (see Figure 4.13, p. 157).

The current research findings are contrary to findings by Roberts et al.'s (2021) research on the public's attitude and acceptance of AI related technologies in South Africa, which concluded that resistance to AI-related technologies was still high. However, given that their research was based on data collected in 2018, individuals' views may have changed since then. Given the increase in the use of new technologies to digitalise and automate of processes resulting from the impact of the Covid-19 pandemic, some individuals' openness to learn and embrace AI technologies may have increased.

5.5.3 Attitude and acceptance of AI technologies

Despite the attitude-acceptance relationship being contested in literature, this research argues that investigating attitude towards the use of a complex technology such as is AI is key in determining the acceptance of AI technologies. Acceptance of AI technologies contributes to the successful implementation and use of AI technologies. Therefore, the attitude-acceptance relationship was investigated. It was hypothesised that attitude towards the use of AI technologies has a significant and positive influence on the acceptance of AI technologies.

The results show that attitude towards use of AI technologies is positively and significantly correlated with acceptance of AI technologies (see Table 4.29, p.150). The linear regression model indicates that attitude toward the use of AI technologies has a significant and positive effect on the acceptance of AI technologies (see Table 4.30, p.151). The results show that the more positive employees are with regards to the use of AI technologies, the more willing they are to embrace and accept the use of AI technologies. Therefore, the hypothesis that attitude

towards the use of AI technologies has a significant and positive influence on the acceptance of AI technologies is supported.

These findings are in line with research that shows the significant role of attitude in technology acceptance research such as research by Eltayeb and Dawson (2016) and Julianto and Yasa (2019) who also investigated the relationship between attitude and acceptance of a new technologies and found attitude to have a significant positive effect on acceptance of a new technology. Alhashmi et al. (2019), Cao et al. (2021) and Na et al.'s (2022) research also demonstrates the significant role of attitude on behavioural intention (acceptance) to use AI technologies. Despite previous studies that have reported the insignificant effect of attitude on the behavioural intention or acceptance of new technologies (Davis & Venkatesh, 1996; Venkatesh & Davis, 2000; Nath et al., 2013), this research reinforced the role of the attitude constructs as a significant predictor of technology acceptance.

Attitude towards the use of AI technologies explains 80% of the variance in the acceptance of AI technologies. Other research investigating the attitude-acceptance relationship have reported a lower variances in this regard. For example, research by Eltayeb and Dawson (2016) found that attitude explained 38.2% of the variance in the acceptance of personal cloud computing, while Julianto and Yasa (2019) found that attitude explained 63% of the variance in adoption behaviour of an accounting information system. The high percentage of variance explained in this research can be attributed to how acceptance is defined and measured in this research.

Acceptance is defined and measured in different ways, however, it has been referred to as the intention to use a new technology, typically demonstrated by the eagerness and excitement to use the new technology (Karunaratne & Abeyratne, 2020; Taherdoost, 2018). In this research, given that the use of AI technologies is mandatory, and employees would not have the option of whether or not to use the technology, the definition of acceptance of a technology is expanded to include the comprehensive, persistent and continued use of AI technologies, in line with the concept of extended use of discussed by Po-An Hsieh and Wang (2017). As such, acceptance of AI technologies in this research is determined the extent to which employees express openness, willingness and commitment to integrate and embrace AI technologies in their way of working, and continue to use and learn more about AI technologies

If organisations want to be able to fully leverage the potential of AI and gain competitive advantage, the results of this study support the argument that in mandatory settings, the use of AI technologies should not be a tick-box exercise. Employees still need to use the technologies irrespective of their attitude. However, failure to be cognisant of, to address and manage potentially negative attitudes towards the use of AI technologies can result in the suboptimal use of technology, sabotage or misuse of these technologies, as well as destructive or counterproductive behaviours, which will be costly to the organisation and disrupt the effective implementation of this technology (Brown et al., 2002; Lichtenthaler, 2020). Instead, management should continuously evaluate employees' attitude, acceptance, and behaviours towards the use of AI technologies to understand what factors to address and manage to be able to increase employees' positive attitudes and acceptance of AI technologies.

5.6 Moderator effect of experience and job role on attitude and acceptance of AI

Technology adoption and acceptance research has investigated the moderating effect of various demographical variables in their research. The results have been mixed. Given the complex role and nature of AI technologies (Bartolotta & Gritt, 2021; Füller et al., 2022), it is important to understand variables that would influence the relationship between factors included in this research. The fourth objective of this research was to investigate the moderating role of employees' job role and experience with using AI technologies on the attitude and acceptance relationship. The research question to be answered was:

RQ4: To what extent do employees' job roles and employees' experience with using AI technologies moderate the relationship between attitude towards use of AI technologies and acceptance of the use of AI technologies?

5.6.1 Experience with using AI technologies

If employees are given an opportunity to experience using AI technologies, they will be able to get a better understanding of AI, as well as its potential benefits and value (Chiu et al., 2021). This may strengthen their attitude towards the use of AI technologies and their acceptance of AI which will be based on experience and not hearsay. As a result, the relationship between attitude and acceptance of AI technologies is likely to differ based on whether or not employees have experience with using AI technologies.

It was expected that the direct effect of experience on the attitude and acceptance of AI technologies would be strengthened by employees' experience with the use of AI technologies. For this reason, it was hypothesised that employees' experience with using AI technologies moderates the relationship between attitude towards AI technologies and acceptance of AI technologies.

The results of this research indicate that employees' experience with using AI technologies moderates the positive relationship between attitude and acceptance of AI technologies (see Table 4.31, p.153), even though its effect on the attitude and acceptance relationship is small. The more experience employees have with using AI technologies, the more this strengthens the positive effect of their attitude towards use of AI technologies on acceptance of AI technologies. This would suggest that as employees gain more experience with using AI technologies, not only will they be more positive towards the use of AI technologies, but they will also be more accepting of the use of AI technologies. Therefore, despite the small effect that experience has on the attitude-acceptance relationship, the hypothesis that employees' experience with using AI technologies moderates the relationship between attitude and acceptance of AI technologies is supported.

This research confirms the role of experience with using a new technology as a moderator in research on the adoption, attitude and acceptance of new technologies. Given that the use of AI technologies will only continue to grow, management should consider gradually introducing elements of AI into employees' ways of working to enable employees to start experiencing AI first-hand. By doing so, they will not only be addressing the anxiety towards the use of AI technologies and limited understanding of AI but giving employees an opportunity to start experiencing AI and its impact on their way of working, which will enable employees to be able to make informed decisions regarding their attitudes and acceptance of AI.

5.6.2 Job role

Since literature notes that employees are not a homogenous group and that they would be impacted differently with the use of AI technologies (Ivanov et al., 2020; Noponen, 2019), the research aimed to investigate how an employees' job role would influence the relationship between attitude towards use of AI technologies and acceptance of AI technologies. It was

hypothesised that the relationship between attitude towards use of AI technologies and acceptance of AI technologies would be moderated by employees' job roles.

The results of the research indicate a significant difference between an employees' job role and attitude towards use of AI technologies (see Table 4.23, p.145). Similar results were found when investigating the relationship between an employees' job role and acceptance of AI technologies (see Table 4.27, p.149). However, an employees' job role did not influence the relationship between attitude and acceptance of AI technologies (see Table 4.32, p.154). The findings can be interpreted to mean that the effect that employees' attitude towards the use of AI technologies has on their acceptance towards use of AI technologies will not differ based on employees' job roles. The hypothesis that the relationship between attitude towards use of AI technologies and acceptance of AI technologies is moderated by employees' job role is therefore not supported.

