Adoption of custom artificial intelligence models in South African small and medium-sized enterprises

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DECLARATION

I, **Yanga Mdingi**, hereby declare that this proposal for the Masters of Business Administration submitted to the Wits Business School at the University of Witwatersrand has not been submitted previously for any degree at this or another university. It is original in design and in execution, and all reference material contained therein has been duly acknowledged.

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ABSTRACT

This study quantitatively investigates the potential adoption of custom AI models in South African SMEs using the Technology-Organization-Environment (TOE) framework. The adoption of AI in organizations is influenced by technological, organizational, and environmental elements, which can be examined using the TOE framework to understand the complexities of AI adoption. This research is guided by a post-positivist philosophical perspective to addresses the question: What factors impact the adoption of custom AI models in South African SMEs? The study employed a quantitative research design and survey methodology to collect data from South African SMEs. Participants were selected through a snowball sampling method, and data was gathered using a self-administered online questionnaire based on TOE model constructs, with each item assessed using a five-point Likert scale to capture participant opinions and attitudes.

Statistical analysis, including Pearson correlation and hierarchical regression, revealed significant positive relationships between factors such as top management support, technological competence, competitive pressure, and external support, and the adoption of custom AI models. While perceived compatibility does not have a direct significant effect on AI adoption, the study revealed that it moderates the influence of top management support and technological competence on custom AI adoption. Practical recommendations of this study include prioritizing executive education, developing leadership training programs, recruiting and retaining technologically competent individuals, investing in employee training programs, leveraging external support from technology vendors and partners, recognizing the strategic importance of AI in competitive industries, and balancing efforts on perceived compatibility and management support. The findings provide actionable recommendations for enhancing AI adoption in South African SMEs, helping them overcome adoption challenges and improve competitiveness and sustainability in the local and global markets.

KEYWORDS

Custom AI, AI adoption, SMEs, factors influencing adoption, technological readiness, organizational readiness, environmental readiness, TOE.

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1. Chapter 1: Introduction

1.1. Purpose of the study

The purpose of this research is to conduct a quantitative study to determine factors influencing the potential adoption of custom Artificial Intelligence (AI) Models in South African Small and Medium-sized Enterprises (SMEs). The study adopts Technology-Organization-Environment (TOE) theoretical framework to investigate the factors influencing the potential adoption of custom AI models in South African SMEs.

1.2. Background and Context of the Study

Kalidas et al. (2020), state that SMEs make up around 98% of all enterprises in South Africa, provide roughly 52% of the nation's GDP, employ between 50 and 60 percent of the labour force, and account for 25 percent of the growth in private sector employment. South Africa, with the dawn of democracy also opened its doors to competitive global economy that represented competitive challenges to SMEs. SMEs in South Africa can use AI and related technologies as a way to maintain their competitiveness in the global market. Hansen and Bøgh survey (2021) determined that for SMEs to remain competitive, they need to leverage AI and other 4th Industrial Revolution (4IR) technologies.

AI has transformed business operations by automating tasks, improving productivity, and enabling data analysis to uncover insights and make informed decisions and has particularly benefited areas like customer service and predictive analytics, leading to personalized experiences, accurate customer service, and better predictions for future trends (Ingalagi et al., 2021). As AI continues to evolve and becoming more affordable for many SMEs, its influence on industries is expected to grow, reshaping the business landscape in diverse sectors (Bettoni et al., 2021). AI benefits SMEs by enhancing business environment, facilitating operations, and empowering them to transform business models, leading to increased productivity, wider reach, and potential scaling (OECD, 2021).

Despite the numerous advantages offered by AI, several factors continue to hinder the adoption of this technology among SMEs (OECD, 2021). Awareness and understanding of the potential applications of AI is one of the factors, with SMEs failing to understand how AI can be applied in their business, this may be attributed to the complexity of AI applications, that can overwhelm SME human resources (Lemos et al., 2022). For SMEs that do recognize the potential benefits of implementing AI in their business operations, they still fail to implement AI as they lack a clear strategy on how to go about implementing AI, this can also be attributed by the lack of required competences to implement AI applications within the SMEs (Bettoni et al., 2021; Hansen & Bøgh, 2021). The initial investments required to implement AI applications can be high, this often leads to

SME owners being hesitant to invest in AI due to the associated financial costs, additionally, the cost of training staff and providing adequate technical support can also be prohibitively expensive leading to non-commitment to adopt AI technology (Ingalagi et al., 2021; Schoeman & Seymour, 2022). Bhalerao (2022) found that impediments to AI adoption in SMEs such as knowledge of the benefits, staff skill levels, inadequate financial positions, entrepreneurial orientation of the owners, and quality of data accessible by SMEs can be mitigated by implementing customized AI solutions that cater for the SME.

Custom AI models are AI systems that are developed specifically for a particular use case or business problem. Unlike off-the-shelf AI solutions that are designed to be general-purpose and can be used across different industries and applications, custom AI models are tailored to meet the unique needs of a specific business or organization. In this study AI adoption is categorized in 4 levels as follows:

- **Level 1 - AI already integrated in software or platforms**: At this level, AI capabilities are already embedded in commonly used software or platforms. Users can benefit from AI functionality without any additional effort or customization. Examples include voice assistants like Siri, Google Assistant, and Amazon Alexa are AI-powered technologies. Also email spam filters and autocorrect and predictive text capabilities are examples of integrated AI.

- **Level 2 - Standalone AI applications**: Standalone AI services provide ready-to-use functionalities and can be incorporated into the current systems and processes of the company to enhance their AI capabilities. Virtual customer assistants (VCAs) or voice assistants that interact with customers to provide support and assistance are examples of standalone AI applications.

- **Level 3 - Connect to AI API services**: This level involves connecting to AI application programming interfaces (APIs) provided by third-party vendors or platforms. Users can leverage these APIs to access and utilize advanced AI capabilities. This level offers more flexibility and customization options compared to pre-packaged AI services. Google Cloud Natural Language API or IBM Watson Natural Language Understanding allow companies to integrate advanced language processing capabilities into their applications.

- **Level 4 – Custom AI models through training with data**: The highest level involves customizing AI models by training them with specific organisational datasets. This level requires an in-depth knowledge of data pre-processing, AI algorithms, and machine learning methods. It offers the highest level of control and customization over AI applications by training models with specific data to address unique business challenges and requirements.

Organizations have more control over the AI models and can fine-tune them to achieve higher accuracy and relevance within their specific business contexts.

These levels represent a progression from basic adoption of AI functionalities to more advanced customization and control over AI models. This study will focus on **level 4 - custom AI models** adoption and therefore the term AI.

Shoprite, a leading retail chain in South Africa, has integrated custom AI solutions to optimize its supply chain operations (Shoprite Holdings, n.d.). To enhance Checkers Sixty60's delivery efficiency, Shoprite developed a tailored AI solution that dynamically determines optimal delivery zones, resulting in reduction of delivery times. Leveraging order data, the application overlays a map with a spatial-temporal views to pinpoint the best delivery routes (Shoprite Holdings, n.d.). The Shoprite Group was also successful in implementing a custom AI model for optimizing the ordering of ultra-fresh food. The solution was trained on sales and stock data collected over 2 years, along with various customer buying factors and external variables, to accurately forecast customer demand and provide valuable insights to suppliers (Shoprite Holdings, n.d.). While Shoprite is not an SME, these are examples custom AI solution implemented by a South African company and a typical custom AI models referred to in the context of this study.

From a conceptual perspective the research is grounded on TOE Framework, which proposes that, successful adoption of new technologies depends on technological characteristics, organizational factors, and environmental context (Baker, 2012; Tornatzky et al., 1990). The use of TOE should enable the study to get a comprehensive understanding of the factors impacting adoption of custom AI models by South African SMEs.

1.3. Problem Statement

The research problem for this study is the limited adoption of custom AI models by South African SMEs. This means an important sector of South African economy is missing out on efficiencies, cost saving and innovation associated with AI capabilities. There are several research studies done to address factors affecting AI adoption. Shahadat et al. (2023) utilized DOE and TOE to explore the adoption factors of new technology in SMEs, specifically focusing on AI platform integration. According to the study, technological factors hold greater significance in the adoption technology and AI in SMEs. Gupta et al. (2022) study found that organizational factors like top management support and financial readiness significantly influence employees' behavioural intention to implement AI-enabled applications in the insurance sector, despite all technological and environmental influences. In their study of the primary factors of Saudi Arabian B2B SMEs' adoption of AI methods, Chatterjee et al. (2021) found that the main drivers of AI adoption in Saudi Arabian B2B SMEs were SMEs' AI readiness, professional skills, employee attitude and roadmaps for AI-based technology projects. This study's primary goal is to determine the factors that affect South African SMEs' adoption of custom AI models. This investigation will be guided by the main research question:

> RQ0: *What factors impact the potential adoption of custom artificial intelligence models in South African small and medium-sized enterprises?*

TOE will serve as the study's theoretical foundation, with the fundamental tenet that the adoption of new technology is dependent upon the existence of technological, organisational, and environmental readiness (Horani et al., 2023).

1.4. Justification of the Study

The goal of this study is to identify the factors affecting South African SMEs' adoption of custom AI models. This research topic is appropriate in South Africa's emerging market, and could provide valuable insights to policy-makers, industry stakeholders, and SMEs looking to innovate and remain competitive in the local and global business landscape. SMEs are a key stakeholder in this study and they are the focus of the investigation. The study will provide recommendations that can assist SMEs, SME owners and managers to overcome challenges associated with adoption of AI while leveraging AI to enhance their competitiveness and sustainability.

The South African government and policy-makers could benefit from this study. The adoption of AI technology in SMEs will positively impact the economy by enhancing productivity, reducing costs, and generating new business opportunities. The study findings can be used to influence policies and regulations that support targeted strategies and interventions to foster the adoption of AI technologies among SMEs. The Small Enterprise Finance Agency (SEFA) which has a function to provide development finance to SMEs could benefit from making funding decisions of AI based SMEs. The Small Enterprise Development Agency could adopt the research recommendations on SMEs custom AI models adoption to archive their mandate to helping small businesses start, grow, expand.

Service providers that offer AI solutions to SMEs could benefit from this study. By identifying the factors that influence SMEs' custom AI models adoption, vendors and service providers could tailor their offerings to better meet the needs of SMEs. This study may also be useful to academic researchers and students who are interested in AI and its applications in business, particularly SMEs in the South African environment.

1.5. Delimitations of the Study

Conceptual framework: The study's focus is on the TOE framework's conceptual theory as it relates to South African SMEs' adoption of custom AI. The research will not include or cover a wide variety of research objectives, instead, it is limited to the research purpose of finding the critical success elements for AI implementation in SMEs as directed by the TOE framework.

Geographic scope: The study focuses exclusively on South African SMEs. It will not include larger enterprises or SMEs located outside of South Africa.

Sectoral scope: The study will cover a range of sectors, but it will not be possible to include all industries in South Africa.

Time-frame: As the research is part of WITS MBA program, the time frame of the study will correspond to the duration of Applied Research Project (ARP) which runs from February 2023 until end of February 2024.

Language: The study will be conducted in English, which may limit access to non-English language publications and perspectives.

Company size: The study will focus on SMEs, but will exclude micro-enterprises categories of companies within that range, this is because of the cost of implementing AI solutions within these company range may outweigh the benefits.

AI technologies: The study will cover a range of custom AI models, but it will not be able to include every type of AI application or approach.

Policy context: The adoption of AI in SMEs will be the main emphasis of the study; broader policy problems pertaining to AI ethics, legislation, and governance will not be examined.

1.6. Operational Definitions

In this study, operational definitions will be used to provide clear and concise descriptions of key terms related to custom AI models and their adoption in South African SMEs.

1. **Artificial Intelligence (AI)** - AI is the term used for computer applications that are able to do tasks that would usually require human intelligence, like understanding language (natural language processing) and image recognition. In this study, AI refers to advanced applications that include sales trends predictions systems, consumer preferences and customer recommender systems, decision support systems, and predictive analytics systems (Ingalagi et al., 2021) that are custom build to the requirements of an individual company use case.

2. **Small and Medium-sized Enterprises (SMEs)** – According to the Small Business Development Government Gazette, published on March 15, 2019, SMEs are companies that employ less than 250 people and generate less than R250 million in revenue annually. The

company turnover and count of full-time employees is dependent on the sector the SME is operating.

3. **Custom Artificial Intelligence (AI) models** - AI systems that are developed specifically for a particular use case or business problem. Unlike generic use AI solutions that are designed to be general-purpose and can be used across different industries and applications, custom AI models are tailored to meet the unique needs of a specific business or organization.
4. **Custom AI adoption**: This study defines custom AI adoption within the context of South African SMEs as the process of integrating custom AI models into their business operations and systems. This involves evaluating the potential benefits and risks of AI adoption based on the factors investigated throughout the research.

1.7. Structure of the Paper

Introduction section has covered the background, problem statement, research objective, justification, and delimitations of the study. Literature review looks at custom AI model applications, benefits, challenges, factors affecting adoption, and the theoretical framework. The methodology section details research design, sampling strategy, data collection methods, and analysis. The results section analyses data, discusses implications and limitations, and offers recommendations for SMEs. The conclusion summarizes findings and offers further investigation.

2. Chapter 2: Literature Review

This research aims to determine factors impacting potential adoption of custom AI models by South African SMEs, and thus addresses the research question:

> *What factors impact the potential adoption of custom artificial intelligence models in South African small and medium-sized enterprises?*

This chapter aims to identify research gaps and use the TOE framework to examine factors influencing the adoption of custom AI models by South African SMEs. The chapter provides an overview of AI, its scope, challenges faced, and relevant literature. The chapter concludes by emphasizing the importance of the TOE framework as the theoretical lens of the study and basis for data collection and analysis.

2.1. Definition and Scope of Artificial Intelligence

AI is the creation and implementation of algorithms and software systems that can effectively simulate and replicate human intelligence (Chaudhuri et al., 2022), subsequently, this can be implemented across a broad spectrum of business operations, encompassing social media, data analysis, customer acquisition, and the collection and categorization of pertinent information to aid in future decision-making (Bhalerao et al., 2022). In a business environment the main goal of AI is to enhance organizational performance and efficiency, minimize costs, increase sales, and provide flexible and interactive solutions to meet diverse business and customer needs (Bhalerao et al., 2022). The scope of AI is broad and includes various techniques and applications, such as machine learning, robotics, and expert systems which can be used in different industries (Dennehy et al., 2023). The potential of AI to revolutionize many aspects of society, including healthcare, finance, education, public services, and manufacturing, has been widely recognized (Kusters et al., 2020), and its adoption is increasingly seen as critical for organizations to remain competitive (Lu et al., 2022). (Hansen & Bøgh, 2021).

2.2. Importance of AI in SMEs

AI is rapidly becoming an essential part of modern business strategy, and SMEs are not immune to its influence (Rawashdeh et al., 2023). When combined with a suitable digital business strategy, SMEs can utilize AI solutions to either gain a competitive edge or to sustain their position in increasingly competitive markets they operate in (Borges et al., 2021). Adoption of AI can serve as a catalyst for SMEs to develop innovative business models, formulate novel organizational strategies, establish strategic business partnerships, and achieve overall transformation of SMEs (Lu et al., 2022). AI technology can significantly enhance product and service innovations, providing SMEs with a competitive edge in the market. By using AI, SMEs can also reduce business risks and improve demand forecasting, enabling better decision-making and planning while benefiting from the ability to innovate business models, allowing SMEs to explore new markets and revenue streams (Lu et al., 2022). These benefits and opportunities highlight the impact of AI on SMEs and their ability to survive and thrive in a rapidly changing business landscape.

2.3. Challenges of AI Adoption in SMEs

Some of the obstacles preventing SMEs from adopting AI include insufficient AI proficiency, high initial costs and time commitments, inadequate infrastructure and resources, as well as limited expertise and small-scale of the enterprise (Bhalerao et al., 2022). On the other hand, Bettoni et al., (2021) found that SMEs frequently encounter difficulties implementing new technologies because of a lack of funding and a lack of awareness of technological changes. The utilization of AI in SMEs is restricted due to a lack of knowledge of its advantages and limited resources for its adaptation (Ingalagi et al., 2021). The lack of AI skilled labour within the SMEs is a major factor in AI adoption by SMEs (Iftikhar & Nordbjerg, 2021). Without employees with specialized AI knowledge, SMEs may struggle to identify and implement the most effective AI solutions for their specific business needs or even know which AI technologies exist and how they could be used to the SME's advantage (Hansen & Bøgh, 2021).

The other significant challenges associated with AI adoption include organization readiness, technology complexity, technology compatibility, and lack of financial resources (Lu et al., 2022). The complexity and compatibility of AI technologies may pose a significant challenge, particularly for smaller organizations with limited technological infrastructure (Hansen & Bøgh, 2021). Financial resources can also be a major barrier to AI adoption, as these technologies can be costly to implement and maintain. From a technological perspective, challenges such as data quality and security may also impact the success of AI adoption in SMEs (Bhalerao et al., 2022; Schoeman & Seymour, 2022; Tjebane et al., 2022).

2.4. Empirical Review of Literature

This literature review synthesizes current research on AI adoption challenges in South African SMEs, identifies gaps, and explores factors influencing custom AI models adoption. The findings are summarized in Table 1

Table 1 Research Themes

Theme	No. of Articles	References	Research Gap
Low Adoption of AI in SMEs	2	(Schoeman & Seymour, 2022); (OECD, 2021)	Include SMEs with different characteristics and sizes to identify additional themes.
Organisational Factors influencing Artificial Intelligence Adoption	3	(Tjebane et al., 2022)	Study conducted in construction industry in South Africa, a gap to include more industries to generalise the findings.
		(Ingalagi et al., 2021)	The research's conceptual framework needs to be tested in various countries, considering factors like organizational culture, market pressure, and technical infrastructure for further AI adoption studies.
		(Kademeteme & Twinomurinzi, 2019)	Future research could gather information from different settings, specifically the emerging economy nations.
Challenges and Benefits of AI Adoption in SMEs	4	(Bhalerao et al., 2022)	The study is an exploratory research examining existing knowledge on a topic of AI adoption and identify relevant information that could be used in further research
		(Bunte et al., 2021)	The authors suggest a need for more comprehensive studies involving diverse SMEs across various industries and regions to fully comprehend the challenges and opportunities associated with AI adoption.
		(Amankwah-Amoah & Lu, 2022)	Demographics factors such as customs, and norms differ between countries and can impact the adoption of AI. The knowledge of these country-specific factors could help organizations develop better strategies for implementing AI.
		(Lu et al., 2022)	Authors identified lack of research on cost of AI solutions for SMEs as a hindering factor to the adoption of AI in SME sector.
Success factors impacting AI adoption	4	(Merhi, 2023)	The researcher recommends examining how the identified variables affect the effectiveness of AI systems in various contexts, such as emerging nations and organizations with varying degrees of technological development, resources, and sizes. Future study should fill in these gaps.
		(Baabdullah et al., 2021)	The authors identify AI infrastructure and AI awareness as two important variables that

Theme	No. of Articles	References	Research Gap
			require further investigation in AI adoption by SMEs.
		(Rawashdeh et al., 2023)	Future research could explore how SMEs can adapt their operations and management practices to fully realize the benefits of AI adoption
		(Gupta et al., 2022)	More representative and varied sample techniques should be used in future research to increase the study's generalizability and validity of findings.