Although employees' job roles did not moderate the relationship between attitude and acceptance of AI technologies in this research, the differences and similarities across the employees' different job roles provided insight into employees' attitude and acceptance of AI technologies across the different levels within South African financial services organisations. This is significant because most research on attitude and acceptance of AI has focused on specific groups of employees within the organisation and has not always provided insight into the attitudes and acceptance of AI technologies across different job roles and job levels.

5.7 Revised research model

Figure 5.2 presents the revised research model depicting only significant variables in this research model based on the research results discussed in this chapter, with the beta coefficients from the regression analysis carried out. This research model can be tested further in future research on employees' attitudes and acceptance of AI technologies to determine the significance of these factors in similar industries within emerging market economies, as well as in other industries within this context. In doing so, this will contribute to the current limited research on employees' attitudes towards the use of AI technologies in mandatory settings within emerging market economies.

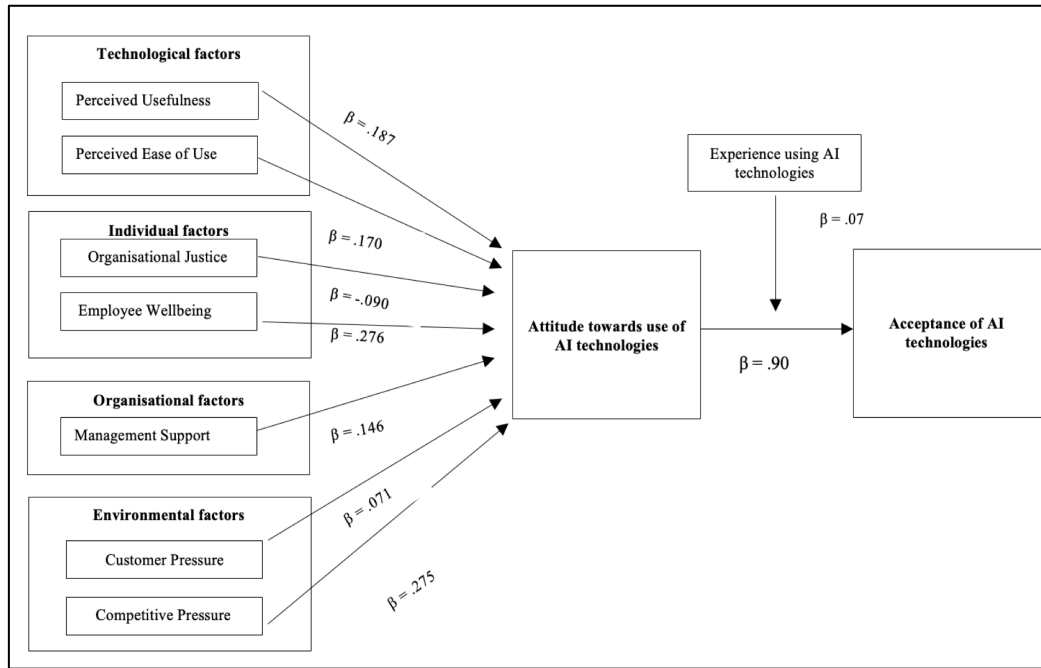


Figure 5.2 Revised research model

5.8 ITOE model for implementation AI

The fifth and final research objective was to use the findings of this research to develop a model that can be used to facilitate the successful implementation and use of AI technologies within organisations. The research question to be answered was research question 5:

RQ5: What model can organisations use to facilitate the successful implementation and acceptance of AI technologies?

Having conducted the research and analysed the results from the research, including the textual responses provided by employees, a model for organisations to consider when implementing AI technologies is proposed. This model includes all factors that positively and significantly influence attitude and acceptance of AI technologies, independently and/or when combined with other factors. Figure 5.3 presents the ITOE (individual, technological, organisational and environmental) model for implementing AI.

Kim and Crowston (2011) proposed three different stages of adoption of a new technology, which include the pre-adoption stage (*examining a technology to consider adopting*), adoption stage (*intention to adopt, purchase and use*) or post-adoption stage (*continued use or abandonment of technology*). Building further on this and incorporating findings from this research, four stages of implementing AI technologies are proposed in the ITOE model. The

four main implementation stages include pre-implementation stage, decision stage, implementation stage and post-implementation stage. Although all the factors influencing attitude towards the use of AI technologies should be considered and managed throughout the different stages of implementing and using AI technologies, main factors to be considered at each stage of the process are listed below in Figure 5.3. A summary of each stage is provided below.

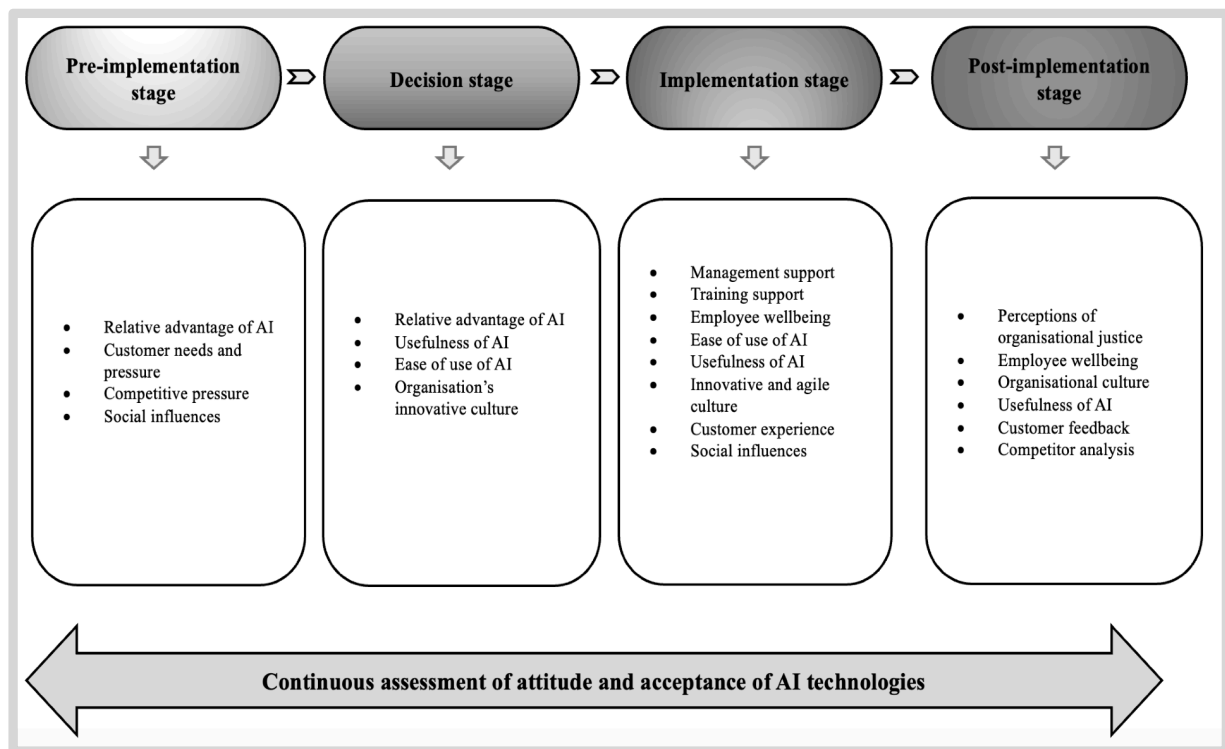


Figure 5.3 ITOE model for implementing AI

5.8.1 Pre-implementation stage

The use of AI technologies continues to grow and become more prevalent in how people live, work and engage with others (Biswas et al., 2020). Therefore, understanding of AI, what it can do, as well as its benefits is key (Mogaji & Nguyen, 2021; Ndoro et al., 2020). Chiu et al.'s (2021) research on employees' pre-adoptive perceptions of AI highlights that the perceived benefits of the AI's capabilities in terms of increased flexibility, reliability, efficiency, and successful integration with other systems is positively related to attitude towards the use of AI technologies. Similar results are reported in this research as the relative advantage of AI has a positive and significant effect on attitude towards use of AI technologies.

Applying a problem driven approach is also key to ensure that the implementation and use of AI technologies is targeted at solving a particular problem. This will also make it easier to

determine its usefulness. Therefore, during the pre-implementation stage, the focus should be on understanding the AI technologies available and the relative advantage or potential benefits of using the AI technologies over current and/or alternative systems.

Given that organisations operate within a broader ecosystem and are enabled as well as inhibited by external and environmental factors (Gupta et al., 2022; Nguyen et al., 2022), being cognisant of external and environmental factors influencing the attitude and acceptance of AI technologies is vital. For example, in line with previous research by for example, Na et al. (2022), Sartori and Bocca (2022) and Ye et al. (2019), this research notes that environmental factors such as customer pressure due to the varying and changing customer needs, competition within the industry and social influence have a significant effect on attitude and acceptance of AI technologies.

Understanding and managing the above will enable management and decision makers to develop appropriate business cases for implementing and using AI technologies. In addition, management should focus on getting employees' buy-in when implementing and using AI technologies and being able to control the narrative regarding the why and how of implementing and using of AI technologies within the organisation, to enable them to be able to deal with any misconceptions from various social influences surrounding AI from the onset. This is especially important given that research shows that social influences can either have a positive or negative effect on attitudes towards the use of AI technologies. Although this research found social influences to have a positive impact on the attitudes and acceptance of AI technologies, Na et al. (2022) found that social influence which include beliefs and suggestions from others have a negative effect on attitude and acceptance of AI technologies.

5.8.2 Decision stage

In making the decision to implement AI within the organisation, it is important to consider the technical aspects and benefits of AI technologies available, as this research shows that technological factors such as perceived usefulness, perceived ease of use and relative advantage have a positive and significant effect on the attitude AI technologies. Investigating and understanding the perceived usefulness, perceive ease of use and relative advantage of the AI technologies is key in determining which type of AI technology to implement as well as to enable organisations to develop and formulate an effective AI strategy. As noted by Pumplun

et al. (2019) and Weinert et al. (2022) an AI strategy is key in providing guidance to the processes, implementation, and use of technologies.

This research shows that an innovative culture has a significant and positive effect on attitude towards use of AI technologies. Given that an organisation's culture is unique to each organisation (Hubbard & Rogers, 2019), during the decision stage, decisions on the how and when the AI technology should be implemented should consider the organisation's readiness for AI technologies as well as the processes, agility and ways of working within the organisation.

As noted in the literature, in mandatory settings, senior management, AI developers and/or IT experts are the ones typically involved in the evaluation and decision making of new technologies (Kar & Kushwaha, 2021), and should consider the perceived usefulness, perceived ease of use, as well as relative advantage of each AI technology available, since they are the decision makers of what AI technologies to implement, how and when. However, as much as possible, organisations are encouraged to be flexible and open to involve and collaborate with the actual users of the AI technologies early on before implementing the new technologies (Raisch & Krakowski, 2021; Siderska et al., 2023). Creating opportunities for employees with limited experience of AI to familiarise, engage and experiment with AI technologies will enable employees to start getting a feel of the technology and gain better understanding of the AI technologies even before it is formally implemented.

5.8.3 Implementation stage

Once the decision to implement the AI technology is made, a process to implement AI within the organisations follows. The successful implementation of innovative technologies within an organisation depends on an effective change management process (Hubbard & Rogers, 2019). Between the pre-implementation and implementation stage, investigating and understanding employees' initial attitude and experiences with using AI technologies, is imperative to ensure that feedback is obtained from the actual users of the AI technologies implemented. The feedback can be used to inform further decisions on how to proceed with the implementation and use of AI technologies.

The extent to which employees using the AI technologies perceive and experience AI technologies implemented to be user-friendly and useful in improving and supporting employees' performance better than previous or alternative systems and technologies used is important to investigate. This is key because the perceptions and experiences of decision makers and actual users of the AI technologies may differ. For example, this research shows that there is significant relationship between employees' job role and attitude towards use of AI technologies and acceptance of AI technologies. Employees in top management/executive roles and those in Professional IT roles share similar views towards the use of AI technologies as they are typically the AI creators and decision makers (Kar & Kushwaha, 2021), which differ from those in middle management, first line management, professional non-IT roles and administrative role, who are mainly the actual users of the system.

Individual factors such as perceptions of organisational justice and employee wellbeing are also significant predictors of attitude towards the use of AI technologies in past research as well as in this research. This emphasises the need for management to be aware of and manage perceptions of fairness and justice with regards to the type of AI to be implemented, by being clear on the intent and objective of implementing AI technologies from the onset, as well ensuring fair processes, communication and transparency throughout the implementation process of AI technologies within the organisation.

In addition, consideration should be given to factors that would impact employees directly such as employees' wellbeing as these would need to be proactively addressed to prevent or manage employees' resistance to the use of AI technologies from the onset. Past research by Cao et al. (2021) as well as this current research highlights the significance of wellbeing concerns. Management should recognise and manage the uncertainties regarding aspects of employees' wellbeing, such as job security, autonomy, stress and anxiety, by ensuring effective communication, fairness and transparency through the implementing and use of AI technologies.

Organisational factors such as management support, training support and an innovative culture have been shown to enable facilitating conditions for the successful implementation of AI technologies (Ghaleb et al., 2021; Qin et al., 2020). Organisational factors have also been identified as significant factors influencing the adoption, attitude and acceptance of AI technologies. The findings of this research concur with previous research as management

support, training support and an innovative culture are all significant predictors of attitude towards the use of AI technologies. Management must therefore provide employees with sufficient guidelines on the use of AI technologies, access to training and resources, as well as opportunities for employees to give feedback on the use of AI technologies. Continuous innovation, collaboration and agility should be embedded in the organisation's way of working. Sufficient training must be provided to enable employees to get a better understanding of AI, as well as be more comfortable, receptive and confident with using AI technologies.

Consideration should also be given to external or environmental factors such as customers and employees' social influences. Analysing the impact of AI technologies is key to ensure that the use of AI technologies meets customers' needs and creates a positive experience for customers (Flavián et al., 2021; Sartori & Bocca, 2022). In addition, as noted earlier, management needs to be mindful of the impact of social influences from colleagues, social media, and significant others which have an influence on employees' attitude and acceptance of AI technologies. This is why Chen et al. (2020) recommends that management engage with employees throughout the implementation process to discuss the AI strategy, process and objective of the implementation and use of AI technologies.

Consideration should also be given to the impact of AI on the different job roles. This research showed a significant difference between employees' job roles and attitude towards use of AI technologies. Similar results were evident in terms of the relationship between employees' job roles and acceptance of AI technologies. This confirms that although all jobs will be impacted by use of AI technologies (Bhargava et al., 2020; Lane & Saint-Martin, 2021), the experiences, attitude, acceptance and impact of AI will differ across different job roles.

5.8.4 Post-implementation stage

Although measuring usage in terms of the number of people using AI technologies gives an indication of the adoption rate, it is more valuable to measure the extended and continued use of AI technologies, especially if organisations want to leverage the potential of AI. Therefore, the focus should not only be on the initial use of AI technologies, but the continued and extended use of AI technologies. This will enable organisations to prevent and manage the potential underuse or misuse of new technologies (Brown et al., 2002). Failure to drive, manage and promote the extended or continued use of technology will result in employees and

organisations failing to leverage fully the potential of AI technologies resulting in an opportunity costs for employees and the organisation (Floridi et al., 2018).