2.4.1. Low Adoption of AI in SMEs

Schoeman and Seymour (2022) study on seven medium-sized SME organizations found inhibiting factors preventing AI adoption, including fear of losing control, perceived lack of IT maturity, and lack of understanding of technology integration. The study emphasizes the need for education and training on AI technology, addressing control and trust concerns. However, limitations include a small sample size and not reaching theoretical saturation. Future research should include SMEs with different characteristics and sizes.

OECD (2021) emphasize the presence of an SME gap in adopting AI solutions across several countries. They highlight that in Korea, small enterprises reported a lack of awareness of work-related AI applications or services compared to large businesses. Similarly, in Denmark, a higher proportion of large enterprises used AI compared to small enterprises. In Canada, large companies were significantly more likely to utilize automated inspection systems than SMEs. The OECD report show a general low adoption of AI amongst SMEs, this represent a research gap in determining factors influencing the potential adoption of AI in SMEs.

2.4.2. Organisational Factors Influencing Artificial Intelligence Adoption

The study by Tjebane et al. (2022) identifies 17 organisational elements that encourage AI adoption in South Africa's construction industry. These include management support, employee skills, and data quality. However, challenges such as insufficient knowledge and awareness of AI's potential benefits remain. The research provides guidance for organizations considering AI adoption in the construction industry. The investigation's limitations lie in its focus on South African construction experts, limiting its generalizability beyond this context and the SME sector as a whole.

A (2021) study by Ingalagi et al. explored AI adoption from a leadership viewpoint. They found that strong leadership commitment, organizational preparedness, external support, employee buy-in, and competitive pressure all play a significant role in driving AI adoption in SMEs. Their research concluded that successful AI adoption can empower SMEs to make intelligent management decisions, ultimately improving their effectiveness. To encourage this adoption, they suggest government involvement and the creation of affordable AI service providers. However, they acknowledge the need for further research to explore additional factors like organizational culture, competitive pressure, and technological factors.

Kademeteme, E., & Twinomurinzi, H. (2019) discovered that user and organisational factors can affect the assessment of new ICTs in the adoption literature. However, the study found that the theorized distinct individual characteristics of SME owners, such as age, gender, duration of familiarity with either the current or emerging ICT, and length of employment, do not impact determining the usefulness of current or emerging technology. This means that unique user traits/attributes may not apply when evaluating ICTs in the 4IR such as AI technologies. The findings of this study have applications in management and practice, indicating that SMEs should focus on new innovation theories to evaluate emerging digital technologies.

2.4.3. Success Factors Impacting AI Adoption

The Merhi (2023) study outlines four primary elements that influence the effective deployment of AI: organisation, technology, process, and environment. Technology is the most influential category, followed by ethics. The study encourages practitioners to focus on technology, specifically data governance, security, confidentiality, and integrity. the study provides a comprehensive list of variables affecting AI adoption and encourages further research to identify additional success factors. The findings offer valuable insights for practitioners in the field.

A different set of success factor are evaluated by Baabdullah et al. (2021) using the TOE framework to study AI adoption in Saudi Arabian B2B SMEs. They found that factors such as technology road mapping, attitude, infrastructure, and awareness significantly influence AI adoption, which in turn affects AI-enabled relational governance, performance, and customer interaction. Although the study's scope is limited to supplier perspectives, it contributes to understanding AI adoption in SMEs and the B2B sector.

Rawashdeh et al. (2023) study explores AI adoption in SMEs through accounting automation. The study emphasizes the importance of AI compatibility with SMEs' current practices and culture, and the underestimated influence of interconnected technology elements. The study focused on the United States and on accounting automation as a mediating variable, did not consider other factors like government policies, funding access, and social and cultural factors, suggesting the results may not be generalizable to other contexts or industries.

Gupta et al. (2022) study explores the factors influencing employees' behavioural intention to adopt AI-enabled applications in the Indian insurance industry. They use the TOE framework to analyse technological, organisational, and environmental factors. The research adds to the body of knowledge on AI adoption in the insurance sector by highlighting possible advantages, identifying drivers and inhibitors, and analysing adoption determinants. The research focused on understanding the effects and implications of AI on individual employees within organizations and thus there is a research gap on the organizational impact on AI adoption.

2.4.4. Challenges and Benefits of AI Adoption in SMEs

Bhalerao et al. (2022) research explores AI adoption challenges in SMEs, revealing barriers like lack of technical expertise, financial instability, and lack of awareness about AI's benefits. On the other hand, the study found that customized AI technologies can help SMEs in improving their decision-making, employee management, inventory management, customer base creation, and protection against cyberattacks. The study identifies three main elements that affect SMEs’ implementation of AI, which include the proficiency of employees in AI capabilities, their awareness of the advantages of adopting AI, and organizations access to reliable and valuable data. Conversely, the study revealed that hindrances to implementation of AI among SMEs encompass inadequate knowledge about the advantages of AI, insufficient IT skills among staff, organization financial fragility, organization size, and entrepreneurial disposition. The research underscores the importance of understanding AI's significance and overcoming obstacles for SMEs to gain a competitive edge from its benefits.

Although AI offers various benefits to companies and can assist in problem-solving across different domains of SME business operations, the benefits and economic impact of AI are not often measured and companies often blindly trust that AI is beneficial without evidence (Bunte et al., 2021). In their study on the challenges and solutions related to the application of AI in SMEs, Bunte et al. (2021) identifies the importance of measuring the economic impact of implementing new technologies and methods in a company, specifically AI. The study was based on interviews with 411 individuals from 68 companies, most of which are SMEs. The findings of the study were that, only 5% of the interviewees in a study indicated that they quantified the economic effects of implementing AI within their organization. The study raises the critical point that it does not make sense to implement AI without knowing the concrete positive impact it will have and the magnitude of the savings or boost in revenue that will result from AI adoption. Therefore, measuring the economic success of AI is crucial to determine if it helps a company stay competitive, and hence the adoption of AI custom solutions by SMEs. Based on these finding, this study will investigate relative advantage of AI adoption which will measure the perceived benefit of adopting custom AI models.

In a study to explore the factors that affect the growth of AI in Africa, the study by Amankwah-Amoah & Lu (2022) identifies barriers to the development of large-scale AI in Africa as inadequate infrastructure, dysfunctional institutions, a shortage of qualified AI professionals, and restricted access to cutting-edge AI tools. The study highlights the potential the possible policy ramifications for Africa as a frontline market for AI growth and provides insights into the factors that need to be considered to support its growth. The paper discusses the importance of internet and digital technologies in creating gender-inclusive education, reducing poverty, and fostering innovation in Africa. The limitations in the study, is on the focus on individual countries, and proposes that future work be done into examining country-specific factors that affect AI adoption.

COVID-19 pandemic has underscored the necessity on SMEs to create more resilient systems to cope with the challenges they faced. Lu et al. (2022) examine the difficulties that SMEs confront during the COVID-19 pandemic and the potential advantages and disadvantages of AI implementation for their survival and growth. The authors argue that SMEs need to embrace technology, particularly AI, to move forward, and they examine the possibilities and limitations of AI transformation in SMEs. The study recognizes SMEs as crucial employment and economic growth drivers and identifies AI transformation challenges such as resource limitations and knowledge gaps in AI strategy development. The paper identified opportunities for applying AI to improve SMEs' productivity, customer experience, and supply chain management. To mitigate the challenges of cost related to AI adoption, the authors also recommend further research be done in exploring how SMEs can build cost-effective and reasonable AI solutions.

2.4.5. Conclusions

In summary the literature review highlights the low adoption of AI in SMEs globally and this phenomenon is the same with South African SMEs. The studies identify factors such as management support, employee skills, perceived lack of IT maturity, lack of understanding of the technology, cost, and organizational readiness among others, as crucial for successful AI adoption. Research underscores the importance of organisational and management elements in implementing AI technologies, particularly in SMEs in emerging countries like South Africa. This highlights the necessity of top management's dedication, organisational preparedness, external assistance, and employee acceptance of AI. Literature emphasize the importance of measuring the economic impact of AI implementation in SMEs to determine its positive impact and competitiveness. Therefore, it is necessary for SMEs to comprehend the advantages of AI and find ways to overcome the obstacles hindering them from taking full advantage of AI. Measuring the economic impact of AI implementation is crucial to determine if it gives economical advantage to SMEs and hence the adoption of AI custom by SMEs. Through literature review it was found that SME owners' distinct individual characteristics, such as age, gender, years of experience using existing or emerging ICT, and years of experience in the organization, did not have a significant role in the SMEs AI adoption.

2.5. Theoretical Review of Literature

Theoretical frameworks serve as a lens through which the research problem can be analysed, providing a structured approach to understanding complex phenomena and can be used to develop hypotheses, guide data collection and analysis, and help to interpret research findings (Alsheibani et al., 2018). This research aims to analyse the factors influencing the potential adoption of custom AI models by South African SMEs. Theoretical literature review will allow this study to gather key theory and concepts to answer the research primary question:

> *What factors impact the potential adoption of custom artificial intelligence models in South African small and medium-sized enterprises?*

Researchers have employed a number of theoretical frameworks to assess the implementation of new technologies, particularly AI. The Technology Acceptance Model 2 (TAM), an extension of Fred Davis' original model, incorporates additional factors to forecast user acceptance and adoption of IT systems (Venkatesh & Davis, 2000). Davis (1985) introduced the Theory of Acceptance and Utilization (TAM), as an information systems theory that describes how users accept and use technology. The primary goal of TAM is to comprehend the driving force behind users' willingness to use specific technologies and have been utilized in numerous studies and research that focus on evaluating user acceptance of computer-based information systems (Wibowo, 2019). The limitation on TAM is its considerable emphasis on the technology factor at the expense of all other factors that affect technology adoption, this limits the explanatory and predictive power of TAM (Awa et al., 2016).

The Unified Theory of Acceptance and Use of Technology (UTAUT2) is a widely used model for understanding and predicting technology adoption (Jain et al., 2022; Venkatesh, 2022). Venkatesh et al., (2003) developed the original UTAUT by expanding upon the TAM to include additional variables that could potentially impact the adoption of technology. The UTAUT2 framework extends the original UTAUT framework by incorporating additional constructs and contextual factors to improve its applicability (Venkatesh et al., 2012, 2016). To understand the adoption and use of technology, UTAUT2 integrates a number of aspects, including performance and effort expectation and social influence (Marikyan & Papagiannidis, 2021; Venkatesh, 2022).

Adopting custom AI models is more than adopting software or the technology, SMEs also require an organizational competence and favourable environmental conditions to effectively implement AI (Phuoc, 2022). TOE model is regarded as the most favourable framework for examining the adoption of AI due to its emphasis on the distinct context of the adoption process and its capacity to assess the factors that impact AI adoption (Alsheiabni et al., 2019; Maroufkhani et al., 2023). Because TOE covers the technological, organizational and environmental factors relevant to organisations adoption of custom AI models, this study will utilize the TOE as its theoretical foundation. The selection of the TOE for this study is based on its widespread application within the field of information systems (Awa et al., 2016), and its factors have been examined in the implementation of several technologies, including Blockchain technology (Malik et al., 2021), resource planning (ERP) (Awa et al., 2016), CRM (Cruz-Jesus et al., 2019), and AI technologies (Alsheiabni et al., 2019; Alsheibani et al., 2018; Na et al., 2022; Neumann et al., 2022). There are many theoretical frameworks that can be used in technology adoption research, but this research investigated TOE, TAM, UTAUT, and UTAUT2 because of their robust and extensive validation in the field of technology adoption research. These models offer comprehensive insights into the factors influencing individual and organizational acceptance and use of new technologies, making them relevant for examining the adoption of custom AI models in South African SMEs. The frameworks specifically address factors relevant to both individual and organizational technology adoption, making them suitable for examining the adoption of custom AI models in the SME sector.

2.5.1. The TOE Theoretical Framework and Hypotheses

The TOE framework was first introduced by Tornatzky, Fleischer and Chakrabarti (1990) as a tool to help understand technology adoption in organizations. The framework acknowledges that technology adoption is impacted not only by the technology's attributes but also by internal organisational and external environmental factors (Baker, 2012; Rawashdeh et al., 2023; Tornatzky et al., 1990).

Tornatzky, Fleischer, and Chakrabarti (1990) initially presented the TOE framework as a tool to aid in understanding the adoption of technology in organisations. The framework acknowledges that elements inside the organisation and external environmental factors have an impact on technology adoption in addition to the technology's inherent qualities (Baker, 2012; Rawashdeh et al., 2023; Tornatzky et al., 1990). According to literature, TOE proposes that technology adoption is influenced by three main factors (Alsheiabni et al., 2019; Baker, 2012; Rawashdeh et al., 2023):

- Technological Factors: The TOE framework uses the term "technological factors" to describe the attributes and aspects of the technology that may have an impact organization’s adoption of technology. These factors encompass the technology's complexity, compatibility with current systems and procedures, the level of maturity, the availability of support and expertise, and the adoption and maintenance cost of technology.

- Organizational Factors: These refer to the internal characteristics of an organization that may impact its ability to adopt new technology. These factors include the organization's size, structure, culture, resources, leadership, and communication processes of the organisation.
- Environmental Factors: The external elements in the TOE framework include regulatory, economic, social, and cultural factors that influence the adoption process of new technology.

The TOE model has been used in numerous environments, including technology adoption in cybersecurity, financial services, big data, cloud computing, and AI (Lihniash et al., 2019; Maroufkhani et al., 2023; Wallace et al., 2021; Yang et al., 2015). It has also been applied to the adoption of AI in SME environments (Alsheiabni et al., 2019; Alsheibani et al., 2018; Gupta et al., 2022; Rawashdeh et al., 2023). Baker (2012) emphasized the impact of various factors on the adoption of technology, which vary based on technology, organizational context, and environment the organisation is operating in. Hence, previous research studies that used TOE as their theoretical framework have used different factor variables to analyse the impact of TOE constructs in the adoption of relevant technology in specific organizational and environmental context. This study aims to analyse TOE factor influencing South African SMEs' adoption of custom AI models, focusing on their unique challenges related to limited technological resources, organizational limitations, and challenging environmental factors.

2.5.1.1. Technological Context

The technological dimension encompasses all the available technologies within and outside an organization (Cruz-Jesus et al., 2019). This includes the technologies already in use within the organization as well as those that are available for adoption but have not been adopted yet (Baker, 2012; Cruz-Jesus et al., 2019).

Relative Advantage (RAD)

The perceived advantage of an innovation over existing strategies influences organization's adoption of new technology, such as AI (Alsheibani et al., 2018). The usage of AI in various applications has enabled businesses to lower costs, elevate service quality, and improve customer experiences, thereby delivering clear advantages in terms of strategic and operational efficiency (Phuoc, 2022). Previous literature has shown that relative advantage significantly influences performance, growth, expansion, product development, and technology adoption in organizations (Alsheibani et al., 2018; Gupta et al., 2022; Shahadat et al., 2023), hence, this study hypothesises that:

H1a: Relative advantage has a positive influence on adoption of custom AI models in South African SMEs.

Perceived Complexity (PCX)

Perceived complexity of a technology is determined by the its level of difficulty associated with understanding and using the innovation (Maroufkhani et al., 2023; Phuoc, 2022). The level of complexity in technology adoption is determined by the difficulty in comprehending and utilizing the technology within an organization. AI related technologies can be complex and difficult to understand, and this introduces barrier to custom AI models adoption. Perceived complexity of a new technology increases uncertainties and risks associated with adoption and is a critical predictor of technology acceptance (Awa et al., 2017). Integration of AI applications may be affected by perceived complexity, as more complex transformations and applications may lead to greater resistance to new technology adoption (Gupta et al., 2022; Phuoc, 2022). Accordingly, it is hypothesised that:

> *H1b*: Perceived complexity has a negative influence on adoption of custom AI models in South African SMEs.

Perceived Compatibility (PCM)

Compatibility is crucial in technology adoption, as it aligns with an organization's existing procedures and infrastructure to the new technology (Lu et al., 2022; Neumann et al., 2022). AI requires large data volumes, and if AI data requirements compatible with current IT systems, then it is less costly and time-consuming to adopt (Phuoc, 2022). Companies' work practices and culture also influence adoption (Rawashdeh et al., 2023) and top management support is more likely with technology compatibility, as they are unlikely to support it if it is perceived as incompatible (Maroufkhani et al., 2023). Effective AI adoption requires a robust business case and alignment with current strategies (Alsheibani et al., 2018). Accordingly, this study proposes that:

> *H1c*: Perceived Compatibility has a positive influence on adoption of custom AI models in South African SMEs.

Perceived Cost (PCS)

SMEs face financial and resource constraints in adopting new technologies. The acquisition and implementation costs of custom AI are high for SMEs, resulting in less interest from owners and managers in technology adoption. Due to a shortage of resources including monetary resources, human resources, SMEs have a greater relative cost of innovation than larger firms (Shahadat et al., 2023). SMEs need to consider the cost and financial return of digital technology when adopting AI and the cost of AI may affect profitability and increase consumer cost which may lead to SMEs falling into a digital trap caused by the lack of comprehending value delivered by AI adoption (Lu et al., 2022). Therefore, this study hypothesises that:

H1d: Perceived cost has a negative influence on adoption of custom AI models in South African SMEs.

2.5.1.2. Organizational Context

The TOE framework identifies organizational factors influencing adoption decisions of new technologies, highlighting the interplay between technological, organizational, and environmental factors (Alsheiabni et al., 2019; Tornatzky et al., 1990).

Top Management Support (TMS)

Top management's support can significantly influence innovation adoption (Awa et al., 2017). Their commitment to new technologies can positively impact the organization's vision, allocation of resources, and the provision of capital funds (Alsheibani et al., 2018). Leadership support increases functional efficiency and creates a positive atmosphere that aids integration with existing systems (Gupta et al., 2022). Previous research indicates that the participation of management is essential for introducing new technologies in SMEs. Management can allocate organisational resources to the technology adoption process, and their vision influences the extent of AI integration in the organization (Baker, 2012; Ingalagi et al., 2021). Accordingly, this study proposes the following hypothesis:

H2a: Top management support has a positive influence on adoption of custom AI models in South African SMEs.