As much as employee's perceptions of organisational justice, employee wellbeing and culture may influence their attitude towards the use of AI technologies, the use of AI technologies also influences employees perceptions of organisational justice, employee wellbeing and culture. Therefore, as employees get used to working with AI technologies, continuous evaluation of the impact of AI technologies on employees and the organisation's way of working is key. Regular market analysis of the organisations' external environment (e.g. customers and competitors) is also essential in continuing to inform the effective implementation and use of AI technologies. Further, the usefulness of the AI technologies implemented should be evaluated to assess whether it is still valuable and serving the intended purpose.

5.8.5 Continuous evaluation of attitude and acceptance of AI technologies

This research shows the significant effect that employees' attitude has on the acceptance of AI technologies. Recognising that employees, as actual users of the system, can make or break the successful implementation and use of AI technologies in mandatory settings is essential. From the onset, and throughout the process, an assessment of employees' attitude and acceptance of AI technologies should be conducted and monitored. Attitude and acceptance of a technology tend to change over time (Fast & Horvitz, 2017), therefore the continuous evaluation of employees' attitude and acceptance of AI technologies crucial.

Using surveys, conducting workshops on AI related topics, as well as having open discussions with teams and individuals to get feedback on their experiences and perceptions of the implementation and use of AI technologies will enable the continuous identification and management of factors that could potentially cause resistance towards the use of AI technologies or inhibit the successful implementation of AI technologies.

5.9 Summary

This chapter provided a discussion of the research findings in relation to the research questions and research objectives. A discussion of the demographic variables, and how they relate to attitude and acceptance of AI technologies was presented. This was followed by a discussion of the results from the hypotheses testing of the effect of each of the technological, individual organisational and environmental factors, on attitude towards use of AI technologies. Key

determinants of attitude towards use of AI technologies were identified. The results of the analysis of the relationship between attitude and acceptance of AI technologies were also discussed, as well as the effect of employees' experience with using AI technologies and employees' job role on the attitude-acceptance relationship. The ITOE model for implementing AI was also presented as discussed. All research questions were answered, and the objectives of the research were met.

CHAPTER 6: CONCLUSION

6.1 Introduction

As the research on attitude and acceptance of AI technologies and its impact is still growing, there is currently uncertainty and inconsistency in literature on this (Cao et al., 2021; de Saint Laurent, 2018; Siderska et al., 2023). Most research has been conducted in developed than in developing or emerging market economies (Ahmad et al., 2020; Georgieff & Hye, 2022). In addition, most of the available research investigating the adoption, attitude and acceptance of AI technologies within organisations has been conducted from the perspective of senior management, IT senior professionals and/or AI experts, who are also typically the AI decision makers (Kar & Kushwaha, 2021), which is the case in mandatory settings. The views of other groups of employees as the users of the AI technologies implemented are limited. Given this and the fact that AI technologies are complex technologies (Hanif, 2021; O'Shaughnessy et al., 2023) there was a need to investigate how AI technologies can be implemented and used effectively within mandatory settings, in emerging market economies.

Therefore, to address the research problems above and contribute to research on the implementation and use of AI technologies, the research set out to investigate and determine factors influencing employees' attitude and acceptance of AI technologies. The research was conducted within a mandatory setting, across employees occupying different job roles/levels in the South African financial services organisations, to be able to capture the views and experiences of not only the AI developers/experts and decision makers, but users of AI technologies as well. Based on the research findings, a model that can be used to facilitate the successful implementation and use of AI technologies in organisations was developed. This chapter provides a summary and conclusion of the research conducted. Theoretical and practical implications as well as recommendations for management and future research are also presented.

6.2 Summary of research findings

A cross sectional survey was carried out to investigate individual, technological, organisational and environmental factors influencing the attitude and acceptance of AI technologies. The research was carried out within the financial services industry in South Africa and 410 valid responses were analysed. Textual responses to the open ended questions, which were provided

by some of the participants, were also analysed and used to substantiate the survey results. The below summarises the research findings.

6.2.1 Factors influencing attitudes towards use of AI technologies

The first objective of the research was to analyse the extent to which the individual, technological, organisational, and environmental factors independently influence employees' attitudes towards the use of AI technologies in the financial services industry in South Africa. The below provides a summary of the research results.

6.2.1.1 Technological factors

Technological factors in this research include perceived usefulness, perceived ease of use and relative advantage. The results show that all three factors have a significant and positive effect on attitude towards use of AI technologies. Perceived usefulness is the strongest predictor of attitude towards use of AI technologies amongst the three technological factors, followed by perceived ease of use and relative advantage. Technological factors explained the highest variance in attitude towards the use of AI technologies, 74% (see Table 4.14, p.127), compared to individual, organisational and environmental factors which were able to explain a variance of 71%, 57% and 68% respectively. Management should therefore consider technological factors (perceived usefulness, perceived ease of use and relative advantage) in the design, selection, implementation and use of AI technologies.

6.2.1.2 Individual factors

Organisational justice and employee wellbeing both have a significant and positive effect on attitude towards the use of AI technologies. However, employee wellbeing has a larger effect on attitude towards the use of AI technologies amongst these two individual factors (see Table 4.15, p.130). These research findings contribute to the limited research on the effect of organisational justice and employee wellbeing on attitude towards use of AI technologies, and support research findings by Cao et al. (2021) that highlight the significance of personal wellbeing concerns on attitude towards the use of AI technologies. The results also highlight the importance of ensuring fairness throughout the implementation and use of AI technologies. If concerns of fairness and employees' wellbeing are not addressed and managed, employees may have negative attitudes towards the use of AI technologies, and fail to leverage the potential of AI technologies.

6.2.1.3 Organisational factors

Despite organisational factors indicating the lowest percentage of explained variance in attitude towards the use of AI technologies as noted above, each of the organisational factors which include management support, training support and innovative culture has a significant and positive effect on attitude towards the use of AI technologies (see Table 4.16, p.132). Management support has the largest effect on attitude towards use of AI technologies amongst these three organisational factors, followed by training support and innovative culture. The results support research findings by Qin et al. (2020) and Gupta et al. (2022) that indicate the significant role of the organisational context in the attitude and adoption of advanced technologies.

Given that each of these organisational factors have a significant effect on attitude towards use of AI technologies, the role of management support throughout the implementation and use of AI technologies is highlighted, together with the need to provide opportunities and support for training to gain experience and better understanding of AI technologies. In addition, creating and enabling an innovative culture that facilitates the successful implementation and use of AI technologies is imperative.

6.2.1.4 Environmental factors

Each of the environmental factors, which include social influence, customer pressure and competitive pressure have a significant effect on attitudes towards use of AI technologies (see Table 4.17, p.134). Amongst these three environmental factors, competitive pressure has the largest effect on employee's attitude towards the use of AI technologies. The research findings support findings by Thowfeek et al. (2020) on the drivers of AI in the banking industry and by Gupta et al. (2022) on the adoption of AI in the insurance industry that environmental factors are significant determinants of AI adoption. The results indicate that employees may be open and positive about using AI technologies when they perceive its use to enable them to successfully manage and meet customer demands and keep up with trends and competitive pressures. In addition, given the various sources of social influences, and the significant impact that social influence has on employees' attitude towards the use of AI technologies, management should focus on being proactive about creating positive narratives within the organisation regarding the implementation and use of AI technologies.

6.2.2 Key determinants of attitudes towards use of AI technologies

The second objective of this research was to determine which technological, individual, organisational, and environmental factors are the most influential determinants of employees' attitude towards the use of AI technologies. This multidimensional approach indicated that all the significant technological, individual, organisational and environmental factors explain variance of 83% in attitude towards the use of AI technologies (see Table 4.19, p.139). This shows that the combined effect of all these factors is higher than the effect of these factors independently. The results support the need to consider broad and comprehensive factors when investigating factors influencing attitude towards the use of AI technologies. The following provides an indication of the key determinants of attitude towards use of AI technologies from the analysis of the combined effect of all the 11 technological, individual, organisational and environmental factors identified to be influencing attitude towards the use of AI technologies.

With regards to the technological factors, perceived usefulness and perceived ease of use are significant and key influential determinants of attitude towards use of AI technologies. However, relative advantage is not a key determinant of attitude towards use of AI technologies when all the 11 factors are analysed together. This result could be explained by the fact that in mandatory settings, employees generally have limited say or input in the decision to adopt and implement AI technologies. As a result, their perceptions of the relative advantage of using AI technologies over the old or current systems or alternative technologies may be less relevant. Employees may be more concerned about and prioritise other technological, individual, organisational and environmental factors.

In terms of the individual factors, employee wellbeing and organisational justice are both identified as key influential determinants of attitude towards use of AI technologies. In addition, employee wellbeing is identified as the most significant and key determinant of attitude towards the use of AI technologies amongst all the individual, technological, organisational and environmental factors.

From the three organisational factors, management support is the only significant and key influential factor in determining attitude towards the use of AI technologies. Training support and innovative culture are not key determinants of attitude towards use of AI technologies when all the 11 factors are analysed together. This may indicate that employees may be more concerned about the more immediate impact of AI technologies on their basic needs and

concerns, such as their wellbeing, job security, and other support provided, than the availability of training. Further, given that most organisations in the financial services industry tend to be bureaucratic, hierarchical, less flexible, with some departments working in silos (Kruse et al., 2019), employees may be used to this way of working, making the need for a flexible and innovative culture less important in determining their attitude towards use of AI technologies when other technological, individual, organisational and environmental factors are considered.

When investigating key determinants of attitude towards the use of AI technologies from all factors (technological, individual, organisational and environmental) identified to be influencing attitude towards the use of AI technologies, competitive pressure and customer pressure are key influential environmental factors in determining attitude towards the use of AI technologies. Competitive pressure is the second most influential factor amongst all the technological, individual, organisational and environmental factors. Social influence is not identified as a key determinant of attitude towards use of AI technologies when all the 11 factors are analysed together. It would appear that when taking into account other factors that influence employees attitude towards the use of AI technologies, employees may focus on their own experiences and perceptions of AI technologies and less on external influences from others regarding their views on the use of AI technologies.

In summary, when investigating key determinants of attitude towards the use of AI technologies from all factors (technological, individual, organisational and environmental) identified to be influencing attitude towards the use of AI technologies, the results from both the multiple regression and stepwise regression indicate that employee wellbeing, competitive pressure, perceived usefulness, management support, perceived ease of use, organisational justice and customer pressure are key determinants of attitude towards the use of AI technologies. Relative advantage (a technological factor), training support and innovative culture (organisational factors) and social influence (an environmental factor) are not.

6.2.3 Attitude and acceptance of AI towards AI technologies

The third objective was to investigate the attitude and acceptance relationship, specifically in terms of the extent to which employees' attitude towards the use of AI technologies influences their acceptance of AI technologies. The results indicate that attitude towards use of AI technologies has a significant and positive influence on the acceptance of AI technologies (see Table 4.30, p.151). The more positive employees are towards the use of AI technologies, the

more accepting there are towards its use. Therefore, attitude towards use of AI technologies is a significant predictor of acceptance of AI technologies.

The research findings also indicate that gender, experience with using AI technologies and employees' job role each have a statistically significant relationship with attitude towards the use of AI technologies, as well as with acceptance of AI technologies. Males, those with experience using AI technologies and those in IT or senior management roles, are more likely to be positive and willing to accept the use of AI technologies than their counterparts. Age is neither related to attitude towards the use of AI technology nor related to acceptance of AI technologies.

From the research findings, employees report positive attitudes and high levels of acceptance of AI technologies within South African financial services organisations. A positive shift in employees attitudes and acceptance of AI technologies may be imminent, as some of the previous literature and research had highlighted the prevalence of negative attitudes and resistance to the use of AI related technologies (Lichtenthaler, 2020; Roberts et al., 2021). In addition, these results could be attributed to the fact that since the financial services industry has generally been regarded as an industry that is quick to adopt new technologies (Guo & Polak, 2021; Mogaji & Nguyen, 2021), the evidence of positive attitudes and high levels of acceptance of AI technologies is therefore not surprising.

The Covid-19 pandemic challenged and changed the way people live, work, interact with each other, as well as interact with advanced technologies such as AI technologies, which played a key role in enabling individuals and organisations to do things they needed to do virtually. Sheth (2020) and Biswas et al. (2020) also note that the COVID-19 pandemic shifted businesses' strategies to invest in the use of AI technologies in doing business and servicing customers. Gupta et al. (2022) and Noreen et al. (2023) also concur with this and note that the global pandemic motivated companies to fast track and prioritise their digitalisation and automation plans to use AI technologies in order to be able to survive and remain competitive in their industries. This could also explain the positive attitudes and acceptance of AI technologies amongst participants in this research.

Despite employees in this research reporting positive attitudes towards the use of AI technologies and high levels of acceptance of AI technologies, management should use the

research findings to proactively address and manage the technological, individual, organisational and environmental factors identified in this research as influencing attitude and acceptance of AI technologies. Ivanov et al. (2020) gave a similar recommendation to management and urged management to not adopt a false sense of complacency given that the results of their research indicated that employees had a low fear of automation. Instead, management is encouraged to proactively work together with their employees to ensure the successful implementation and use of AI technologies.

6.2.4 Moderating effect of experience and job role on attitude and acceptance of AI

The fourth objective of this research was to investigate the moderating effect of employees' job role and employees' experience with using AI technologies on the attitude-acceptance relationship. The results of this research indicate that the relationship between employees attitude towards the use of AI technologies and the use of AI technologies is moderated by employees' experience with using AI technologies (see Table 4.31, p.153), but not by employees' job roles (see Table 4.32, p.154).

6.2.5 ITOE model for implementing AI

The fifth objective of this research was to use the research findings to develop a model that can be used to facilitate the successful implementation and use of AI technologies within organisations. Based on the research findings, a four stage ITOE model for organisations to use when implementing and using AI technologies was developed (see Figure 5.3, p.190). The model highlights ITOE factors, which include individual, technological organisational and environmental factors to consider during each phase of implementing and using AI technologies. The importance of continuously evaluating employees attitudes and acceptance of AI technologies throughout the process is highlighted. Overall, the model provides guidelines to enable management to consider broad and comprehensive factors that not only influence employees' attitude and acceptance of AI technologies, but the successful implementation and use of AI technologies.

6.3 Theoretical and practical implications

The contribution of this research is highlighted in the theoretical and practical implications noted below.

6.3.1 Theoretical implications

First, this research highlights the need to consider a multidimensional perspective that considers broad factors influencing the attitude and acceptance of AI technologies when investigating complex technologies such as AI technologies. However, the principle of parsimony should still be maintained.