Technological Competence (TCM)

The technological competence of an organization's internal resources, include infrastructure, professional expertise, technological awareness, and service experience (Baabdullah et al., 2021). Gupta et al. (2022) found that technological competence is crucial for adopting technological transformations and organizations with higher technological competence are expected to have an easier time adopting technological changes. Adopting AI in SMEs faces significant challenges due to a lack of AI expertise and understanding and this scarcity of talent and expertise presents challenges for most SMEs in the AI field (Lu et al., 2022). Thus, this research posits the following hypothesis:

H2b: Technological competence has a positive influence on adoption of custom AI models in South African SMEs.

Financial Readiness (FRD)

Financial preparedness of a corporation is an important aspect in technology adoption since it demonstrates the company's ability and willingness to invest in new technology. Limited financial and labour resources faces by SMEs leads to a greater challenge in innovation and adoption of new technologies (Gupta et al., 2022). The cost of digital technology can be a significant challenge for SMEs, who often have limited resources and need to carefully consider the costs and benefits of technology adoption. In the case of AI, the costs can be particularly high, as it often requires specialized hardware, software, and expertise (Lu et al., 2022). Introducing AI-based technology can be a challenge for organizations with limited cash flows such as the SMEs, and it may also affect profitability and increase costs for consumers (Lu et al., 2022). We propose the following hypotheses based on these findings:

H2c: Financial readiness has a positive influence on adoption of custom AI models in South African SMEs.

2.5.1.3. Environmental Context

The TOE framework considers external factors affecting an organization's competitiveness and efficiency, including technology adoption (Na et al., 2022). These factors include regulatory frameworks, industry structure, competitors, suppliers, and customers (Alsheibani et al., 2018). Social, cultural, and legal considerations influence technology adoption decisions, and organizations may be encouraged or discouraged from adopting new technology because of these environmental factors (Baabdullah et al., 2021; Phuoc, 2022).

Competitive Pressure (CPR)

The level of competition in an industry affects the adoption rate of technology by SMEs as it enhances firm performance and dynamic capability (Shahadat et al., 2023). Competitive pressure from customers, suppliers, and competitors is a significant factor in driving firms to adopt new technology (Ingalagi et al., 2021). The adoption of new technology by competitors produces pressure on firms, as those who successfully implement new AI technology can gain a competitive advantage (Gupta et al., 2022; Phuoc, 2022). The introduction of technological innovations has the power to drastically change the competitive environment, modify the dynamics of competition, and change the structure of industries (Phuoc, 2022; Shahadat et al., 2023). Hence, the following hypothesis is proposed:

H3a: Competitive pressure has a positive influence on adoption of custom AI models in South African SMEs.

External Support (ESP)

SMEs may be more inclined to adopt a technology if they receive support from a third-party service provider who can help with implementation and offer ongoing support (Maroufkhani et al., 2023). This type of support can reduce the risk and costs associated with technology adoption, and it can also provide SMEs the expertise and resources that is not available within SMEs (Ingalagi et al., 2021). Additionally, external support provides a level of legitimacy of the technology, which can be important in industries where there is pressure to conform to certain standards or practices, hence the support from external partners, such as business vendors, supply chain partners, and IT service providers, is essential for SMEs to improve their capabilities (Ingalagi et al., 2021). Lack of AI knowledge and IT infrastructure is a common issue for small firms (Lu et al., 2022), and they need external support to address these challenges. Based on this viewpoint, this study has developed a hypothesis.

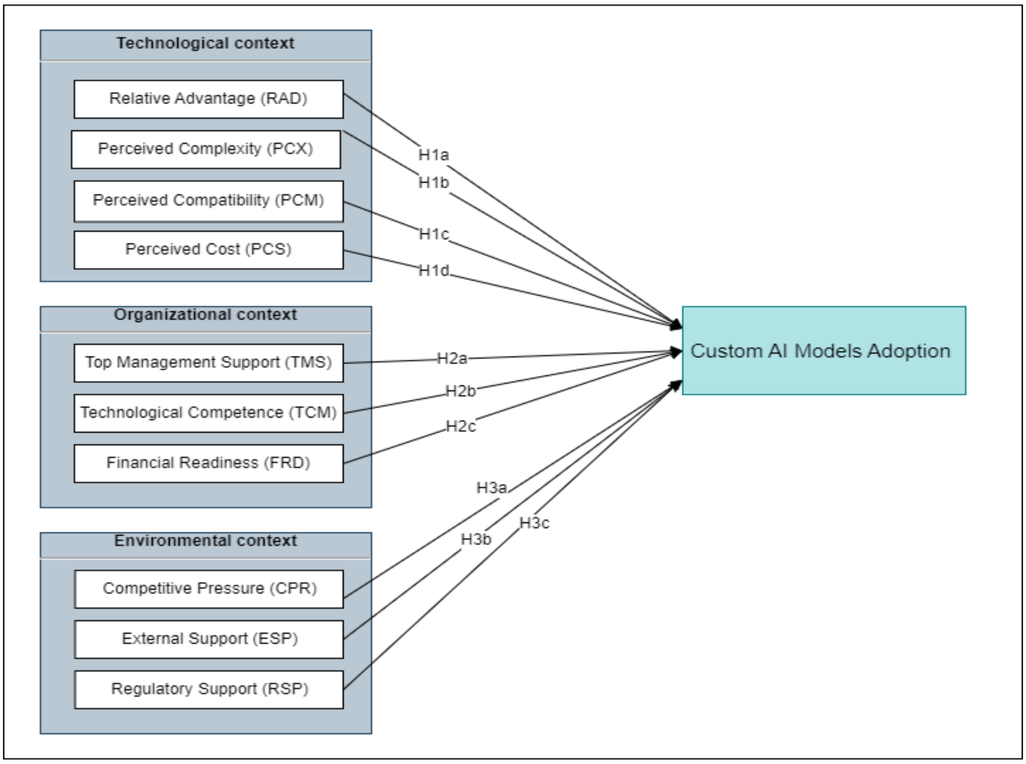
> *H3b*: External support has a positive influence on adoption of custom AI models in South African SMEs.

Regulatory Support (RSP)

Regulatory concerns involve government support to encourage the implementation of AI advances in organisations (Alsheibani et al., 2018). In order to create an environment that is advantageous for AI, government and regulatory support is essential, this can then encourage the widespread adoption of AI (Horani et al., 2023), which leads to the following hypothesis:

> *H3c*: Regulatory Support has a positive influence on adoption of custom AI models in South African SMEs.

Figure 1 Theoretical Framework of custom AI models Adoption in South African SMEs



The study explores the key success factors influencing the adoption of custom AI models from technological, organizational, and environmental perspectives, using the TOE model as illustrated in Figure 1.

2.5.2. Conclusions

According to the theoretical assessment of literature, the adoption of AI in organisations is influenced by a number of elements, including technological, organisational, and environmental aspects. These factors can be examined using the TOE framework, which offers a structured method to understanding the complexities of AI adoption. The TOE technology dimension takes into account available technology, technology complexity, cost, and new technology compatibility, all of which can help with AI adoption. The organizational dimension includes elements such as organizational readiness, human resources, and financial readiness of the organisation, while the environmental dimension considers external issues such as industry, competitors, and stakeholders.

3. Chapter 3: Research Methodology

This chapter will provide information to enable the reader to evaluate the appropriateness of the methods used and to replicate the study. This chapter discusses the research design which includes the selection of the research approach, sampling strategy, methods and techniques that was used to collect, analyse and interpret data. This section will also address ethical considerations, and potential biases that may affect the results.

3.1. Research Design

Post-positivism is a philosophical perspective that suggests that knowledge is not absolute or objective, but rather is constructed by individuals within a particular context. Post-positivists hold that knowledge is tentative and subject to reconsideration as new information arises (Creswell & Creswell, 2018). Post-positivism advocates for the use of quantitative research methods, which are designed to gather empirical data for analysis through statistical approaches (Creswell & Creswell, 2018). Post-positivist research is typically hypothesis-driven, and seeks to test theoretical predictions against observable phenomena (Creswell & Creswell, 2018). This perspective also places a strong emphasis on rigorous research design, including usage of proper controls, random sampling, and other methods to minimize bias and error (Creswell & Creswell, 2018).

This research adopted a post-positivist philosophical assumption to guide data collection, analysis, and the interpretation of results. This entailed developing research questions, choosing variables, formulating hypotheses, designing data collection tools, and utilising quantitative research methods to acquire and interpret numerical data.

Quantitative research is a systematic and structured approach that aims to gather numerical data and analyse it statistically to uncover patterns, relationships, and trends (Bickman & Rog, 2008). This research approach relied on the principles of objectivity, replicability, and generalizability to draw conclusions and inferences about a broader population from a sample (Creswell & Creswell, 2018). This study utilised a quantitative research approach, which is ideal for analysing correlations between variables, measuring their magnitudes, and evaluating hypotheses (Creswell & Creswell, 2018). The chosen approach enabled collecting quantitative data on the aspects that influence the adoption of custom AI models in South African SMEs.

Survey research design is a widely used quantitative research approach that involves gathering data from participants using standardized questionnaires (Sekaran & Bougie, 2016). The use of survey methods with questionnaires is widely favoured due to their ability to gather standardized data efficiently from a large pool of respondents (Saunders et al., 2019). A survey research design involves gathering data from a sample of a population to quantitatively describe trends, attitudes, and opinions, or to examine relationships between variables within that population (Creswell & Creswell, 2018).

This study applied a quantitative research design, involving the distribution survey questionnaire to a sample of SMEs in South Africa. Survey research design was particularly suitable due to its ability to gather data on attitudes, perceptions, and behaviours from a large number of participants. The questionnaire consisted of close-ended questions that offered response options in the form of Likert scales or multiple-choice formats. This format allows for collection of numerical data for statistical analysis. To confirm the survey instrument's validity and reliability, the research employed established measurement scales and constructs relevant to the adoption of AI. These scales were adapted from previous studies and validated to suit the specific context of South African SMEs.

3.2. Data Collection

This section outlines the procedures employed to gather primary data, ensuring the reliability and validity of the findings. Online survey was used as a data collection method for this study. The use of electronic survey was based on the advantages offered by this method such as the ease to administer, as respondents can access and complete the questionnaire online, expands the potential pool of respondents and enhances the diversity of the sample, furthermore, electronic questionnaires are cost-effective, as they eliminate the need for printing and postage expenses associated with traditional paper-based surveys (Sekaran & Bougie, 2016).

Data collection was conducted through Qualitrix online survey platform from a target sample that consist of a representative selection of South African SMEs. The statistical software packages, IBM SPSS Statistics was used for statistical analysis in this study. Both Qualitrix and SPSS were chosen based on the software being made available by WITS Business School. Correlation analysis, regression analysis, and descriptive statistics, was performed to identify factors influencing the adoption of custom AI models.

3.2.1. Population and Sample

The study examines South African SMEs as the population of the study. The Small Business Development Government Gazette, 15 March 2019 defines SMEs as businesses with fewer than 250 employees and annual revenue not exceeding R250 million. However, there is a lack of a systematic census or periodic survey to capture the full range of SMEs and their performance in South Africa (The Small Business Institute, 2019). This absence of dependable, and consistent data has resulted in varying estimates regarding the number of SMEs in South Africa. The State of Small Business in South Africa 2023 report by Trade & Industrial Policy Strategies (TIPS) estimated the count SMEs in South Africa amounted to 710,000 in 2022 (Trade & Industrial Policy Strategies (TIPS), n.d.). TIPS is a South African independent, non-profit, economic research institution and for this study the estimated 710,000 SME numbers was regarded as the population of this study.

Krejcie and Morgan (1970) provides a simplified approach to determining sample size by introducing a table that serves as a reliable guideline for sample size decision making. The table is based on scientific formula for sample size decisions by the research division of the National Education Association. The table values are calculated based on degree of accuracy expressed as a proportion .05 and the table value of chi-square for 1 degree of freedom at the desired confidence level (Krejcie & Morgan, 1970). The table makes easy use of determining sample size as no calculations are needed to use it. Using the estimated N = 710,000 SME numbers as the population size of this study and the table values from Krejcie and Morgan (Krejcie & Morgan, 1970) the estimated sample size for this research was 382.

3.2.2. Sampling Procedure

This research utilized a snowball sampling technique, a non-probability method where participants were participants are recruited based on referrals from initial participants who matched the study's sample requirements (Parker et al., 2019). Snowball sampling is particularly beneficial when studying difficult-to-reach or niche groups, since it allows for the identification of participants who may not be immediately accessible through typical sampling approaches (Parker et al., 2019). However, it is crucial to highlight that snowball sampling may introduce biases and limit generalizability, as participants are selected based on referrals and may share similar characteristics or experiences (Parker et al., 2019).

Using the snowball strategy, the data collection kicked off with the placement of the survey link on researchers LinkedIn page and sending of WhatsApp and email messages within a select group of contacts, including researchers professional and personal networks. To expand reach, the research formed a strategic collaboration with Vivre Consulting, a strategy consultancy firm focusing on value innovation and strategy for businesses and non-profit organizations. Collaboration with Vivre Consulting involved the distribution of the survey link across the company's diverse social media platforms such Twitter, Instagram, Facebook and LinkedIn. The data collection phase spanned from November 1, 2023, to January 15, 2024.

The survey generated a total of 83 replies. A data clean-up was done and the following data items were removed. One data item was excluded due to non-consent, 12 were incomplete, and 13 did not meet the criteria for SMEs (company employee size > 250). Additionally, entries with more than 14 missing values (25% of number of columns) were excluded, followed by mode imputation of the remaining missing values. Following the screening and data cleaning procedures, 55 responses was retained for subsequent analysis.

3.3. The Research Instrument

In this study, the research instrument employed was a predetermined self-administered online questionnaire as shown in Table 16 (see Appendix A2: Research Instrument). The survey questionnaire was utilized to examine the TOE model constructs, incorporating valid and reliable constructs derived from previous studies. All items with the exception of Section E – Demographics section were measured on a 5-point Likert scale. Likert scales are frequently employed to assess individuals' opinions and attitudes by measuring their degree of agreement or disagreement with particular assertions. The scales usually span from 1 (strongly disagree) to 5 (strongly agree), including a neutral midpoint (neither agree nor disagree) for participants to express their stance (Sekaran & Bougie, 2016). The survey questionnaire was created in English without any translation to other South African languages. The study utilized existing literature-derived measurement items, which were then customized to fit the specific research context for validity and reliability.

Items were modified to fit this study's context, and hence the questionnaire was taken through validation process via 6 individuals that formed a validation group, 2 MBA candidates, 2 Master of Science in Computing Graduate, a Software Architect and a Business Analyst working in an ICT sector. The validation group was asked to evaluate the questioner on clarity of the questions, relevance of the questions, completeness of the questions, questions understandable, not biased or leading, and if survey is easy to navigate. Changes were made based on the feedback provided.

3.3.1. Goodness of Measures

Reliability: The reliability of a measure evaluates consistency and absence of bias, ensuring that the measurement remains consistent true throughout time and among various instrument items. It reflects the stability and consistency of the measure in capturing the concept, serving as an indicator of its quality (Sekaran & Bougie, 2016). This study adopted an inter-item consistency reliability measure using Cronbach's coefficient alpha. Cronbach's alpha assesses the consistency of responses to a group of questions on a scale, with a coefficient ranging from 0 to 1, with values of 0.7 or higher indicating strong internal consistency (Creswell & Creswell, 2018; Saunders et al., 2019).

Table 2 Cronbach's Alpha Reliability of Measures

High-Level Factors	Constructs	No. of Items	Items deleted	Cronbach's Alpha
Dependent Variable	Custom AI adoption	5	None	0. 92
Technological	Relative Advantage	4	None	0.86
	Perceived Complexity	5	None	0.86
	Perceived Compatibility	4	None	0.93

	Perceived Cost	5	None	0.84
Organizational	Top Management Support	5	None	0.94
	Technological Competence	4	None	0.94
	Financial Readiness	3	None	0.84
Environmental	Competitive Pressure	5	None	0.82
	External Support	4	None	0.84
	Regulatory Support	4	None	0.91

To assess the internal consistency and reliability of the measurements, the study used Cronbach's alpha. Table 2 shows alpha coefficient values for each constructs with the range from 0.796 to 0.945, signifying scale reliability and thus justifying their retention for subsequent analysis.

Sekaran and Bougie (2016) suggested that when using validated measures as validated by other studies, it is unnecessary to re-establish their validity for each individual study. This research utilized constructs and measurement items derived from existing literature customized to align with the specific context of this research and therefore will not conduct validity test of the constructs used.

3.4. Data Analysis

All questioner item of this study were assessed using a 5-point Likert scale. Though Likert scale produces ordinal data, they are often treated as if they represent interval data in statistical analyses. This assumption allows for the use of parametric tests like mean, standard deviation, and inferential statistics to test hypotheses (Sekaran & Bougie, 2016). IBM Statistical Package for Social Sciences (SPSS) V28.0 was chosen as suitable statistical software packages to conduct the multivariate statistical analysis in this study.

3.4.1. Data Transformation

A total of 83 responses were collected from the survey. A data clean-up was done as detailed in section 3.2.2. Industry item of the questioner allowed the user entered values on selection of the other option. Values to these entries were recoded as follows. Business Administration was consolidated into Real Estate and Business Services, IT Sales into ICT Services, Arts and Culture into Wholesale and Retail Trade, Industry association into Real Estate and Business Services, and Broadcasting into ICT Services.

In the data analysis phase, a step involved the transformation of the "Industry" variable, which initially comprised ten distinct categories. Among these categories, "ICT Services" and "Finance and Insurance" collectively accounted for a substantial proportion, totalling 56.4%. Recognizing the significance of these two categories, data transformation process was done on the industry field. The transformation involved the creation of a new variable named "Services" consolidating the specific industries of ICT Services and Finance and Insurance into this single category (1), with the rest of industry categories consolidating to category 0. This transformation allowed examining of the unique characteristics and responses associated with these service-oriented industries. The variable Services was in turn used as a control variable to the hierarchical regression used to test the independent variables.

3.4.2. Descriptive Analysis

Descriptive statistics are essential in summarising and characterising the important aspects of the obtained data of this research. Descriptive statistics include various measures like frequency distribution, central tendency, dispersion, and measures of shape.