Second, the inclusion of individual factors such as perceptions of organisational justice and employee wellbeing into the extended TAM and TOE frameworks to provide a comprehensive analysis of factors influencing attitude and acceptance of new technologies which was done in this research is still novel to TAM and TOE research. However, the research findings highlight the need to include such factors in TAM-TOE research.

Third, the inclusion of broad and relevant factors increases the explanatory power of the extended TAM and TOE framework. This was also evident in that factors included in this research were able to explain more variance in attitude towards the use of technologies when combined (83%), than when addressed and analysed separately (highest variance was 74% for technological factors).

Fourth, the results of this research indicate that the technological, individual, organisational and environmental factors included in this research are able to explain a high variance in attitude towards the use of AI technology (83%). A variance lower than 60% is generally regarded as weak (Ozili, 2023).

Fifth, as indicated in the literature review and the discussion of the research findings, the role of the attitude construct in technology acceptance research has been widely contested, as well as the attitude-acceptance relationship. As noted in the literature review in Chapter 2, the attitude construct was removed from later extensions of the TAM because it was found to be an insignificant predictor of behavioural intention/acceptance of technology (Brown et al., 2002; Hwang et al., 2016; Sun & Zhang, 2006). The research highlights the significant role that attitude plays in the adoption, implementation and use and acceptance of AI technologies, since attitude towards use of AI technologies was found to significantly influence acceptance towards use of AI technologies.

Sixth, the moderating effect of employee's job role and experience with using AI technologies included in this extended TAM and TOE model addresses the criticism and limitation of the TAM model not including moderating factors in its model (Sun & Zhang, 2006). Lastly, acceptance of AI technologies has been defined and measured in different ways. This research extends the definition and measurement of the acceptance construct to include behaviours that indicate the continued and extended learning, application and use of AI technologies, specifically in mandatory settings. The definition provides a basis for a comprehensive analysis and interpretation of the acceptance and continued use of new technologies.

6.3.2 Practical implications

First, this research was able to identify technological, individual, organisational and environmental factors that influence attitude towards use of AI technologies. If these factors are not proactively managed, they may contribute to and reinforce any negative attitudes towards use of AI technologies present. Negative attitudes towards the use AI technologies are detrimental to an organisation, since they may result in employees underusing or misusing AI technologies, which inhibits the successful implementation and use of AI technologies (Floridi et al., 2018), and prevent employees and organisations from leveraging fully the potential of AI technologies.

Second, this research highlights and confirms that as noted by Noponen (2019), employees should not be treated as a homogeneous group when investigating views or impact of AI technologies. Given that all employees will be impacted by the use of AI technologies in one way or the other, understanding how employees' different roles may be influenced by the use of AI technologies can enable both management and employees to be proactive about upskilling on AI technologies and to ensure AI readiness.

Third, the research findings highlight the importance of investigating attitude towards use of AI technologies as this has a direct effect on the acceptance of AI technologies. Management is therefore urged to focus on effectively managing factors influencing attitudes towards the use of AI technologies to enable employees to be positive towards the use of AI technologies, as this would limit resistance towards the use of AI technologies.

Fourth, the research contributes to limited AI research in emerging market economies, and develops the ITOE model for implementing AI technologies. The use of this model can prevent

the need to copy models from developed countries that are then used in developing or emerging market economies.

6.4 Recommendations from the research

Based on the research findings, the following recommendations to improve employees' attitude and acceptance of AI technologies, as well as the overall implementation and use of AI technologies are presented.

- Providing support and assistance related to training and understanding of AI technologies is crucial. This will enable employees to learn and gain experience with using AI technologies. Training and understanding of AI technologies will also help address some of the potential fears, concerns and mixed-views and misconceptions surrounding AI, which if left unaddressed, may results in resistance towards the use of AI technologies.
- Clear explanation, open communication and consistency around the implementation and use of AI technologies, as well as ensuring fairness throughout the implementation and use of AI technologies is also important as it contributes to understanding and alignment regarding the implementation and use of AI technologies within the organisation.
- Given the significant effect of technological factors on attitude towards use of AI technologies, when sourcing and deciding on AI technologies to implement, management should consider the usefulness, ease of use and relative advantage of the AI technology. These are factors that can be considered in the design, development and selection of AI software and tools
- Management should make an effort to become aware of and address concerns that impact employees wellbeing (job security, autonomy, career growth, work stress), which is a key determinant of attitude towards use of AI technologies. Personal wellbeing concerns could negatively impact not only the attitude towards use of AI technologies, but inhibit the successful implementation and use of AI technologies.
- Management support is a key determinant of attitude towards use of AI technologies. Effective leadership and management support throughout the implementation and use of AI technologies is key. Management also plays a critical role in the development, communication, translation, and implementation of the AI strategy. As such, organisations should ensure that they have capable management to facilitate this.
- Developing innovative, flexible and agile and collaborative cultures and processes is key to enable experimentation, effective implementation and use of AI technologies. This will

also enable organisations to adapt and adjust to customer and competitive pressures, which are key in influencing attitude and acceptance of AI technologies.

- This research indicates that employees' attitudes towards the use of AI technologies are influenced by environmental factors such as customer pressure, competitive pressure and social influence. Using AI technologies to digitalise and automate processes will enable employees to better meet customer demands in this digital driven world, as well as keep up with technological trends, adjust to customer pressures in the market and gain competitive advantage. In addition, management should be proactive and clear in terms of communicating the AI strategy, as well as the implementation process so that employees do not rely on hearsay regarding the organisation's plans where AI is concerned.

6.5 Future research

By integrating and extending the TAM and TOE framework, this research hoped to address the limitations with the TAM and TOE framework. Each of the 11 technological, individuals, organisational and environmental factors have a positive effect on the attitude towards the use of AI technologies.

However, when combining all these factors to determine key influential determinants of attitude towards use of AI technologies, 7 of the 11 factors are identified as key and influential determinants of attitude towards use of AI technologies. Attitude has a significant effect on acceptance of AI technologies. Experience with using AI technologies moderates this attitude-acceptance relationship, while employees' job roles do not. A revised research model including the key influential determinants of attitude towards use of AI technologies, attitude towards use of AI technologies, acceptance of AI technologies, and experience using AI technologies as a moderating variable to the attitude-acceptance relationship, as depicted in Figure 5.2, p.188 can be validated in similar future research as well as in other industries and contexts, e.g. voluntary settings or developed countries.

Although the online survey attempted to capture more understanding of employees' attitude and factors to consider when implementing AI technologies by including open-ended questions in the questionnaire, the nature and format of the online survey did not enable employees to explain and elaborate substantively, making the data difficult to analyse and interpret. Responses were one-word responses or short phrases. Further studies can consider a qualitative research approach, that enables employees to explain and provide deeper understanding of

employees' attitude and acceptance, as well as identify additional factors influencing their attitude and acceptance of AI technologies.

Given that attitudes towards AI technologies has been shown to change over time (Fast & Horvitz, 2017), future research can conduct a longitudinal study to assess changes in attitude and acceptance of AI technologies over time.

The ITOE model for implementing AI that was developed as an outcome of this research can also be tested in future research on the adoption, attitude, and acceptance of AI technologies in various contexts. This could be within mandatory settings in other emerging market economies, as well as in other industries other than the financial services industry, to enable the validation and improvement of the ITOE model. In addition, the model can also be tested in voluntary settings, where users have a choice on whether or not to use AI technologies, as this will make it possible to determine the extent to which this model would be applicable in such settings.

6.6 Concluding remarks

AI is still in the early stages (Tjebane et al., 2022), and there is no one-size-fits all approach to successfully implement and use it (Füller et al., 2022). However, investigating attitude and acceptance of AI technologies will not only enable organisations to prepare, implement and use AI effectively, but will also enable organisations that already work with AI find better ways of increasing their ability to leverage the full potential of AI. Understanding factors to be managed that impact employees' attitude and acceptance of AI technologies is not only crucial for the successful implementation and use of AI technologies but will enable the acceleration of the growth in the use of AI technologies.