Table 3 Sample Characteristics

Demographic	Category	Frequency	Percent
Industry	ICT Services	21	38.18
	Finance and Insurance	10	18.18
	Agriculture and Mining	5	9.09
	Real Estate and Business Services	5	9.09
	Construction	4	7.27
	Education and Healthcare Services	3	5.45
	Accommodation and Food Services	2	3.64
	Manufacturing	2	3.64
	Transport and Logistics	2	3.64
	Wholesale and Retail Trade	1	1.82
Company Size	Micro	8	14.55
	Small	20	36.40
	Medium	27	49.10
Company Age	0-2	0	0
	3-5	4	7.5
	6-10	16	30.2
	11-15	10	18.9
	16+	23	43.4
Company Location	Gauteng	39.00	70.91
	KwaZulu-Natal	7.00	12.73
	Western Cape	4.00	7.27
	Eastern Cape	3.00	5.45
	Free State	1.00	1.82
	Mpumalanga	1.00	1.82
Participant Role	Employee	27.00	49.09
	Manager	11.00	20.00
	Owner/Founder	11.00	20.00
	Managing Director	6.00	10.91

This study performed descriptive statistics as describe by Sekaran and Bougie (2016). This study employed frequency distribution statistics to understand the distribution pattern and identify the most common or dominant responses. The sample characteristics of the respondents as shown in Table 3 offer insights of data representation within the study. In terms of SME industry statistics, the highest proportion is in ICT Services at 38.18%, followed by Finance and Insurance at 18.18%. The two item (ICT Services and Finance and Insurance) constituted more than 50% of the total responses. Regarding company size, the distribution is spread across various categories, Medium-sized companies (49.10%) are the majority of the responses, followed by small (36.40%) and micro (14.55%) businesses. Given the limited sample size, this research opted to incorporate all 8 respondents representing micro businesses, despite the initial intent to exclude micro enterprises from the target group. Concerning company age, 30.2% of respondents fall within the 6-10 years bracket, 18.9% in the 11-15 years range, and 43.4% have been in operation for 16 years or more. The majority of the companies, accounting for 70.91%, are located in the Gauteng province with the rest of the provinces taking marginal values of respondent count. Lastly, in terms of participant roles with in the company, 49.09% are employees contributing the highest number of respondents to the study.

Central tendency measure mean determines the typical or central value around which the data tend to cluster to provide insights into the average or representative value of the variable under consideration. Dispersion measure standard deviation examine the spread or variability of the data points, it indicates how much the individual data points deviate from the central tendency measures, providing information about the data's diversity or consistency. Skewness indicates whether the data are skewed towards one tail or the other, while kurtosis reflects the degree of data concentration around the mean and the presence of outliers (Sekaran & Bougie, 2016).

Table 4 Descriptive statistics.

High-Level Factors	Constructs	Items	Mean	SD	Skewness	Kurtosis
Technological Context	Relative Advantage	Relative advantage 1	4.32	0.91	-1.47	2.30
		Relative advantage 2	4.06	1.04	-1.06	0.46
		Relative advantage 3	4.30	0.95	-1.48	2.05
		Relative advantage 4	4.11	0.99	-1.09	0.81
	Perceived Complexity	Perceived complexity 1	2.43	1.10	0.40	-0.86
		Perceived complexity 2	3.13	1.40	-0.07	-1.42
		Perceived complexity 3	3.06	1.29	-0.22	-0.99
		Perceived complexity 4	3.11	1.35	-0.07	-1.28
		Perceived complexity 5	2.91	1.36	0.13	-1.29
	Perceived Compatibility	Perceived compatibility 1	3.28	1.25	-0.13	-1.03
		Perceived compatibility 2	3.36	1.19	-0.25	-0.96
		Perceived compatibility 3	3.60	1.23	-0.54	-0.77
		Perceived compatibility 4	3.30	1.17	-0.32	-0.74
	Perceived Cost	Perceived cost 1	2.13	1.14	0.85	-0.11
		Perceived cost 2	2.36	1.23	0.63	-0.66
		Perceived cost 3	2.41	1.08	0.32	-0.79

		Perceived cost 4	2.43	1.17	0.20	-1.16
		Perceived cost 5	2.19	1.02	0.96	0.76
Organizational Context	Top Management Support	Top management support 1	3.74	1.16	-0.30	-1.11
		Top management support 2	3.66	1.25	-0.53	-0.82
		Top management support 3	3.40	1.18	-0.61	-0.45
		Top management support 4	3.34	1.16	-0.17	-1.07
		Top management support 5	3.36	1.38	-0.41	-1.16
	Technological Competence	Technological competence 1	2.57	1.28	0.19	-1.18
		Technological competence 2	2.96	1.37	-0.11	-1.29
		Technological competence 3	2.81	1.23	-0.08	-1.14
		Technological competence 4	2.98	1.37	-0.25	-1.25
	Financial Readiness	Financial readiness 1	3.03	1.22	-0.01	-0.94
		Financial readiness 2	2.98	1.23	0.04	-1.09
		Financial readiness 3	3.21	1.21	-0.41	-0.62
Environmental Context	Competitive Pressure	Competitive pressure 1	3.40	1.19	-0.69	-0.32
		Competitive pressure 2	3.38	1.27	-0.53	-0.78
		Competitive pressure 3	3.74	1.19	-0.73	-0.34
		Competitive pressure 4	2.96	1.33	-0.13	-1.24
		Competitive pressure 5	3.40	1.10	-0.68	-0.18
	External Support	External support 1	4.72	0.60	-2.57	7.78
		External support 2	4.68	0.64	-2.29	5.62
		External support 3	4.66	0.68	-2.16	4.50
		External support 4	4.28	0.77	-0.54	-1.09
	Regulatory Support	Regulatory support 1	2.98	1.23	0.10	-0.75
		Regulatory support 2	2.60	1.08	-0.09	-0.87
		Regulatory support 3	2.70	1.12	0.03	-0.86
		Regulatory support 4	2.87	1.22	-0.13	-0.95
Dependent Variable	Custom AI models Level of adoption	Custom AI adoption	1.89	0.99	0.72	-0.70
	Custom AI models adoption intention	Custom AI adoption intention 1	3.64	1.44	-0.73	-0.88
		Custom AI adoption intention 2	3.75	1.25	-0.67	-0.86
		Custom AI adoption intention 3	3.79	1.36	-0.70	-1.01
		Custom AI adoption intention 4	3.79	1.43	-0.88	-0.67

The descriptive statistics as presented in Table 4. The descriptive analysis reveals elevated kurtosis values for variables for External support 1, 2 and 3, standing at 7,785, 5,616, and 4,504, respectively. These high kurtosis values indicate that the distributions of these variables have heavy tails and more outliers than a normal distribution. This suggests potential non-normality and the need for further investigation into the underlying data distribution and potential outliers.

3.5. Exploratory Factor Analysis

Exploratory factor analysis (EFA) is a multivariate statistical technique used to find a small number of underlying factors that explain the relationships between multiple observed variables (Fabrigar et al., 1999; Ford et al., 1986; Watkins, 2018). EFA assumes that observed variables are influenced by underlying factors, called latent variables, which are inferred from correlation patterns between the observed variables (Watkins, 2018). While EFA is ideally suited for larger sample sizes, often recommended to be over 100 (Jung & Lee, 2011; Mundfrom et al., 2005), it can be cautiously used with smaller samples in some situations such as when factors are well defined or their number is limited (de Winter et al., 2009). This study leverages the well-established TOE framework to provide a strong theoretical basis for examining the factors influencing AI adoption. By focusing on a limited number of robust theoretical constructs, the research design mitigates some of the risks associated with smaller sample sizes.

The study utilised Exploratory Factor Analysis (EFA) to uncover underlying relationships within a dataset and identify latent constructs or factors that contribute to observed patterns in the data. The study used a guide by Humble (2020) to determine the latent variables and assign each items to a specific factor or construct.

Table 5 Exploratory Factor Analysis Selection Criteria

Test	Measure used	Selection Criteria
Dataset Suitability Assessment	The Kaiser-Meyer-Olkin (KMO) measure (Kaiser, 1970; Sofroniou & Hutcheson, 1999)	>=0.7
Appropriateness for EFA analysis	Bartlett Test of Sphericity (Kaiser, 1970; Sofroniou & Hutcheson, 1999)	$p < 0.05$
Extraction Method	Principal Axis Factoring	
Rotation Method	Promax rotation method	
Selection of Latent Variables	Kaiser criterion (Humble, 2020; Kaiser, 1970)	Retain only eigenvalues exceeding one and Cumulative percentage of variance elucidated by factors with eigenvalues > 1 > 50%.
Factor Extraction	Factor loadings (Comrey & Lee, 2013)	Good: 0.55.

Table 5 outlines the selection criteria for EFA analysis, using the Kaiser-Meyer-Olkin (KMO) measure to assess dataset suitability. A KMO value near 1 indicates robust, meaningful factors, while a value of 0.5 or below is mediocre. Additionally, the Bartlett Test of Sphericity indicates the presence of relationships among variables, signifying the appropriateness of factor analysis (Kaiser, 1970; Sofroniou & Hutcheson, 1999).

The selection of latent variables (factors) to be retained was done using a guideline by Humble (2020), retaining only eigenvalues exceeding one, this criterion is commonly referred to as the Kaiser criterion. It is advantageous if the total proportion of variance explained by components with eigenvalues greater than one is over 50% (Humble, 2020). Promax Oblique Rotation involves permitting factors to exhibit correlations. This rotation methodology is considered more realistic in most datasets, as it acknowledges that the underlying factors may not be entirely independent of each other (Corner, 2009). In line with the principles outlined by Comrey and Lee (2013), this study employs a minimum residual method for factor extraction. According to Comrey and Lee's guidelines factor loadings above 0.71 are regarded as exceptional, loadings at 0.63 are considered very good, serving as the threshold for demonstration purposes in this study, loadings of 0.55 are deemed good, a loading of 0.45 is characterized as fair, and Loadings falling within the range of 0.32 are considered poor.

The research utilized Principal Axis Factoring with Promax rotation method for data extraction, evaluated using KMO measure and Bartlett Test of Sphericity to determine datasets suitability for factor analysis. The research used Kaiser criterion in determining the selection of latent variables, considering factors with eigenvalues greater than one (>=1). Furthermore, based on Comrey and Lee (2013) only latent factors with factor loadings of at least 0.55 extracted for use in further analysis.

3.5.1. Exploratory Factor Analysis of Technological Factors

The evaluation of Technological Factors was done on 18 items. KMO indicated a high sampling adequacy (KMO = 0.803), supporting the suitability of the dataset. The significance of Bartlett's test of Sphericity (Approx. Chi-Square = 715.140, df = 153, $p < 0.001$) provides further support for the suitability of factor analysis.

Table 6 Technological Factors Pattern Matrix

	Factor			
Variable	**1**	**2**	**3**	**4**
Relative advantage 1			0.81	
Relative advantage 2			0.90	
Relative advantage 3			0.84	
Relative advantage 4			0.62	
Perceived complexity 1				
Perceived complexity 2		0.69		
Perceived complexity 3		0.65		
Perceived complexity 4		0.99		
Perceived complexity 5		0.90		
Perceived compatibility 1	0.91			
Perceived compatibility 2	0.90			
Perceived compatibility 3	0.81			
Perceived compatibility 4	0.78			
Perceived cost 1				0.91
Perceived cost 2				0.91
Perceived cost 3				
Perceived cost 4				0.61
Perceived cost 5				

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

Table 6 shows factor loadings of variables on four identified factors through Promax rotation with Kaiser normalization. The four extracted factors are named factor 1 “Perceived compatibility”, factor 2 “Perceived complexity”, factor 3 “Relative advantage”, and factor 4 named “Perceived cost”. The analysis of total variance explained analysis revealed that four factors extracted collectively account for a substantial portion, specifically 73,17%, of the total variance present in the dataset. This implies that the identified factors contribute significantly to explaining the variability observed across the set of variables under consideration. Table 17 in Appendix B shows Total Variance Explained for technology factors.

3.5.2. Exploratory Factor Analysis of Organizational Factors

The high value of 0.892 obtained from the KMO measure suggests that the dataset is appropriate for factor analysis. Bartlett's Test of Sphericity was highly significant (Chi-Square = 603.928, df = 66.000, Sig. < 0.001), justifying the application of factor analysis on Organisational Factors.

Table 7 Organizational Factors Pattern Matrix

	Factor	
Variable	1	2
Top management support1		0.94
Top management support2		0.86
Top management support3		0.73
Top management support4		0.76
Top management support5		0.99
Technological competence 1	0.78	
Technological competence 2	0.80	
Technological competence 3	0.90	
Technological competence 4	1.01	
Financial readiness 1	0.71	
Financial readiness 2		
Financial readiness 3		

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization
a. Rotation converged in 3 iterations.

Two factors were extracted as show by Table 7, collectively explaining a substantial 74.51% of the total variance in the dataset. Identified factors were Technological competence: This factor encompasses variables related to the technical proficiency and capabilities of the organization. Top management support: This factor includes variables indicative of the extent of support and endorsement provided by top management towards custom AI models initiatives. Total Variance Explained for organisational factors is shown in Appendix B Table 18.

3.5.3. Exploratory Factor Analysis of Environmental Factors

The KMO indicated a satisfactory value of 0.764, affirming the dataset's suitability for factor analysis. Bartlett's Test of Sphericity was highly significant (Chi-Square = 426.328, df = 78.000, Sig. < 0.001), justifying the application of factor analysis.

Table 8 Environmental Factors Pattern Matrix

	Factor		
Variable	1	2	3
Competitive pressure 1			0.66
Competitive pressure 2			0.80
Competitive pressure 3			0.77
Competitive pressure 4			0.61
Competitive pressure 5			
External support 1		0.83	
External support 2		0.92	
External support 3		0.89	
External support 4			
Regulatory support 1	0.87		
Regulatory support 2	0.80		
Regulatory support 3	0.81		
Regulatory support 4	0.88		

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Table 8 shows three environmental factors extracted, collectively explaining a substantial 71.98% of the total variance in the dataset as show by Table 19 in Appendix B. Identified factors are Regulatory support: comprises variables associated with the level of support and influence from regulatory bodies towards custom AI models. External Support: encompasses variables indicating the extent of external support from stakeholders, such as governmental agencies, industry associations, and community groups. Competitive pressure includes variables reflecting the competitive dynamics faced by the organization such as market conditions and the competitive landscape on business strategies.

3.5.4. Exploratory Factor Analysis of Dependent Variable

KMO measure of sampling adequacy of 0.842, signifying its appropriateness for factor analysis. Bartlett's Test of Sphericity was highly significant (Chi-Square = 307.43, df = 10.000, Sig. < 0.001), justifying the use of factor analysis. This latent variable encapsulates the essence of the dataset, explaining a substantial 77.57% of the total variance.

The extraction process resulted in the identification of a single dominant factor. The nature of the dataset led to an unrotated solution, indicating a clear and singular structure.

Table 9 Dependent Variable Factor Matrix

	Factor
Variable	**1**
Custom AI adoption level 1	
Custom AI adoption intention 1	0.95
Custom AI adoption intention 2	0.95
Custom AI adoption intention 3	0.99
Custom AI adoption intention 4	0.87

Extraction Method: Principal Axis Factoring.

a. 1 factors extracted. 6 iterations required.

Table 10 shows the retained factors after Exploratory Factor Analysis. From initial pool of 47 items resulted in the identification of 10 factors. Notably, the Financial readiness construct did not find support from any of the items, suggesting a distinct pattern in the dataset where this particular aspect lacks substantive representation. Financial readiness was excluded from all further analysis.

Table 10 Summary of retained factors

High-Level Factors	Constructs	No of Items	EFA Extracted Items	% of Variance Explained
Dependent Variable	Custom AI adoption	5	4	77.54
Technological	Perceived Compatibility	4	4	43.72
	Perceived Complexity	5	4	11.59
	Relative Advantage	4	4	10.16
	Perceived Cost	5	3	7.69
Organizational	Technological Competence	5	5	62.13
	Top Management Support	4	5	12.38
	Financial Readiness	3	None	
Environmental	Regulatory Support	5	5	34.10
	External Support	4	3	20.76
	Competitive Pressure	4	4	17.12

3.6. Inferential Analysis

This study used correlation analysis to examine the relationships between variables and identify potential multicollinearity (Sekaran & Bougie, 2016). Examining the correlation coefficients helps evaluate the degree of correlation between variables and identify if there are any redundant or highly interrelated variables that may affect the interpretation of the regression results and to determine potential multicollinearity amongst them. Following the factor analysis, multiple regression analysis was done to analyse the correlation between identified variables from the factor analysis and the actual adoption of custom AI models. Correlation analysis and regression analysis was done as part of section 4, Data Analysis and Results and thus the discussion of correlation analysis and regression analysis is provided in that section

3.6.1. Multiple Regression Statistical Assumptions

To ensure the validity and reliability of the regression results, several key regression analysis statistical assumptions must be met. For this study to validate statistical assumptions, the data was examined to ensure it met the assumptions of linearity, homoscedasticity, normality of residuals, and absence of multicollinearity as described by Tabachnick et al (2013). This subsection discusses the critical statistical assumptions underlying multiple regression analysis: linearity, homoscedasticity, normality of residuals, and no multicollinearity. Evaluating these assumptions is crucial for producing accurate and interpretable regression models.

Linearity and Homoscedasticity: This assumption requires that the relationship between the dependent variable and each of the independent variables is linear to ensures that changes in the predictor variables result in proportional changes in the outcome variable (Osborne & Waters, 2002; Tabachnick et al., 2013). Homoscedasticity implies that the variance of the residuals is constant across all levels of the independent variables. If the residuals display a pattern or if their variance changes across levels of the predictors, the assumption of homoscedasticity is violated (Osborne & Waters, 2002; Tabachnick et al., 2013). A recommended approach for testing the linearity assumption is to examine residual plots, this can be visually inspected using scatterplots as produced by the statistical software when running multiple regression analysis (Osborne & Waters, 2002). B5: Residuals Plots - Hierarchical Regression from figure 4 to figure 10 show residual plot of IVs used in multiple regression. With the exception of service and external support all residuals plots are randomly scattered, indicating a linear relationship between the independent and dependent variables.

Normality of Residuals: The residuals should be approximately normally distributed; which assumption is important for making valid inferences about the regression coefficients (Tabachnick et al., 2013). Normality of residuals can be evaluated using visual methods like histograms and Q-Q plots, as well as statistical tests such as the Shapiro-Wilk test. This study used Q-Q plots as presented in Appendix B6: Q-Q Plots - Hierarchical Regression. The plots show that data points fall along the reference line, which indicates that the data distribution matches the theoretical distribution well.