This research set out to investigate and determine factors influencing employees' attitudes and acceptance of AI technologies within mandatory settings, in the South African financial services industry. Overall, the research finds that most employees are positive about the use of AI technologies and are embracing and accepting the use of AI technologies. It is evident that the successful implementation and use of AI technologies should consider technological, individuals, organisational and environmental factors included in this research. The significant influence of employees' attitude in technology acceptance is supported. The ITOE model for

implementing AI technologies is developed to facilitate the effective implementation and use of AI technologies was presented.

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APPENDIX A: PERMISSION LETTER

Dear **Name of senior manager/departmental manager**

I am currently a PhD student at Wits Business School, at the University of Witwatersrand. I am seeking permission to conduct my research in your department or organisation.

The research is titled *Attitude and acceptance of Artificial Intelligence (AI) technologies in the South African financial services industry* (which would include insurance, banking, asset/wealth management, financial advisory or regulatory/compliance and risk management) under the supervision of Dr Christoph Maier.

The research will entail conducting a survey in the form of an online questionnaire to be distributed to employees in your organisation. Individuals can take part in the survey whether they currently use AI related technologies in doing their work. The questionnaire will take between 15-20 mins to complete. Participants will be asked to give their consent before taking part in the survey. No employee will be required to provide their name. Each response will be completely anonymous, and confidentiality is guaranteed. Employees will be asked to provide some demographic information, which will be used purely to establish patterns between different demographic groups. Individual privacy will also be maintained in all published and written data resulting from the study. Participation will be completely voluntary and involves no risk, penalty, or loss of benefits whether an employee participates. Participants may withdraw from the survey at any stage. The results will be communicated in my PhD dissertation. Nonidentifiable information of the employees and organisations participating in this research this be collected in the research survey or include in the research report. A copy of this will be made accessible.

I therefore request permission in writing to have employees in your department or organisation take part in this survey. The permission letter should please be on your organisation's headed paper, signed and dated, and specifically referring to myself by name and the title of my study.

Please let me know if you require any further information.

I look forward to your response as soon as is convenient.

Thank you in advance.

Regards
Ruth Wotela

APPENDIX B: QUESTIONNAIRE

Questionnaire on attitude and acceptance of the use of AI technologies

This survey is for academic purposes only. All information that is collected in this study will be treated with confidentiality. At no time will the names of any individual or organisation be identified.

Instructions: Please indicate your response to the following questions by clicking on the appropriate response. Your responses will be recorded automatically and sent directly to the researcher.

Demographic information

1. Please indicate your gender

☐	Male	☐	Female	☐	Non-binary/third gender	☐	Prefer not to say
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2. Please indicate your age group

☐	18 – 30 years	☐	31 – 40 years	☐	41 – 50 years	☐	51 – 50 years	☐	>60
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3. Please select the role that mostly describes you in the organisation.

☐	Top management/executive	☐	Senior Manager of a business unit/division	☐	Middle
☐	Manager of projects or processes	☐	Team Lead/Supervisor	☐	Professional (IT – related)
☐	Professional (non-IT related)	☐	Administrative		

4. Which of the following best describes the main services provided by your organisation as a financial services institution?

☐	Short-term insurance (e.g. car, home, cell phone, travel insurance)
☐	Long-term insurance (e.g. life insurance, pension, disability cover, funeral policies)
☐	Banking (e.g. retail, commercial, investment, mutual)
☐	Asset management
☐	Wealth management
☐	Financial advisory
☐	Regulatory, compliance and risk management

5. Please select all the business applications of AI technologies that currently apply or would apply in your organisation

☐	AI technologies applied in the process of credit vetting, scoring and decisions
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☐	AI technologies used to analyse data, provide insights, and make recommendations/predictions
☐	AI technologies such as chatbots/virtual assistants used to engage customers
☐	AI technologies used to detect fraudulent activities and/or cybersecurity attacks
☐	AI technologies used for document analysis and processing
☐	AI technologies used to authenticate and authorise users
☐	AI technologies used to enhance the automation of workflow processes
☐	Other (please specify) (8)

6. Do you have experience with using AI related technology to assist with your work?

☐

Yes

☐

No

Please indicate your views towards the use of AI technologies within your organisation

	Strongly Disagree	Disagree	Somewhat disagree	Neutral	Somewhat Agree	Agree	Strongly Agree
<i>Q7. Please indicate the extent to which you think the use of AI technologies enhances (would enhance) your personal or job performance</i>							
I find AI technologies useful in doing my work							
Using AI technologies would help me finish tasks quicker							
Using AI technologies enhances my job performance							
Using AI technologies makes it easier for me to do my work							
<i>Q8. Please indicate the extent to which you think using AI technologies will be useful in doing your work</i>							
I find AI technologies easy to use (user-friendly)							
It will be easy for me to become skillful at working with AI technologies							
The AI technologies we use are clear and understandable							
I do not get frustrated when working with AI technologies							
<i>Q9. Please indicate the extent to which you think using AI technologies is beneficial</i>							
AI technologies enable more efficient processes and ways of working							
Using AI technologies enables better integration of our processes and services							
Using AI technologies gives me greater control over my work							
There are more advantages than disadvantages to using AI technologies							
<i>Q10. Please indicate the extent to which you feel the application and use of AI technologies is done fairly</i>							
The use and application of AI technologies in the organisation is explained to me clearly							
The implications of the use of AI technologies on my work has been discussed with me clearly							
I am able to express my views and concerns regarding the use of AI technologies							
The use of AI technologies has been applied consistently within the organisation							
Overall, the implementation and use of AI technologies has been fair							
<i>Q11. Please indicate the extent to which you feel using AI technologies has on your professional and overall well-being</i>							
Using AI technologies contributes positively to my job satisfaction							
Using AI technologies enhances my career development opportunities							
Using AI technologies makes my work less strenuous							
Using AI technologies enables me to engage and collaborate better with others							
Using AI technologies reduces autonomy in my work							
Using AI technologies make me feel anxious and/or stressed							

I think my job could be replaced with AI technologies							
Q12. Please indicate your views of the support from management towards the use of AI technologies							
Management provides clear guidelines on the use and implementation of AI technologies							
Management supports training on the use of AI technologies							
Management provides the necessary access to resources and software needed to make use of AI technologies							
Management seeks feedback on the use of AI technologies							
Q13. Please indicate your views on training provided on the use of AI technologies in the organisation							
The organisation provides training on the use of AI technologies							
Training provided helps me understand AI technologies better							
Training provided gives me confidence to use AI technologies in my work							
I am more receptive to using AI technologies because of the training I have received							
Q14. Please indicate your views of the culture of the organisation towards the use of AI technologies							
Our culture is flexible and agile							
Our culture is innovative and supports the use of new technologies such as AI							
Our culture supports collaboration across different areas of the organisation using AI technologies							
Our culture enables us to effectively integrate AI technologies in our way of working							
Q15. Please indicate the extent to which others' beliefs influence your attitude towards the use of AI technologies							
People close to me positively influence my views towards using AI technologies.							
People who are important to me think that it is good for me to use AI technologies							
The media positively influences my views on the use of AI technologies							
Q16. Please indicate your views on the influence that customers have on the use of AI technologies							
Our customers expect us to use AI technologies in servicing them							
Using AI technologies improves the products and services we offer our customers							
The use of AI technologies helps us retain our customers							
The use of AI technologies helps us attract more customers							
Q17. Please indicate your views on the influence that competitors have on the use of AI technologies							
The use of AI in our industry puts pressure on us to use AI technologies							
Most of our competitors are using AI technologies							
I think our competitors are doing well because they use AI technologies							
Using AI technologies enables our organisation to be competitive							
Q18. Please indicate your attitude towards the use of AI technologies							
I like using AI technologies in doing my work							
Using AI technologies makes my work interesting							
I feel positive about using AI technologies							
I see value in using AI technologies in doing my work							
Overall, I am in favour of the use of AI technologies in the organisation							
Q19. Please indicate your views on your willingness to continue using AI technologies							
I will continue to find ways of making use of and integrating the use AI technologies in my work							
I will continue to learn and increase my knowledge of AI technologies							
I will provide support to others using of AI technologies in their work							
I will recommend the use of AI technologies to others							
It is valuable for me to learn more about AI technologies even when it may not be compulsory/mandatory							
Q20. How would you describe your overall attitude towards the use of AI technologies in doing your work?							
Q21 What factors do you think should be taken into account when using AI technologies in doing your work?							
Q22 What factors do you think should be taken into account when using AI technologies in your organisation?							