No Multicollinearity: Multicollinearity occurs when two or more independent variables in the regression model are highly correlated, making it difficult to determine the individual effect of each predictor which can inflate the standard errors of the coefficients, leading to unreliable estimates (Tabachnick et al., 2013; Teo, 2014). Multicollinearity can be assessed using variance inflation factors

(VIF) (Fein et al., 2022; Humble, 2020). Values of the variance inflation factor (VIF) that are near to one suggest the absence of multicollinearity, whereas values more than 10 indicate the presence of multicollinearity (Humble, 2020). Appendix B8: Collinearity Statistics show VIF tables for the 2 multiple regression analysis done. All values are closer to 1 indicating an absence of multicollinearity on the dataset used.

3.7. Ethical Considerations

Ethical issues play a crucial role in research. The researcher participated in an ethics training workshop at Wits University focused on "Ethics in Research and Applying for Ethics Clearance." The researcher obtained ethical approval from the Wits ethics committee before distributing the questionnaire. A copy of Ethics Clearance Certificate can be found on Appendix A3: Ethics Documentation.

The current research conducted the study with integrity, ensuring participant rights and well-being, and maintaining trust and credibility. Sekaran and Bougie (2016) identifies a list of ethical considerations that this study adhered to:

Confidentiality and Privacy: Researchers have a responsibility to treat the information provided by respondents as strictly confidential and to safeguard their privacy. Preserving the confidentiality of individual respondents and subgroup data is vital, and alternative methods can be used to anonymize the data while preserving its richness.

Sensitivity and Respect: Personal or intrusive information should not be solicited unless absolutely necessary for the research. If such information is required, it should be treated with extreme care, with precise justifications given for its collecting. Respondents' self-esteem and respect must constantly be preserved.

Voluntary Participation and Informed Consent: Respondents should not be coerced or forced to partake in the survey. The Respondents' decision to partake or not should be respected. Informed consent should be sought from the subjects, even when data collection is automated or involves recording interviews or videos.

Un-intrusive Observation: Nonparticipant observers should minimize their intrusion in qualitative studies to prevent personal values from biasing the data. Researchers should explicitly state their assumptions, expectations, and biases to ensure transparency and allow managers to make informed decisions regarding data quality.

Compliance with Antispam Legislation: When posting survey invitations on social networks, discussion groups, or chat rooms, researchers should be aware of and abide by antispam legislation and guidelines to avoid being perceived as spam.

Data Reporting Integrity: It is essential to maintain the utmost honesty and accuracy in reporting the collected data. Misrepresentation or distortion of the data is strictly prohibited.

3.8. Chapter Summary

The Research Methodology chapter focused on outlining the approach and techniques used to conduct the study. The study adopted a post-positivist philosophical perspective, recognizing the constructed nature of knowledge within specific contexts, aligning with the hypothesis-driven nature of the research. The chosen research design was quantitative, employing survey research to collect data from South African SMEs. The population, defined by the Small Business Development Government Gazette, consisted of SMEs with less than 250 employees. A snowball sampling technique was employed, resulting in 83 initial responses, with a subsequent data clean-up retaining 55 responses for analysis.

The research instrument was a self-administered online questionnaire, aligning with TOE model constructs, additionally, every item included in the questionnaire was assessed using a five-point Likert scale. allowing for the assessment of participant opinions and attitudes. The questionnaire's reliability was assessed using Cronbach’s coefficient alpha, yielding values between 0.796 and 0.945, indicating scale reliability. The EFA process in this research employed Principal Axis Factoring with Promax rotation. The KMO measure was used to assess the dataset's fitness for factor analysis, and the Bartlett Test of Sphericity evaluated the significance of relationships among variables. Kaiser criterion was applied, retaining latent variables. Additionally, only latent factors with factor loadings of at least 0.55 were considered for further analysis. EFA resulted in the identification of 10 factors from an initial pool of 47 items of the questionnaire. Notably, the Financial readiness construct did not find substantive representation in the dataset. The Research Methodology chapter ensured a robust approach to data collection, and reliability assessment in exploring the factors influencing the potential adoption of custom AI models in South African SMEs.

4. Chapter 4: Data Analysis and Results

The objective of this chapter is to provide an overview of the results derived from the data analysis of the study. By incorporating correlational analysis, regression, and moderation analysis, the chapter analyses the relationships between the research variables in a comprehensive manner. Initially, correlational analysis was employed to investigate the associations between variables, shedding light on their strength, size, direction, and significance. Subsequently, statistical regression analysis is used to determine the variables that warrant inclusion in the hierarchical multiple regression model, prioritizing them based on their significance. Finally, the chapter delves into moderation analysis, providing insights into how specific variables may moderate the influence of independent variables to the dependent variable.

4.1. Correlation Analysis

The Pearson correlation analysis was conducted to determine the presence and strength of a linear relationship between the independent factors and the dependent variable adoption of custom AI models.

Table 11 Consolidated Correlation Matrix

Variable	1	2	3	4	5	6	7	8	9	10
1. Custom AI adoption	—									
2. Perceived compatibility	0.47***	—								
3. Perceived complexity	0.32*	0.43**	—							
4. Relative advantage	0.37**	0.52***	0.62***	—						
5. Perceived cost	0.37**	0.47***	0.54***	0.47***	—					
6. Top management support	0.73***	0.59***	0.30*	0.42**	0.28*	—				
7. Technological competence	0.64***	0.60***	0.60***	0.53***	0.44***	0.65***	—			
8. Regulatory support	0.40**	0.28*	0.11	0.14	0.08	0.57***	0.43**	—		
9. External support	0.10	-0.10	-0.12	-0.01	-0.13	0.03	0.003	-0.15	—	
10. Competitive pressure	0.67***	0.36**	0.30*	0.38**	0.26***	0.66	0.50***	0.39**	-0.15	—

Note: N =53, * = p < .05, ** = p < .01, *** = p < .001

Table 11 below shows the results of Pearson correlation results. The results show that with the exception of external support all other variables show strong positive correlations with custom AI adoption. Notably, perceived complexity and perceived cost also show a positive correlation with custom AI adoption deviating from the expected negative association from theory.

The results Table 11show that perceived compatibility ($r = 0.471$, $p < 0.001$) has significant positive correlation with custom AI adoption. The coefficient (r) is 0.471 is suggesting a moderate positive relationship but significant, $p < 0.001$. This implies that as perceived compatibility increases, the likelihood of higher levels of custom AI adoption also increases. There is empirical support for the hypothesis H1c below

H1c: Perceived compatibility has a positive influence on adoption of custom AI models in South African SMEs. - Supported

The correlation results perceived complexity ($r = 0.325$, $p < 0.01$) in Table 11 indicates a positive correlation between perceived complexity and custom AI adoption. The positive correlation suggests that as perceived complexity increases, there is a tendency for higher levels of custom AI adoption. This finding contradicts the hypothesis that perceived complexity would have a negative influence on the adoption of custom AI models in South African SMEs.

H1b: Perceived complexity has a negative influence on adoption of custom AI models in South African SMEs. – Not supported

The Pearson correlation result in Table 11 of relative advantage ($r = 0.366$, $p < 0.01$) indicates a significant positive correlation between relative advantage and custom AI adoption. The positive correlation suggests that as the perceived relative advantage increases, there is a corresponding increase in custom AI adoption. This outcome aligns with hypothesis H1a, which posited that relative advantage would have a positive influence on the adoption of custom AI models in South African SMEs.

H1a: Relative advantage has a positive influence on adoption of custom AI models in South African SMEs. - Supported

The result ($r = 0.372$, $p < 0.01$) in Table 11 reveals a significant positive correlation between perceived cost and custom AI adoption. This finding contradicts hypothesis H1d, which proposed that perceived cost would have a negative influence on the adoption of custom AI models in South African SMEs. The positive correlation suggests that as perceived cost increases, there is also an increase in custom AI adoption among South African SMEs. Therefore, based on the correlation result, it does not support the hypothesis H1d.

H1d: Perceived cost has a negative influence on adoption of custom AI models in South African SMEs. – Not supported

There is a positive correlation of 0.727 between top management support and the adoption of custom AI models in South African SMEs as shown in Table 11. This correlation is statistically significant, at $p < 0.001$. This finding strongly supports hypothesis H2a, which posited that top management support has a positive influence on the adoption of custom AI models in South African SMEs.

H2a: Top management support has a positive influence on adoption of custom AI models in South African SMEs. - Supported

The Pearson correlation between technological competence and adoption of custom AI models ($r = 0.640$, $p < 0.001$), which indicates a positive and strong correlation between the two variables. This result aligns with hypothesis H2b, which posited that technological competence has a positive influence to the adoption of custom AI models in South African SMEs. This means that as technological competence increases, so does the adoption of custom AI models. Therefore, hypothesis H2b is supported by the data.

H2b: Technological competence has a positive influence on adoption of custom AI models in South African SMEs. – Supported

Table 11 shows the Pearson correlation result ($r = 0.400$, $p < 0.01$) indicating a positive correlation between regulatory support and the adoption of custom AI models. This means there's a tendency for higher levels of regulatory support to be associated with increased adoption of custom AI models. However, the strength of this relationship is considered moderate, suggesting other factors likely influence adoption as well. This supports the hypothesis H3c.

H3c: Regulatory Support has a positive influence on adoption of custom AI models in South African SMEs. – Supported

The Pearson correlation coefficient for external support and adoption of custom AI models is 0.096, which is close to zero. This indicates a very weak relationship, meaning there is no correlation amongst the variables, and therefore, the data does not support hypothesis (H3b) that external support will have a positive influence on adoption of custom AI models in South African SMEs.

H3b: External support has a positive influence on adoption of custom AI models in South African SMEs. – Not supported

The Pearson correlation coefficient in Table 11 for competitive pressure and adoption of custom AI models ($r = 0.668$, $p < 0.001$) indicating a positive and strong correlation. This means that as competitive pressure increases, so does the adoption of custom AI models. This finding supports hypothesis H3a, suggesting that competitive pressure positively influences custom AI models adoption in South African SMEs. The significant positive correlation implies that, in this specific context, there is evidence to conclude that competitive pressure increases the likelihood of adopting custom AI models.

H3a: Competitive pressure has a positive influence on adoption of custom AI models in South African SMEs. – Supported

The Pearson correlation results reveal significant relationships between several contextual factors and the adoption of custom AI models in South African SMEs, however, it should be noted that correlation does not imply causation (Barrowman, 2014; Fein et al., 2022). While the study found correlation on some variables and the adoption of custom AI models, it is possible that other factors could be involved. The next section employs hierarchical multiple regression statistical method to assess the hypotheses of this study.

4.2. Hierarchical Multiple Regression

The study employed a hierarchical regression to explore the influence of different factors on the dependent variable custom AI models adoption. Prior to incorporating the focal variables into the regression model, a stepwise approach was undertaken. This involved employing statistical regression and correlation analysis to assess the individual significance of each focal variable. Subsequently, only significant variables were included in the final models. The models were constructed sequentially, with each step introducing additional independent variables to gauge their impact on the outcome. In the context of custom AI model adoption, the sequence of environmental factors followed by organizational factors and then technological factors can be justified based on these logical considerations:

- Environmental Factors: Understanding the broader industry trends related to AI adoption is crucial. SMEs need to assess the current landscape, identify competitors' strategies, and evaluate the demand for AI solutions in the industry.
- Organizational Factors: Once environmental factors are considered; organizations should align their internal structures to support AI adoption. This involves evaluating existing processes, roles, and responsibilities to ensure that they are conducive to integrating AI technologies.
- Technological Factors: With a clear understanding of the market and organizational readiness, the focus can shift to selecting or customizing AI models that align with specific business objectives. This involves evaluating the technical capabilities, scalability, and compatibility of AI technologies with existing systems.

Table 12 Hierarchical Regression Including Interaction of Perceived Compatibility and Top Management Support

Predictor	Model 1			Model 2			Model 3			Model 4			Model 5		
	B	SE	β	B	SE	β	B	SE	B	B	SE	β	B	SE	β
Intercept	-0.23	0.18		-0.09	0.14		-0.12	0.12		-0.12	0.12		-0.06	0.12	
Services	0.56*	0.25	0.30	0.33	0.19	0.18	0.39*	0.16	0.21	0.40*	0.16	0.21	0.41*	0.16	0.22
Competitive Pressure				0.68**	0.10	0.66	0.32*	0.12	0.31	0.33*	0.12	0.32	0.27*	0.12	0.26
External Support				0.21*	0.10	0.21	0.14	0.08	0.15	0.16	0.09	0.17	0.16	0.08	0.16
Top Management Support							0.48**	0.11	0.50	0.40*	0.13	0.42	0.43*	0.13	0.45
Perceived Compatibility										0.11	0.10	0.11	0.09	0.10	0.10
Top Management Support ⁎ Perceived Compatibility													-0.123*	0.08	-0.12
F		5.02*			17.46**			22.31**			18.16**			16.02**	
R^2		0.09			0.52			0.65			0.66			0.68	
Adjusted R^2		.07			0.49			0.62			0.62			0.63	

** = p < 0.01, * = p < 0.05
Dependent Variable: Custom AI adoption

Table 12 show results of Hierarchical multiple regression, the model details is discussed below.
Model 1: The initial model included the services variable, representing the consolidation of ICT Services and Finance and Insurance industries. The initial model ($F(1, 51) = 5.02$, $p = 0.029$, $R^2 = 0.090$) showed a modest R^2 indicating that 9% variance in custom AI models adoption was explained. F Change statistics suggested that the model was statistically significant. The coefficient for Services was found to be ($\beta = 0.30$, $p < 0.05$), indicating a significant positive influence to the dependent variable.

Model 2: Building upon the first model, the second model ($F(3, 49) = 17.46$, $p < 0.001$, $R^2 = 0.517$) introduced external support and competitive pressure. The F Change statistics were highly significant, indicating the improved model's efficacy. Competitive Pressure has a positive association ($\beta = 0.66$, $p < 0.01$), and External Support also shows a positive relationship ($\beta = 0.21$, $p < 0.05$). Furthermore, R^2 substantially increases to 0.52 indicating the increased predictive power of model 2.

Model 3: The third model $F(4, 48) = 22.31$, $p < 0.001$, $R^2 = 0.650$ expanded the variables to include top management support indicating a significant positive relationship ($\beta = 0.50$, $p < 0.01$). This model explained 65% variance in custom AI adoption, and F Change statistics remained highly significant. All predictors in this model had a significant impact on AI Adoption. The R^2 again increases to 0.65 indicating that model 3 is an improvement from model 2.

Model 4: The final model $F(5, 47) = 18.16$, $p < 0.001$, $R^2 = 0.659$ integrated perceived compatibility alongside the existing variables. The final model maintained an R^2 of 0.659, highlighting that the additional variable did not significantly contribute to the variance explained. perceived compatibility did not reach statistical significance, but top management support remained a strong predictor. The R^2 slightly increases to 0.659, which is a marginal improvement from Model 3.

Model 5: The interaction term (top management support ✻ perceived compatibility) is included, and it is not significant ($\beta = -0.12$). Competitive pressure, external support, technological competence maintained a strong predictive power. The R^2 increases to 0.68, which is a small improvement from Model 3. Moderation term is discussed further in section 4.3.

In summary, the models as shown in Table 12 demonstrate that the inclusion of industry type ("services"), external support, competitive pressure, technological competence, and top management support significantly enhances the predictive capacity for custom AI adoption intention. Model 4, while maintaining a high R2, suggests that Perceived compatibility did not yield a meaningful improvement in explanatory power.

The hierarchical regression analysis revealed the dynamics that impact the adoption of custom AI models by south African SMEs. Services variable consistently shows a positive and significant relationship with custom AI adoption across all models, suggesting that companies offering service-based businesses are more likely to adopt custom AI models.

Competitive pressure was added in Model 2 and shows a positive influence on custom AI adoption ($\beta = 0.66$, $p < 0.01$). The analysis strongly supports hypothesis *H3a*. Competitive pressure has the strongest individual effect among all variables and shows a significant and positive relationship with custom AI adoption, confirming its positive influence to custom AI adoption.

H3a: Competitive pressure has a positive influence on adoption of custom AI models in South African SMEs. - Supported

External support also included in Model 2, demonstrates a positive influence on custom AI adoption ($\beta = 0.21$, $p < 0.05$). The analysis partially supports hypothesis H3b. External support shows a positive and significant relationship with AI adoption, suggesting it does play a role in encouraging adoption. However, its effect is smaller compared to other variables like competitive pressure and top management support.

H3b: External support has a positive influence on adoption of custom AI models in South African SMEs. - Supported

Top management support, introduced in Model 3, exhibits a significant and positive influence on custom AI adoption ($\beta = 0.50$, $p < 0.01$), supporting hypothesis H2a. Top management support consistently shows a significant and positive relationship with AI adoption, confirming its positive influence.

H2a: Top management support has a positive influence on adoption of custom AI models in South African SMEs. - Supported

Perceived compatibility introduced in Model 4, alone has no significant effect on AI adoption in any model. Although it does not show a statistically significant influence on custom AI adoption ($\beta = 0.11$, $p > 0.05$), its inclusion indicates an attempt to explore its impact. The hypothesis H1c is not supported by the current analysis. While perceived compatibility alone does not direct influence on adoption, it moderates the influence of top management support on custom AI adoption.

H1c: Perceived compatibility has a positive influence on adoption of custom AI models in South African SMEs. – Not supported

External environment underlined the importance of external factors in shaping custom AI model Adoption. Competitive pressures notably emerged as a robust determinant. Organizational factor top management support played a key role, emphasizing the organizational leadership's impact on custom

AI model Adoption. However, technological competence did not exhibit a significant influence. Perceived compatibility did not yield a significant impact. This suggests that, in this study context, perceived compatibility might not be a decisive factor in custom AI model Adoption.

Table 13 shows a second hierarchical regression performed with perceived compatibility moderating effect of technological competence on custom AI adoption. Models 1 and 2 contain the same results as the previous hierarchical regression already discuss and will not be discussed again.

Model 3: The introduction of technological competence significantly improves the model fit compared to Model 2 (R-squared increases from 0.52 to 0.62). This demonstrates that technological competence is a significant factor in explaining the variation in custom AI adoption. Technological competence has a positive and significant coefficient ($\beta = 0.37$), meaning increased levels of technological competence are linked with increased adoption of custom AI models. The positive and significant coefficient indicates that higher technological competence is associated with increased adoption, strongly supporting H2b.

> *H2b: Technological competence has a positive influence on the adoption of custom AI models in South African SMEs. – supported*

Model 4: Introducing perceived compatibility does not does not lead to a substantial improvement in model fit compared to Model 3, suggesting it might not contribute significantly to the overall explanation. Perceived compatibility itself does not directly and significantly impact adoption but moderates the effect of technological competence in Model 5.

Table 13 Hierarchical Regression Including Interaction of Perceived Compatibility and Technological Competence

Predictor	Model 1			Model 2			Model 3			Model 4			Model 5		
	B	SE	β	B	SE	β	B	SE	B	B	SE	β	B	SE	β
Intercept	-0.23	0.18		-0.09	0.14		-0.04	0.13		-0.06	0.13		0.02	0.14	
Services	0.56*	0.25	0.30	0.33	0.19	0.18	0.28	0.17	0.15	0.31	0.17	0.17	0.28	0.17	0.15
Competitive Pressure				0.68**	0.10	0.66	0.49**	0.11	0.48	0.47**	0.11	0.46	0.45**	0.11	0.44
External Support				0.21*	0.10	0.21	0.18*	0.09	0.18	0.19*	0.01	0.20	0.21*	0.09	0.21
Technological Competence							0.37**	0.10	0.37	0.28*	0.12	0.28	0.30*	0.12	0.30
Perceived Compatibility										0.14	0.11	0.15	0.12	0.11	0.13
Technological Competence ✻ Perceived Compatibility													-0.11*	0.09	-0.11
F		5.02*			17.46**			19.42**			16.14**			13.83**	
R^2		0.09			0.52			0.62			0.63			0.64	
Adjusted R^2		.07			0.49			0.59			0.59			0.60	

** = $p < 0.01$, * = $p < 0.05$

Dependent Variable: Custom AI adoption

4.3. Moderation of Perceived Compatibility on Top Management Support → Custom AI Adoption

A moderation analysis was conducted using top management support, custom AI adoption, and perceived compatibility. The bootstrapping procedure was used to determine confidence intervals for the moderation term coefficient, with 5,000 resamples and the Bias-Corrected and Accelerated (BCa) method.

Table 14 Moderation of Perceived compatibility on Top management support → Custom AI adoption

Parameter	Base Model			Interaction Model		
	B	90% BCa CI	β	B	90% BCa CI	β
Constant	-0.12	-0.34 to 0.11		-0.06	-0.30 to 0.25	
Services	0.40	0.10 to 0.72	0.21	0.41	0.12 to 0.67	0.22
External support	0.16	0.02 to 0.28	0.17	0.16	0.03 to 0.27	0.16
Competitive pressure	0.33	0.11 to 0.54	0.32	0.27	0.01 to 0.51	0.26
Top management support	0.40	0.17 to 0.68	0.42	0.43	0.16 to 0.73	0.44
Perceived compatibility	0.11	-0.11 to 0.31	0.12	0.09	-0.14 to 0.31	0.09
Top management support ⁎ Perceived compatibility				-0.12	-0.30 to -0.01	-0.15

Bootstrap results are based on 5000 bootstrap samples
Dependent Variable: Custom AI adoption

Table 14 shows significant moderation effect by the interaction term was found to be statistically significant as effect size from bootstrap analysis with a 90% confidence interval for the moderation effect revealed a significant within the 90% BCa confidence intervals. This suggest that perceived compatibility plays a moderating role in top management support influence to custom AI adoption. The interaction term is negative and significant (β = -0.15), this suggest that top management support influence on custom AI adoption becomes weaker as perceived compatibility increases.

Figure 2 Moderation effect on Top management support

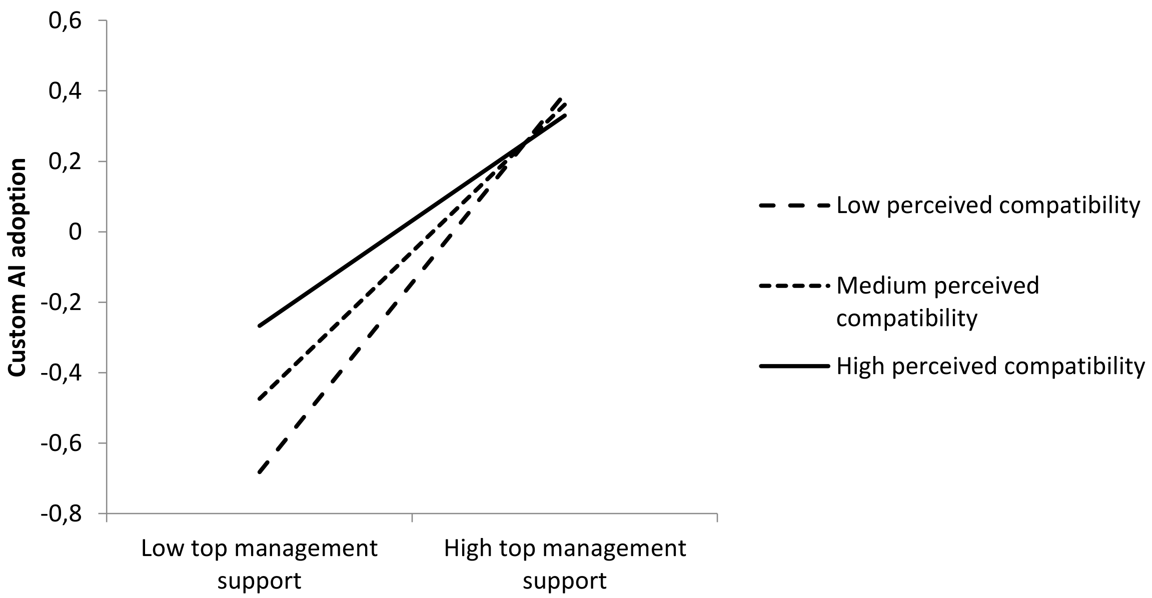


Figure 2 show Low perceived compatibility has step slope compared to medium and high-perceived compatibility, this suggests that companies with low perceived compatibility might need stronger encouragement from management to overcome their concerns and adopt the AI solution.

4.4. Moderation of Perceived compatibility on Technological competence → Custom AI adoption

A second moderation test was run with technological competence as an independent variable, custom AI adoption as the dependant, and perceived compatibility as a moderator. The moderation analysis aimed to explore whether perceived compatibility moderates' technological competence influence on custom AI adoption. The moderation analysis was conducted with 5,000 resamples and employing the Bias-Corrected and Accelerated (BCa) method.

Table 15 Moderation of Perceived compatibility on Technological competence → Custom AI adoption

Parameter	Base Model			Interaction Model		
	B	90% BCa CI	β	B	90% BCa CI	β
Constant	-0.06	-0.31 to 0.19		0.02	-0.26 to 0.30	
Services	0.31	0.01 to 0.64	0.17	0.29	-0.02 to 0.59	0.15
External support	0.19	0.08 to 0.29	0.20	0.21	0.06 to 0.31	0.21
Competitive pressure	0.47	0.28 to 0.66	0.46	0.45	0.24 to 0.65	0.44
Technological competence	0.28	0.08 to 0.50	0.28	0.30	0.08 to 0.51	0.30
Perceived compatibility	0.14	-0.02 to 0.31	0.15	0.12	-0.09 to 0.33	0.12
Technological competence ✻ Perceived compatibility				-0.11	-0.25 to -0.02	-0.11

Bootstrap results are based on 5000 bootstrap samples
Dependent Variable: Custom AI adoption

Table 15 shows the interaction term was found to be statistically significant with the bootstrap analysis showing a 90% confidence interval for the moderation effect revealed a significant within the 90% BCa confidence intervals. The moderation term was statistically significant, suggesting that perceived compatibility does moderate the impact of technological competence on custom AI adoption.

Figure 3 Moderation effect on Technological competence

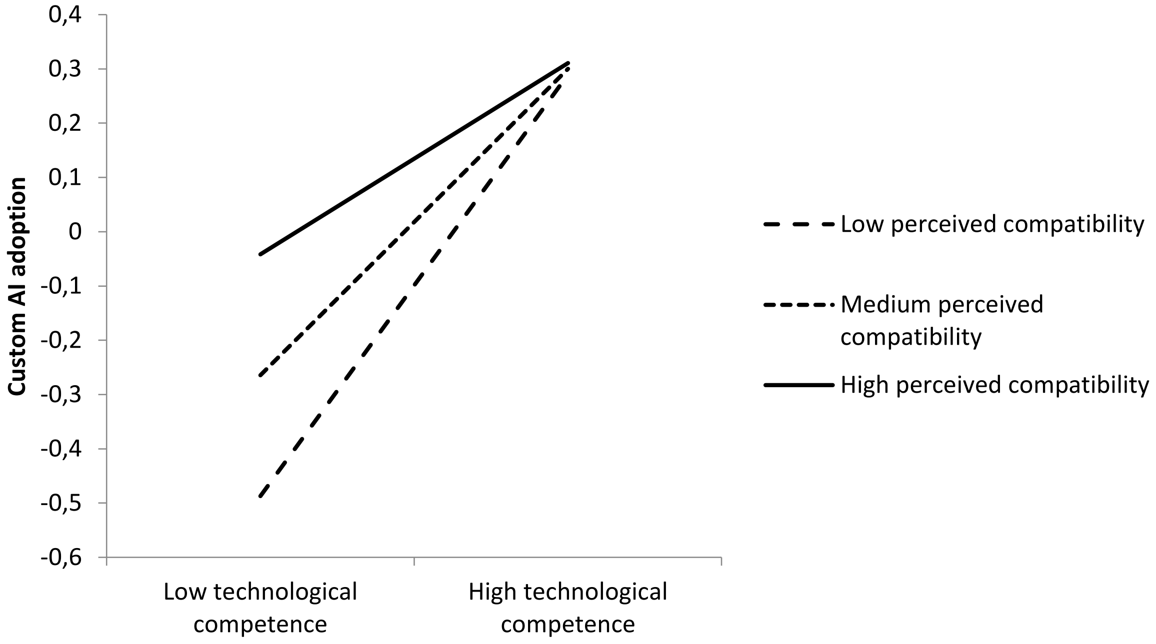


Figure 3 shows varied influence of technological competence to custom AI adoption due to perceived compatibility. SMEs technological competence is affected by all levels of perceived compatibility, but the positive effect of technological competence on custom AI adoption becomes weaker as perceived compatibility increases.

4.5. Chapter Summary

The Pearson correlation analysis revealed significant positive relationships between various factors and the adoption of custom AI models in South African SMEs, providing support for several hypotheses. Factors such as top management support, technological competence, and competitive pressure were found to play crucial roles in influencing the adoption of custom AI in the specific context.

Before integrating the focal variables into the hierarchical regression model, a stepwise procedure was implemented. This included utilizing statistical regression and correlation analyses to evaluate the individual significance of each focal variable. Subsequently only Services, External support, competitive pressure, top management support, technological competence, and perceived compatibility were found to be individual significance to be added to hierarchical regression. The results from regression analysis indicated that external support, competitive pressure, top management support, and technological competence are influential factors in custom AI adoption, supporting hypotheses H3b, H3a, H2a, H2b. The chapter also includes a moderation analysis employing the bootstrapping procedure with 5,000 resamples and the BCa method. The results show a significant moderation effect of perceived compatibility top management support influence of custom AI adoption. A second moderation test with technological competence as the independent variable also shows that perceived compatibility moderates the impact of technological competence on custom AI adoption.

5. Chapter 5: Discussion, Recommendations, and Conclusions

This research addresses the issue of limited adoption of custom AI models among South African SMEs. The study aims to determine the factors that affect the likelihood of South African SMEs adopting customised AI models. This chapter interprets the results of previous chapter, discussing their theoretical implications in academia and the practical implication for SMEs. The chapter further discuss this study limitations, and proposes future research that can be done on adoption of custom AI models by South African SMEs.

Using TOE framework as its theoretical framework, this study focuses on understanding how the TOE factors influence the potential adoption of custom AI models by South African SMEs.

The research questions that guides this research is:

> RQ0: *What factors impact the potential adoption of custom artificial intelligence models in South African small and medium-sized enterprises?*

To answer this question, this study employs a quantitative method, distributing a Likert scales based online survey to a sample of SMEs targeted via the snowball sampling technique. 83 initial responses were obtained, data cleaning and screening refined the final sample size to 55.

The results section performed correlation analysis, evaluating the degree and direction of variable relationships and their correlation the dependent variable. Transitioning to hierarchical multiple regression, the study probed the impact of factors, unveiling their hierarchical significance in predicting custom AI model adoption. Further, moderation analysis was done to examine how perceived compatibility moderates the impact of top management support and technological competence to custom AI adoption.

5.1. Interpretation of the Findings

Pearson correlation serves as a valuable tool for examining whether individual variables linearly relate to the dependent variable. It reveals the direction (positive or negative) and intensity of these associations, along with their statistical significance, allowing us to draw meaningful conclusions about potential influencing factors. While a strong connection between two variables is intriguing, it is crucial to remember that correlation does not equal causation (Barrowman, 2014; Fein et al., 2022), and for this reason the Pearson correlation results alone will not be used to confirm or refute hypotheses; instead, they will be utilized to generate a discussion regarding the relationships among variables.

The Pearson correlation analysis reveals a positive correlation between perceived compatibility and the adoption of custom AI. This suggests that as perceived compatibility increases, there is a parallel increase in the likelihood of custom AI adoption. Consistent with earlier research in adoption of new technology such as Big data, AI, and IoT (Awa et al., 2017; Horani et al., 2023; Maroufkhani et al., 2023; Shahadat et al., 2023), the results suggest that SMEs who perceive that custom AI models aligns well with their current systems, processes, or needs will be more inclined to adopt custom AI models. This positive correlation underscores the importance of perceived compatibility as a potentially influential factor in the decision-making process regarding the adoption of custom AI models.

The observed correlations result between perceived complexity and custom AI adoption reveal a noteworthy positive association between the two variables. This outcome is in contrast to the assertions made by Phuoc (2022), Horani et al. (2023), Maroufkhani et al. (2023), Gupta et al. (2022), and Shahadat et al. (2023), who posited that perceived complexity would negatively influence new technologies adoption by organisations. This contradiction requires a more thorough investigation into the contextual factors or potential methodological differences that could account for these divergent results.

The Pearson correlation results reveal a positive correlation between relative advantage and the adoption of custom AI models by SMEs. The finding supports prior research suggesting that perceived benefits of adopting AI contribute to its adoption in organizational contexts (Gupta et al., 2022; Horani et al., 2023; Phuoc, 2022). The perceived relative advantages of custom AI models compared to traditional solutions may include cost savings through improved efficiency, competitive advantage in the market, and enhancing the overall customer experience. This positive association signifies that as the SME perceived increases in relative advantage, the likelihood of custom AI adoption among those SMEs also tends to increase.

The result reveals positive correlation between perceived cost and custom AI adoption among South African SMEs. However, these findings are in contrast with the expected negative correlation between perceived cost and custom AI adoption and stand in contrast to the outcomes reported by Horani et al. (2023) and Shahadat et al. (2023). These previous studies suggested a negative relationship, implying that as perceived costs increase, the adoption of custom AI models should decrease. The observed discrepancy in the correlation results could be attributed to the dominant presence of ICT firms, constituting 38.18% of the sample, and the Finance industry at 18.18%. These sectors, being technology-intensive, might be more inclined and financially prepared to invest in new technologies, potentially influencing positive correlation between perceived cost and custom AI adoption.

The positive Pearson correlation observed between top management support and custom AI models adoption in South African SMEs indicating that as top management support increases, so does the probability of adopting custom AI models. This correlation aligns with the expectation that support from top management positively influences the decision-making process regarding the adoption of technology like custom AI models. Furthermore, the confirmation of a significant positive influence in the hierarchical multiple regression analysis establishes top management support as a predictor with a causal relationship to the adoption of custom AI models. This implies that when there is strong support from top management, the likelihood of adopting custom AI models in South African SMEs increases. These consistent findings across correlation and regression analyses enhance the robustness of the evidence supporting top management support as a factor influencing the adoption of custom AI models in South African SMEs. The results also support this study's hypothesis H2a which states *Top management support has a positive influence on adoption of custom AI models in South African SMEs.* The findings are also in line with previous research (Awa et al., 2017; Gupta et al., 2022; Horani et al., 2023; Ingalagi et al., 2021; Maroufkhani et al., 2023; Phuoc, 2022; Shahadat et al., 2023) which determined that top management support has a positive influence on adoption of technologies like AI, IoT, big data, and cloud computing.

The positive and strong Pearson correlation between technological competence and the adoption of custom AI models implies that as technological competence increases, there is a corresponding increase in the likelihood of adopting custom AI models in South African SMEs. The alignment of this correlation result with the hierarchical multiple regression findings, indicating a substantial role of technological competence in explaining the variance in custom AI adoption, further supports the significance of technological expertise in driving the adoption of advanced AI solutions within the SME context in South Africa. This results are consistent with the hypothesis H2b: *Technological competence has a positive influence on adoption of custom AI models in South African SMEs*, supporting the notion that a higher level of technological competence positively influences the adoption of custom AI models. The outcomes also support research by (Gupta et al., 2022; Phuoc, 2022) that technological competence plays a crucial role in influencing the implementation process of technologies such AI.

The hierarchical multiple regression results indicate that external support exhibits a positive and significant relationship with AI adoption in South African SMEs. This suggests that when there is strong support from external like technology vendors, supply chain partners the adoption of custom

AI by SMEs will be higher. This is attributed to the likelihood that many SMEs do not have the expertise and knowledge of implementing custom AI models, and may rely on the support of vendors and technology providers. This hierarchical regression findings contrasts with the initial Pearson correlation coefficient, which suggested a very weak relationship between external support and AI adoption. The regression results, aligning with hypothesis H3b: *External support has a positive influence on adoption of custom AI models in South African SMEs*, and confirm that external support has a positive influence on the adoption of custom AI models in South African SMEs. The results support previous research by Horani (2023), Ingalagi (2021) and Phuoc (2022).

According to the regression analysis results, among all the factors, competitive pressure has the largest individual effect and is significantly and positively correlated with the adoption of custom AI models adoption. This finding supports the hypothesis H3a, which posited that *Competitive Pressure has a positive influence on the adoption of custom AI models in South African SMEs.* The Pearson correlation coefficient further strengthens this observation, indicating a positive correlation between competitive pressure and the adoption of custom AI. This implies that, in the competitive landscape of South African SMEs, organizations experiencing higher competitive pressure are likely to adopt custom AI models. The strength of this relationship, as indicated by both correlation and regression analyses, highlights the significant role the competitive pressures plays in shaping the decisions of SMEs regarding the adoption of advanced technologies like custom AI models. This insight is valuable for SMEs operating in competitive environments, highlighting the strategic importance of custom AI adoption to enhance competitiveness and resilience. The results are consistent with prior research results (Gupta et al., 2022; Horani et al., 2023; Ingalagi et al., 2021; Phuoc, 2022; Shahadat et al., 2023).