APPENDIX C: PARTICIPANTS INFORMATION NOTE

Dear Participant,

My name is Ruth Wotela. I am busy with my PhD in the field of Artificial Intelligence (AI) at Wits Business School, at the University of the Witwatersrand, Johannesburg. I am conducting research on employee's attitude and acceptance of Artificial Intelligence technologies within South African financial services organisations under the supervision of Dr Christoph Maier.

Whether or not you currently use AI technologies in doing your work, I request your assistance in taking part in this survey in order to indicate your attitude and acceptance towards the use of AI technologies (e.g. chatbots; robotic or intelligence process automation; speech or visual recognition; machine learning and natural language processing). The questionnaire should take no longer than 20 minutes to complete.

You are not required to provide your name, so your responses are completely anonymous, and confidentiality is guaranteed. No one from the company will see your responses or the completed questionnaires. You are required to please provide some demographic information, which is used purely to establish patterns between different demographic groups. Your participation is completely voluntary and involves no risk, penalty, or loss of benefits whether or not you participate. You may withdraw from the survey at any stage.

The research has been approved by the University Human Research Ethics Committee (Non-Medical); you are welcome to contact telephone +27(0) 11 717 1408, e-mail hrecnon-medical@wits.ac.za

Thank you in advance.

Yours sincerely,

Researcher: Ruth Wotela Email: ruth.wotela1@students.wits.ac.za
Supervisor: Dr Christoph Maier Email: christoph.maier@comazo.de

☐ Yes I consent

☐ No I do not consent

APPENDIX D: ETHICS CLEARANCE CERTIFICATE



Research Office

HUMAN RESEARCH ETHICS COMMITTEE (NON-MEDICAL)
R14/49 Wotela

CLEARANCE CERTIFICATE

PROTOCOL NUMBER: H21/06/39

PROJECT TITLE

Attitude and acceptance of Artificial Intelligence technologies
in the South African financial services industry

INVESTIGATOR(S)

Mrs R Wotela

SCHOOL/DEPARTMENT

Wits Business School/

DATE CONSIDERED

18 June 2021

DECISION OF THE COMMITTEE

Approved
Risk Level: Minimal

EXPIRY DATE

14 September 2024

DATE

09 November 2022

CHAIRPERSON



(Professor J Watermeyer)

cc: Supervisor : Dr C Maier

DECLARATION OF INVESTIGATOR(S)

To be completed in duplicate and **ONE COPY** returned to the Secretary at Room 10004, 10th Floor, Senate House, University. **Unreported changes to the application may invalidate the clearance given by the HREC (Non-Medical)**

I/We fully understand the conditions under which I am/we are authorized to carry out the abovementioned research and I/we guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I/we undertake to submit an amendment of the protocol to the Committee. **I agree to completion of a regular progress report. For Minimal and Low studies, this is due annually on 31 December. For Medium and High Risk studies, this is due twice annually on 30 June and 31 December.**



Signature

10 / 11 / 2022

Date

PLEASE QUOTE THE PROTOCOL NUMBER ON ALL ENQUIRIES

APPENDIX E: CORRELATION MATRIX

Spearman's rho		Perceived usefulness	Perceived ease of use	Relative advantage	Organisational justice	Employee wellbeing	Management support	Training support	Innovative culture	Social influence	Customer pressure	Competitive pressure	Attitude	Acceptance
Perceived usefulness	Correlation	1.000	.761**	.820**	.638**	.757**	.599**	.576**	.496**	.500**	.629**	.638**	.790**	.732**
	Coefficient													
	Sig. (2-tailed)		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Perceived ease of use	N	410	410	410	410	410	410	410	410	410	410	410	410	410
	Correlation	.761**	1.000	.764**	.663**	.769**	.629**	.591**	.531**	.524**	.611**	.637**	.793**	.719**
	Coefficient													
Relative advantage	Sig. (2-tailed)	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	410	410	410	410	410	410	410	410	410	410	410	410	410
	Correlation	.820**	.764**	1.000	.690**	.794**	.668**	.623**	.585**	.571**	.630**	.668**	.791**	.726**
Organisational justice	Coefficient													
	Sig. (2-tailed)	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	410	410	410	410	410	410	410	410	410	410	410	410	410
Employee wellbeing	Correlation	.638**	.663**	.690**	1.000	.694**	.722**	.672**	.612**	.625**	.589**	.583**	.662**	.619**
	Coefficient													
	Sig. (2-tailed)	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
Management support	N	410	410	410	410	410	410	410	410	410	410	410	410	410
	Correlation	.599**	.629**	.668**	.722**	.692**	1.000	.654**	.619**	.554**	.532**	.551**	.701**	.634**
	Coefficient													
Training support	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001	<.001
	N	410	410	410	410	410	410	410	410	410	410	410	410	410
	Correlation	.576**	.591**	.623**	.672**	.659**	.654**	1.000	.577**	.584**	.525**	.588**	.653**	.593**
Innovative culture	Coefficient													
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001	<.001	<.001
	N	410	410	410	410	410	410	410	410	410	410	410	410	410
Social influence	Correlation	.500**	.524**	.571**	.625**	.600**	.554**	.584**	.580**	1.000	.584**	.612**	.596**	.509**
	Coefficient													
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001		<.001	<.001	<.001	<.001
	N	410	410	410	410	410	410	410	410	410	410	410	410	410

Customer pressure	Correlation	.629**	.611**	.630**	.589**	.623**	.532**	.525**	.505**	.584**	1.000	.695**	.676**	.665**
	Coefficient													
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	.	<.001	<.001	<.001
	N	410	410	410	410	410	410	410	410	410	410	410	410	410
Competitive pressure	Correlation	.638**	.637**	.668**	.583**	.663**	.551**	.588**	.525**	.612**	.695**	1.000	.748**	.680**
	Coefficient													
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	.	<.001	<.001
	N	410	410	410	410	410	410	410	410	410	410	410	410	410
Attitude	Correlation	.790**	.793**	.791**	.662**	.835**	.701**	.653**	.584**	.596**	.676**	.748**	1.000	.875**
	Coefficient													
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	.	<.001
	N	410	410	410	410	410	410	410	410	410	410	410	410	410
Acceptance	Correlation	.732**	.719**	.726**	.619**	.750**	.634**	.593**	.523**	.509**	.665**	.680**	.875**	1.000
	Coefficient													
	Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	.
	N	410	410	410	410	410	410	410	410	410	410	410	410	410