The study further run a test on moderation effect of perceived compatibility on top management influence on custom AI adoption. The results show a significant moderation effect which implies that the influence of top management support on custom AI adoption is influenced by the level of perceived compatibility. The findings highlight the importance of considering Perceived compatibility as a crucial factor in shaping the influence of top management support on custom AI adoption. The interaction term is negative and significant; this suggest top management support influence on custom AI adoption becomes weaker as perceived compatibility increases. In other words, when companies highly perceive the compatibility of the AI solution, top management support influence on adoption decreases, this suggests that companies with low perceived compatibility might need stronger encouragement from management to overcome their concerns to adopt custom AI solution. Conversely, companies with high-level support from management might already be inclined to adopt AI regardless of their perceived compatibility. Therefore, further increases in compatibility have a smaller impact on their custom AI adoption decision. Top management support plays a crucial role in encouraging AI adoption, but its influence is moderated by perceived compatibility.

The results of the second moderation test shows the role of perceived compatibility in shaping the relationship between technological competence and custom AI adoption. The significant moderation effect indicates that organizations with different levels of perceived compatibility may respond differently to technological competence, which may result in a varied influence of technological competence to custom AI adoption. The results show, when companies highly perceive the compatibility of the AI solution, the influence of their technological competence on adoption decreases, suggesting when compatibility is high, even companies with lower technological competence might be more likely to adopt custom AI due to the ease of integration and implementation. This also suggests that companies with low technological competence are likely to adopt AI, but only if they determine the custom AI solution as highly compatible with their needs. Perceived compatibility does not directly influence custom AI adoption but moderates the effect of technological competence influence to custom AI adoption.

It must be noted that, the effects of perceived compatibility moderation on both top management support and technological competence influence on custom AI adoption was not part of the initial theory investigated by this study, but understanding these relationships underscores the emphasises the necessity of addressing the interaction of numerous aspects when evaluating the adoption of custom AI model by SMEs.

The research findings highlight the role of key factors in influencing the adoption of custom AI models in South African SMEs. Results confirm the significant positive influence of top management support, establishing it as a predictor with a causal relationship to custom AI adoption. Furthermore, the results underscore the significance of technological competence in driving the adoption of advanced custom AI solutions in SMEs. The alignment of correlation results with regression findings strengthens the argument that a higher level of technological competence positively influences custom AI adoption. The results also shed light on the importance of external support, indicating a positive and significant relationship with AI adoption in South African SMEs. This underscores the role of external entities, such as technology vendors and service providers, in supporting SMEs with limited expertise in implementing custom AI models. Competitive pressure emerges as a potent factor, displaying the strongest individual effect among all variables. In summary, the results support the following study's hypothesis:

> H2a: *Top management support has a positive influence on adoption of custom AI models in South African SMEs.*

H2b: *Technological competence has a positive influence on adoption of custom AI models in South African SMEs.*
H3a: *Competitive Pressure has a positive influence on the adoption of custom AI models in South African SMEs.*
H3b: *External support has a positive influence on adoption of custom AI models in South African SMEs.*

This research has addressed the primary research question:

RQ0: What factors impact the potential adoption of custom artificial intelligence models in South African small and medium-sized enterprises?

As supported by the results of this study, top management support, technological competence, competitive pressure, and external support turned out to be factors that impact the potential adoption of custom AI models in South African SMEs. Perceived compatibility itself does not have a direct and significant effect on adoption of custom AI models but moderates top management support and technological competence influence on custom AI adoption, and therefore can be considered as a factor that influence custom AI adoption by South African SMEs.

5.2. Theoretical contribution

The primary contribution of this study lies in addressing the challenge of limited custom AI adoption among South African SMEs. By investigating the factors influencing this issue, the research contributes valuable insights that can aid SMEs, owners, and managers in overcoming barriers associated with the adoption of custom AI. This contribution is significant as it directly addresses a real-world problem, providing actionable insights for businesses looking to integrate custom AI models into their operations.

The study did not initially incorporate the examination of perceived compatibility moderation effects on the influences of top management and technological competence on custom AI adoption. However, the unexpected findings highlight the intricate interplay of these factors in the adoption process. This unanticipated yet valuable insight emphasizes the complexity of custom AI models adoption dynamics, urging researchers and practitioners to take a holistic perspective when investigating the multifaceted influences on the adoption of custom AI models. Therefore, the biggest theoretical contribution of this research lies in its exploration of the moderating role of perceived compatibility on the influences of top management support and technological competence on custom AI adoption. By uncovering this unexpected aspect, the study adds depth to the understanding of the factors shaping the custom AI adoption process. This contribution extends existing theories by emphasizing the need to consider interactive effects, shedding light on the dynamics that influence the adoption of custom AI models in the context of South African SMEs. The findings encourage further refinement and development of theoretical frameworks that capture the interplay of variables in the custom AI models adoption landscape.

5.3. Practical implications

This study results show that top management support significantly influences the adoption of custom AI models in South African SMEs. This finding highlights that top management plays significant role in the adoption of custom AI model, and practically implies that for those organisations that intend to adopt custom AI model, they should prioritize executive education and awareness programs on the benefits and strategic advantages of custom AI adoption (Chaudhuri et al., 2022; Dhasarathy et al., 2020). Leadership training programs that highlight the impact of custom AI on operational efficiency, competitiveness, and innovation can contribute to a more supportive top management stance towards custom AI models adoption (Iftikhar & Nordbjerg, 2021). Also, the practical implications emphasize the need for proactive efforts in garnering top management support, which extends beyond mere endorsement to active involvement and understanding of the custom AI adoption process (Dhasarathy et al., 2020).

The study findings support the hypothesis that a higher level of technological competence within SMEs positively influences the adoption of custom AI models. In light of this, SMEs should strategically recruit and retain individuals with strong technological backgrounds, adopting a workforce that is not only capable but also enthusiastic about embracing AI innovations (Chiu et al., 2021). This may involve investing in training programs, workshops, and skill development initiatives aimed at empowering employees with the necessary technical know-how to navigate and implement custom AI solutions effectively (Chaudhuri et al., 2022).

The hierarchical multiple regression findings revealing a positive and significant relationship between external support and the adoption of custom AI models in South African SMEs. For SMEs seeking to integrate AI solutions but lacking the in-house expertise, leveraging external support from technology vendors, supply chain partners, and information technology service providers becomes instrumental (Ghobakhloo et al., 2011). This can significantly enhance SMEs' capacity to adopt and effectively utilize custom AI models. Collaborations with external experts can bridge the knowledge gap, providing SMEs with the necessary insights and resources to navigate the intricacies associated with AI adoption (Ghobakhloo et al., 2011). The practical implications of this finding emphasize the strategic importance of external support in driving the acceptance of custom AI models among South African SMEs.

The study results suggest that SMEs operating in competitive industries are more inclined to adopt custom AI models. In practice, this means SMEs operating in sectors characterized by intense competition should recognize the strategic importance of adopting custom AI solutions and should view custom AI adoption as a strategic imperative for sustained success. Practically, SMEs operating in sectors characterized by intense competition should expect their competitors to use custom AI models in their strategy (Lai et al., 2018) and should consider this when devising competing strategies.

Identifying perceived compatibility as a moderating element in both top management support and technological competence influence on custom AI adoption has significant practical implications for South African SMEs navigating the adoption of custom AI. The biggest implication is the diminishing returns between high perceived compatibility and strong management support. The implication is that companies with both high perceived compatibility and strong management support may experience diminishing returns from further improvements in compatibility. This implies that, beyond a certain point, additional efforts to enhance perceived compatibility might not significantly impact the adoption of custom AI models. Instead, these organizations might need to focus on consolidating their gains and redirecting resources toward other aspects of custom AI implementation. This argument also applies on the moderation effects of perceived compatibility on technological competence influence of custom AI adoption.

This study provides these practical recommendations for SMEs:

1. Prioritize Executive Education and Awareness Programs: Organizations intending to adopt custom AI models should focus on educating executives about the benefits and strategic advantages of custom AI adoption.
2. Leadership Training Programs: Develop and implement training programs that highlight the impact of custom AI on operational efficiency, competitiveness, and innovation to foster a supportive top management stance towards AI adoption.
3. Proactive Top Management Support: Ensure active involvement and understanding of the custom AI adoption process by top management, extending beyond just the endorsement of AI adoption.
4. Recruit and Retain Technologically Competent Individuals: Strategically hire and retain employees with strong technological backgrounds who are enthusiastic about AI innovations.
5. Invest in Training Programs: Offer training programs, workshops, and skill development initiatives to empower employees with the technical know-how to implement custom AI solutions effectively.

6. Leverage External Support: Collaborate with technology vendors, supply chain partners, and IT service providers to enhance the capacity to adopt and utilize custom AI models, especially for SMEs lacking in-house expertise.
7. Recognize Strategic Importance in Competitive Industries: SMEs in highly competitive sectors should adopt custom AI solutions as a strategic imperative and anticipate competitors doing the same when formulating strategies.
8. Balance Efforts on Perceived Compatibility and Management Support: Be aware of diminishing returns from further improvements in perceived compatibility when both compatibility and management support are high. Focus resources on other aspects of custom AI implementation beyond a certain point.

5.4. Limitations and future research directions

The study faces limitations related to the data collection process and sample size. Although initially, 83 responses were obtained, the subsequent data cleaning and screening procedures led to a decrease of the final sample size to 55. This diminished sample size may pose challenges for performing robust inferential analysis and generalizing findings to a broader population. The common rule of thumb from literature suggests requiring at least 50 + 8n times the number of independent variables for robust linear regression analysis (Green, 1991; Humble, 2020). The smaller sample size could impact the statistical power of the study, potentially limiting the ability to detect subtle effects or associations among variables. It is important to acknowledge that the representativeness and external validity of the study may be compromised due to the reduction in sample size, and should be exercise caution when generalizing the results beyond the study's specific sample. The study's limitations, particularly in the realm of data collection, warrant consideration as they could influence the breadth and applicability of the obtained insights. Notably, a pronounced sampling bias emerged with the overrepresentation of the ICT and Finance industries, potentially skewing the findings towards these sectors and diminishing the study's generalizability to SMEs in other industries. Additionally, the preponderance of responses from Gauteng province introduces a regional bias, also limiting the generalizability of the study findings to SMEs in different provinces with potentially distinct challenges and dynamics. Subsequent studies could benefit from efforts to diversify the sample, encompassing a broader spectrum of industries and regions to enhance the generalizability and robustness of findings. Adopting a different sampling approach could mitigate some of the limitations associated with the snowball sampling strategy employed in this study. While a small sample size can raise concerns about external validity and distribution assumptions and require larger effects achieve statistical significance with small samples, when attained, statistical significance still confirms validity despite the higher hurdle, clearing it indicates that the findings are robust and reliable (Norman, 2010).

Given the insights from the moderation effects observed in this research, several promising directions for future research can be considered. One area is uncovering industry-specific differences. Do the identified moderation effects, where factors like top management support and technological competence influence AI adoption, remain consistent across different industries? Each sector might possess unique challenges and dynamics that impact how these variables interact. Investigating these industry-specific variations can pave the way for more targeted insights and recommendations tailored to individual sectors.

Another vital area for future research lies in the impact of technological advancements. As the field of AI continues to evolve, emerging trends like natural language processing, AI explainability, and ethical considerations are likely to influence the ways AI is adopted by SMEs. It is crucial to explore how these advancements might moderate the previously observed relationships between top management support, technological competence, and custom AI adoption. Furthermore, future research could delve into the mechanisms through which custom AI adoption affects different aspects of SMEs' operations and organizational structures. This could involve examining changes in workflow processes, resource allocation, decision-making structures, and employee roles and responsibilities resulting from AI implementation. Understanding how these internal dynamics evolve in response to custom AI adoption can shed light on the organizational transformations required for successful AI integration. Moreover, exploring the role of external factors such as market dynamics, regulatory environments, and technological advancements in shaping the long-term impact of custom AI adoption on SMEs would be essential. This could involve examining how changes in market conditions, industry regulations, and technological landscapes influence the effectiveness and sustainability of AI solutions in SMEs.

Lastly, future research directions could also include exploring the long-term effects of custom AI model adoption on South African SMEs' performance and competitiveness. This research could involve conducting longitudinal studies to track the impact of custom AI adoption over an extended period. Examining how SMEs' performance metrics such as productivity, revenue, and market share evolve after implementing custom AI solutions, researchers can assess the sustainability and effectiveness of these technologies in driving business outcomes.

5.5. Conclusions

This research delves into the factors influencing the adoption of custom AI models in South African SMEs. The central research question of this research focuses on understanding the factors shaping the adoption landscape of custom AI models among South African SMEs. Grounded in the TOE framework, the study examines the technological, organizational, and environmental dimensions. The identified factors span the technological context, including relative advantage, perceived complexity, perceived compatibility, and perceived cost; the organizational context, encompassing top management support, technological competence, and financial readiness; and the environmental context, involving competitive pressure, external support, and regulatory support.

Utilizing a quantitative research design, the study employs a structured survey questionnaire distributed through the Qualitrix online survey platform. With a sample obtained through a snowball sampling technique, the research initially garnered 83 responses, later refined to 55 after screening and data-cleaning procedures. The subsequent analysis employs statistical tools such as Pearson correlation and hierarchical regression to delve into the relationships between the identified factors and the adoption of custom AI models by South African SMEs.

The results of this study strongly support the hypotheses, affirming the positive influences of top management support (H2a), technological competence (H2b), competitive pressure (H3a), and external support (H3b) on the adoption of custom AI models in South African SMEs. The primary research question about factors influencing AI adoption is answered, with top management support, technological competence, competitive pressure, and external support identified as crucial contributors that influence custom AI models amongst South African SMEs. Additionally, perceived compatibility is revealed to be influential not directly but as a moderator, shaping the impact of top management support and technological competence on custom AI adoption. The results of this study present an understanding of the complex dynamics shaping the adoption of custom AI models in the SME landscape of South Africa. The study contributes valuable insights to the broader discourse on AI adoption, shedding light on contextual factors unique to South African SMEs and offering a basis for future research initiatives and practical strategies meant at enhancing custom AI adoption in specific business environments. The study's biggest theoretical contribution lies in uncovering the moderating role of perceived compatibility, enriching existing theories and emphasizing the need for frameworks that capture interactive effects in the context of South African SMEs.

This study emphasizes the importance of top management support in driving the adoption of custom AI models in South African SMEs, stressing the importance of executive education and proactive efforts to secure managerial backing. The research supports the notion that heightened technological competence within SMEs positively contributes to custom AI adoption, advocating for strategic recruitment, retention of tech-savvy individuals, and investment in training programs. The positive correlation between external support and custom AI adoption underscores the strategic significance of external collaborations for SMEs lacking in-house capabilities, providing valuable insights and resources. Furthermore, the study indicates that SMEs in competitive industries are more inclined to adopt custom AI solutions, emphasizing the strategic necessity for sustained success in such sectors. Identifying perceived compatibility as a moderating factor suggests that, while high compatibility and strong management support are beneficial, there are diminishing returns, urging organizations to consolidate gains and allocate resources sensibly for effective custom AI implementation a vital insight for South African SMEs navigating this intricate landscape.

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Appendix A

A1: Questionnaire Cover Letter

Dear Participant

My Name is **Yanga Mdingi**, and I am a student at Wits Business School enrolled for a Master of Business Administration degree. This is a questionnaire designed to generate information on the research project titled: **Adoption of custom artificial intelligence models in South African small and medium-sized enterprises.**

The objective of this research is to identify factors impacting the adoption of custom AI models by South African SMEs. I would like to request your experiences as a Business Owner, Manager or an Employee in a South Africa company. Your participation in this study would be greatly appreciated and will contribute to the advancement of knowledge in this area.

The questionnaire will take approximately 10-15 minutes to complete and your responses will remain confidential and anonymous. Your participation is voluntary, and you may choose to withdraw at any time. There is no compensation or benefit for participating in this study, however, your participation will be a valuable contribution to this research which could be leveraged by future researchers.

If you have any questions or concerns, please feel free to contact me on yangamdingi1@students.wits.ac.za

Sincerely,

Yanga Mdingi (MBA Candidate)
Wits Business School
University of Witwatersrand

A2: Research Instrument

Table 16 Measurement instrument

TOE FACTOR	CONSTRUCTS	CODE	MEASUREMENT ITEMS	SOURCES
Technological Context	Relative Advantage (RAD)	RAD1	Companies like mine that adopted custom AI models can enhance the efficiency of their operations	(Gupta et al., 2022; Horani et al., 2023; Maroufkhani et al., 2023; Shahadat et al., 2023)
		RAD2	The introduction of custom AI models in companies like mine can increase their profits	
		RAD3	Custom AI models can improve customer service in companies like mine.	
		RAD4	Custom AI models adoption helps companies like mine identifies new product or service opportunities	
	Perceived Complexity (PCX)	PCX1	Introduction of Custom AI models in my company will not be simple	(Gupta et al., 2022; Horani et al., 2023; Maroufkhani et al., 2023; Wang et al., 2010)
		PCX2	I believe that my company does not understand how Custom AI models will benefit the firm in its growth	
		PCX3	The skills necessary for using Custom AI models are too complicated for our staff	
		PCX4	My company believes that Custom AI models are complex to use	
		PCX5	My company believes that Custom AI models development is a complex process	
	Perceived Compatibility (PCM)	PCM1	Using custom AI models is compatible with existing IT infrastructure in my company	(Horani et al., 2023; Maroufkhani et al., 2023; Shahadat et al., 2023; Wang et al., 2010)
		PCM2	Using custom AI models is compatible with my company’s processes and operations	
		PCM3	Using custom AI models is compatible with our preferred work practices	
		PCM4	Overall, it is easy to incorporate custom AI models into our organization	
	Perceived Cost(PCS)	PCS1	Adopting custom AI models will increase hardware and facility cost	(Shahadat et al., 2023; Wong et al., 2020)
		PCS2	Adopting custom AI models will increase operations and maintenance cost	
		PCS3	The cost of custom AI models is unclear and not easily understandable	
		PCS4	The cost of custom AI models is high for my company	
		PCS5	The costs of integration of custom AI models with existing information systems infrastructure are high	
Organizational Context	Top Management Support (TMS)	TMS1	My company’s executives consider custom AI models adoption strategically important	(Gupta et al., 2022; Horani et al., 2023; Yang et al., 2015)
		TMS2	My company’s executives are likely to make investments in custom AI models	
		TMS3	Our managers support by providing labour resources, finances, and materials for custom AI models adoption	

TOE FACTOR	CONSTRUCTS	CODE	MEASUREMENT ITEMS	SOURCES
		TMS4	Our managers are willing to take risks involved in the adoption of custom AI models	
		TMS5	Our managers have a strong understanding of how custom AI models can be used to increase business performance	
	Technological Competence (TCM)	TCM1	My company has an excellent AI-based infrastructure, including all IT components to support custom AI models	(Gupta et al., 2022; Horani et al., 2023)
		TCM2	My company has good knowledge of custom AI models adoption	
		TCM3	My company possesses sufficient resources (financial, technological…) to adopt custom AI models	
		TCM4	My company has the necessary technical, managerial, and other skills to implement custom AI models	
	Financial Readiness (FRD)	FRD1	My company would have the financial resources to adopt custom AI models	(Gupta et al., 2022)
		FRD2	The financial budgets of the company would be enough to back the adoption of custom AI models	
		FRD3	Obtaining financial support from local banks and/or other financial institutions to adopt custom AI models would be easy	
Environmental Context	Competitive Pressure (CPR)	CPR1	My organization faces competitive pressure to implement custom AI models	(Gupta et al., 2022; Horani et al., 2023; Maroufkhani et al., 2023; Yang et al., 2015)
		CPR2	My organization is at a disadvantage if it does not adopt custom AI models	
		CPR3	My company thinks that custom AI models adoption influences competitiveness in the industry	
		CPR4	My organization keeps a watch on competitors for the custom AI models used in their organisations	
		CPR5	Our company would adopt custom AI models in response to what competitors are doing	
	External Support (ESP)	ESP1	Training should be fairly provided by the vendors of AI technologies	(Horani et al., 2023; Maroufkhani et al., 2023)
		ESP2	It is important that the vendors of custom AI models provide adequate technical support during implementations of custom AI models	
		ESP3	Custom AI models vendors should provide adequate technical support after the implementation of custom AI models	
		ESP4	Vendors must actively market custom AI models adoption	
	Regulatory Support (RSP)	RSP1	South African government policies are in favour of the adoption of AI technologies by the SMEs	(Horani et al., 2023)

TOE FACTOR	CONSTRUCTS	CODE	MEASUREMENT ITEMS	SOURCES
		RSP2	South Africa has a legal framework to solve disputes arising out of the use of AI technologies	
		RSP3	South African regulations are sufficient to protect the use of AI technologies	
		RSP4	South African government actively supports the adoption of AI technologies	
AI adoption	Custom AI models Level of adoption (ADPL)	ADPL1	Could you indicate the extent to which your company has already implemented custom AI	
	Custom AI models adoption intention (ADPI)	ADPI1	My company intends to adopt custom AI model in the near future	(Horani et al., 2023; Lai et al., 2018)
		ADPI2	My company would like to utilize custom AI model to its full potential	
		ADPI3	My company is likely to use custom AI model on a regular basis in the near future	
		ADPI4	My company would highly recommend custom AI model for other firms to adopt	

A3: Ethics Documentation

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/BA2626309/612

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

Project title	Adoption of custom artificial intelligence models in South African small and medium-sized enterprises
Investigator / Researcher	Mr. Yanga Mdingi
Nature of Project	MBA (Research Article)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed confidentialty.
Issue Date of Certificate	2023-07-24
Expiry date	Date of submission of the project / research report
Chairperson	Dr Pius Oba ☎ +27 11 717 3976 +27 82 733 6587 pius.oba@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Ethics Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Signature

13/08/2023
Date:

Appendix B

B1: Exploratory Factor Analysis of Technology Factors

Table 17 Technology Factors Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
Factor	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**
1	7,871	43,725	43,725	7,569	42,047	42,047	5,322
2	2,086	11,590	55,316	1,809	10,048	52,095	5,549
3	1,829	10,161	65,477	1,523	8,462	60,557	5,415
4	1,385	7,694	73,172	1,078	5,986	66,543	4,630
5	0,892	4,956	78,128				
6	0,791	4,397	82,525				
7	0,587	3,259	85,784				
8	0,470	2,613	88,397				
9	0,435	2,418	90,815				
10	0,291	1,615	92,430				
11	0,270	1,498	93,928				
12	0,248	1,377	95,305				
13	0,243	1,348	96,653				
14	0,207	1,151	97,804				
15	0,149	0,829	98,633				
16	0,105	0,581	99,214				
17	0,083	0,463	99,678				
18	0,058	0,322	100,000				

Extraction Method: Principal Axis Factoring.
a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

B2: Exploratory Factor Analysis of Organizational Factors

Table 18 Organizational Factors Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
Factor	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	7,456	62,132	62,132	7,180	59,832	59,832	6,232
2	1,485	12,376	74,508	1,254	10,452	70,284	6,100
3	0,890	7,416	81,924				
4	0,566	4,719	86,643				
5	0,404	3,367	90,010				
6	0,345	2,874	92,884				
7	0,218	1,818	94,702				
8	0,186	1,547	96,249				
9	0,136	1,134	97,383				
10	0,134	1,118	98,501				
11	0,096	0,803	99,304				
12	0,084	0,696	100,000				

Extraction Method: Principal Axis Factoring.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

B3: Exploratory Factor Analysis of Environmental Factors

Table 19 Environmental Factors Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
Factor	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**	**Total**
1	4,433	34,099	34,099	4,126	31,737	31,737	3,564
2	2,699	20,759	54,857	2,416	18,588	50,325	2,851
3	2,225	17,118	71,976	1,820	14,002	64,327	2,807
4	0,841	6,466	78,442				
5	0,714	5,492	83,934				
6	0,454	3,491	87,425				
7	0,377	2,900	90,325				
8	0,349	2,684	93,010				
9	0,263	2,027	95,036				
10	0,192	1,478	96,514				
11	0,176	1,351	97,866				
12	0,153	1,176	99,041				
13	0,125	0,959	100,000				

Extraction Method: Principal Axis Factoring.

a. When factors are correlated, sums of squared loadings cannot be added to obtain a total variance.

B4: Exploratory Factor Analysis of Dependent Variable

Table 20 Dependent Variable Factors Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Factor	**Total**	**% of Variance**	**Cumulative %**	**Total**	**% of Variance**	**Cumulative %**
1	3,877	77,538	77,538	3,724	74,487	74,487
2	0,777	15,531	93,069			
3	0,218	4,368	97,437			
4	0,079	1,578	99,015			
5	0,049	0,985	100,000			

Extraction Method: Principal Axis Factoring.

B5: Residuals Plots - Hierarchical Regression

Figure 4: Residuals Plots - AI adoption

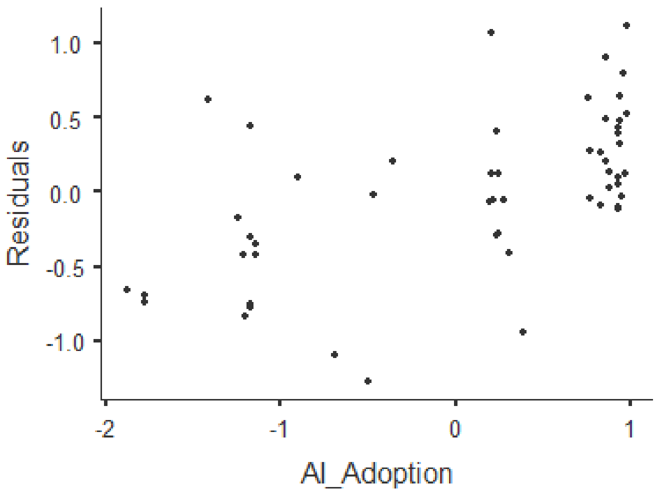


Figure 5: Residuals Plot - Services

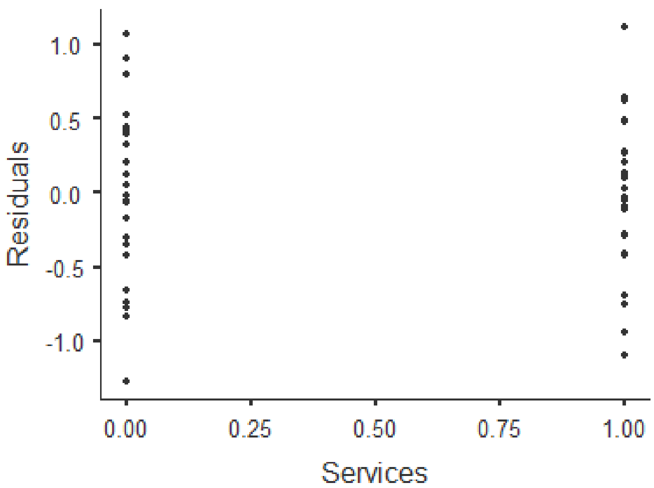


Figure 6: Residuals Plots - Competitive pressure

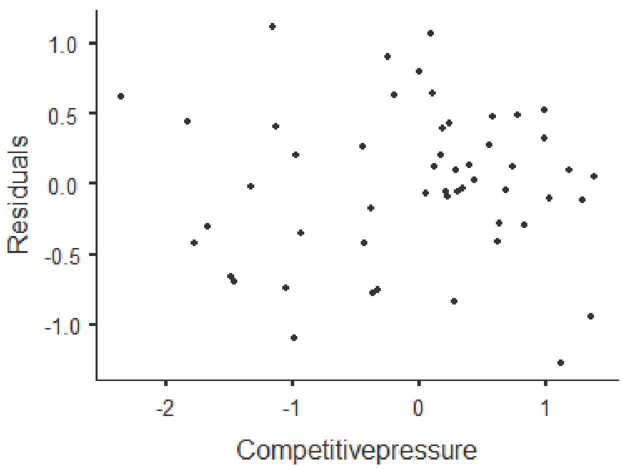


Figure 7: Residuals Plots - External support

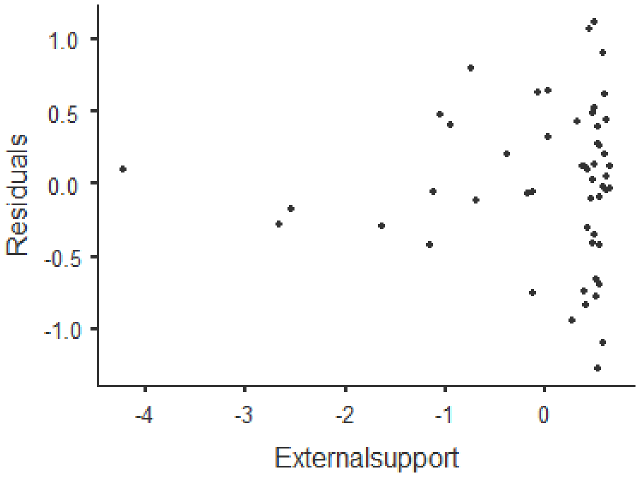


Figure 8: Residuals plot - Top management support

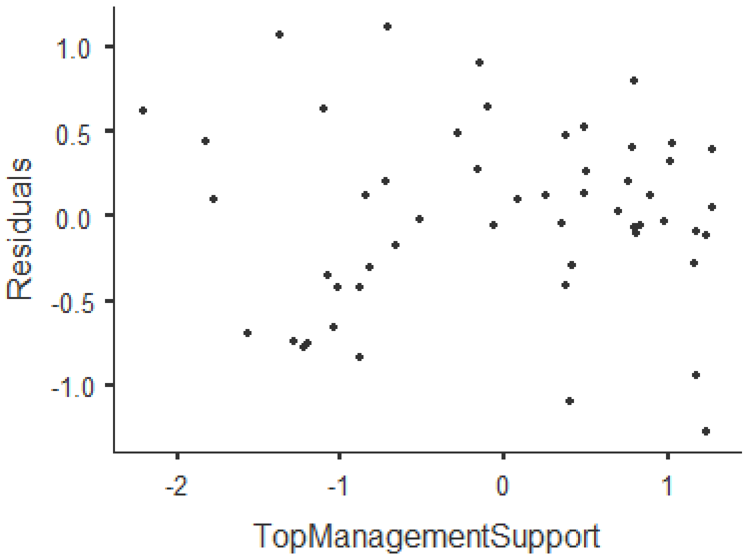


Figure 9: Residuals plot - Technological competence

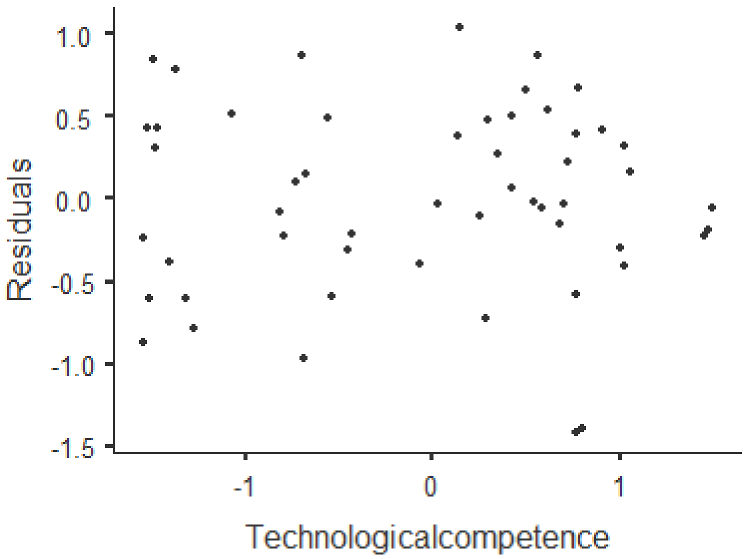
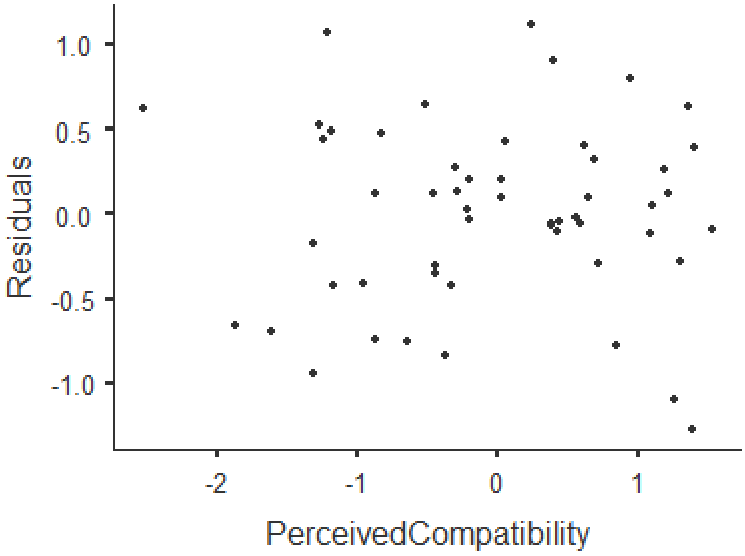


Figure 10: Residuals Plot - Perceived compatibility



B6: Q-Q Plots - Hierarchical Regression

Figure 11: Q-Q Plot - Hierarchical Regression Including Interaction of Perceived Compatibility and Top Management Support

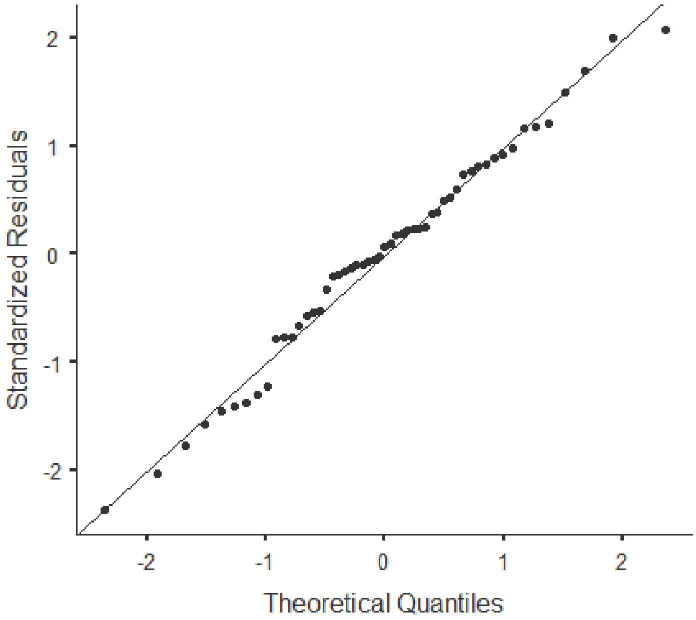
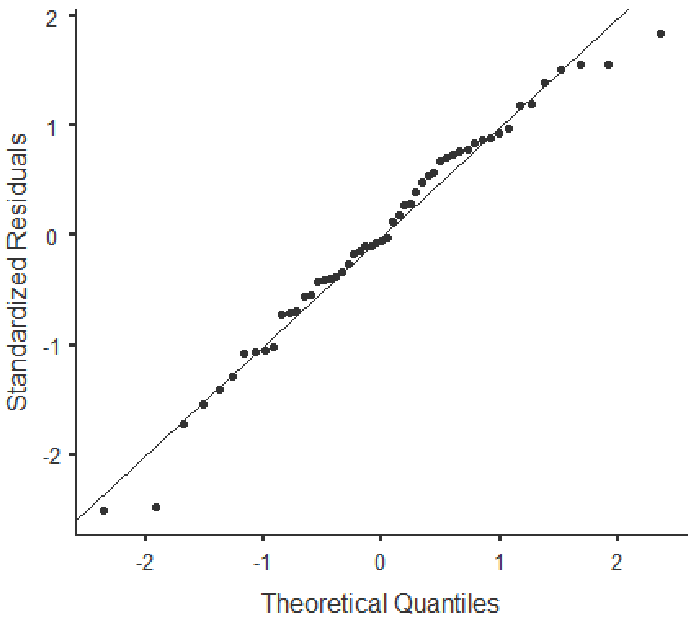


Figure 12: Q-Q Plot - Hierarchical Regression Including Interaction of Perceived Compatibility and Technological Competence



B8: Collinearity Statistics

Table 21: Collinearity Statistics - Hierarchical Regression Including Interaction of Perceived Compatibility and Top Management Support

	VIF	Tolerance
Services	1.06	0.940
Competitive pressure	2.23	0.449
External support	1.09	0.917
Top management support	2.57	0.389
Perceived compatibility	1.63	0.615
Top management support ✻ Perceived compatibility	1.22	0.819

Table 22:Collinearity Statistics - Hierarchical Regression Including Interaction of Perceived Compatibility and Technological Competence

	VIF	Toler-ance
Services	1.12	0.896
Competitive pressure	1.45	0.687
External support	1.08	0.924
Technological competence	1.92	0.520
Perceived compatibility	1.69	0.592
Technological competence ✻ Perceived compatibility	1.17	0.858