

Adoption of Artificial Intelligence (AI) and Job Satisfaction in South African SMMEs

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Abstract

The study investigates the relationship between the theoretically derived determinants of Artificial Intelligence (AI) adoption Perceived ease of use (PEOU) and Perceived Usefulness (PU) and employee Job satisfaction within South African Small, Medium and Micro Enterprises (SMMEs). While Artificial Intelligence (AI) is globally recognised as a driver of efficiency and innovation, its human and organisational implications in resource-constrained environments remain underexplored. Grounded in the Technology Acceptance Model (TAM) and extended by the inclusion of Perceived Organisational Support (POS), this study examines whether Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) the core determinants of technology acceptance (or adoption) directly or indirectly, influence employee job satisfaction in South African Small, Medium and Micro Enterprises (SMMEs), and whether POS moderates these relationships. A quantitative, cross-sectional design was employed, gathering survey data from employees across diverse SMMEs utilising AI-driven systems. Data were analysed using regression-based and moderation techniques. The findings suggest that having a supportive organisational climate containing training, communication and recognition, leads to employees being more inclined to engage with AI positively, which elevates job satisfaction with their work and contributes to organisational resilience. The study contributes theoretically by expanding TAM with a different perspective of psychosocial factors, and practically, by providing ways for SMME managers to implement AI responsibly in developing economies.

Keywords: Artificial Intelligence, Technology Acceptance Model, Perceived Organisational Support, Job Satisfaction, SMMEs, South Africa.

Plagiarism Declaration

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

Tawanda Pasipanodya

3 November 2025

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Table 1: List of Abbreviations

Abbreviation	Full Term
AI	Artificial Intelligence
ANN	Artificial Neural Network
GDP	Gross Domestic Product
ICT	Information and Communication Technology
IFC	International Finance Corporation
JSS	Job Satisfaction Survey
POS	Perceived Organisational Support
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
SEDA	Small Enterprise Development Agency
SMME	Small, Medium, and Micro Enterprise
TAM	Technology Acceptance Model
TAM2	Technology Acceptance Model 2
TAM3	Technology Acceptance Model 3
TOE	Technology–Organisation–Environment Framework
UTAUT	Unified Theory of Acceptance and Use of Technology
UTAUT2	Unified Theory of Acceptance and Use of Technology 2
SPOS	Survey of Perceived Organisational Support

SME	Small and Medium Enterprise
JSat	Job Satisfaction
4IR	Fourth Industrial Revolution
OECD	Organisation for Economic Co-operation and Development

CHAPTER 1: INTRODUCTION TO RESEARCH PROBLEM

1.1 Background of the Study

Small, medium and micro enterprises (SMMEs) in South Africa are operating under undetermined economic conditions. According to a study on the subject approximately 60% - 80% of these enterprises fails in the first two years of their existence, which is a state of affairs unparalleled in developing economies (Mhlongo & Daya, 2023; Msimango-Galawe & Hlatshwayo, 2021). This is a worrying trend, for SMMEs are indispensable to the economy of South Africa, since they represent about 34% of Gross Domestic Product (GDP) and 60% of employment opportunities (SEDA, 2024). If SMME surviving enterprises were just a little better in number, the macroeconomic value possible would be incalculable (IFC, 2017; SEDA, 2024). One of the reasons for their comparatively underperformance to peer economies is that SMMEs in South Africa utilise fewer sophisticated digital technologies (Durst et al., 2023). Comparative international evidence suggests that small and medium enterprises generally have only modest levels of basic digital adoption and many of the more sophisticated digital technologies remain unutilised (OECD, 2021). In South Africa, structural constraints such as a lack of digital competence, inadequate infrastructure, and lack of financial resources, widen the technology readiness gap (SEDA, 2024; World Bank, 2023).

In this context, artificial intelligence (AI) is both an opportunity and a threat. Machine learning, predictive analytics, and process automation can enable the possibility of improved productivity, reduced cost of operations, and better decision quality (Wamba-Taguimdje et al., 2020). However, we have not placed much emphasis on the people component of technological change. Particularly, how employees perceive and react to AI technologies as well whether their perceptions of these technologies predict lasting job satisfaction has not received sufficient empirical attention in the South African small and medium enterprises (SMME) context (Morandini et al., 2023). As employee well-being is a direct influence on commitment, retention and performance, it is important to understand the attitudinal antecedents of technology acceptance (Baxi & Atre, 2024; Murire, 2024; Rambe, 2024).

1.2 Research Problem

The labour market in South Africa is characterised by high levels of unemployment, widespread inequality, and profound skills shortages (World Bank, 2021). The introduction of AI technologies into this context carries substantial implications for workers' sense of security, the clarity of their

job roles, and job satisfaction overall. As stated, AI has the potential to enhance operational efficiency for the business, while all the time adding uncertainty for the worker and unraveling established working arrangements.

Most studies about workplace AI have centered on large, well-resourced corporations based in developed economies, often taking a theoretical rather than empirical approach (Bıçakcıoğlu Peynirci, 2023). While there are some notable exceptions, such as the Saudi Arabian Technology-Organisation-Environment (TOE) framework survey and the PLS-SEM/ANN studies conducted across several sectors (Badghish & Soomro, 2024), the scarcity of context-appropriate, practitioner-focused research on AI in resource-constrained SMMEs remains substantial (Le Dinh et al., 2025). The effects of the COVID-19 pandemic clearly showed the impact of technological unpreparedness on the business environment (Durst et al., 2023). South African SMMEs lag behind their peers within the OECD as a result of, amongst others, the failure to utilise cutting-edge technologies (Durst et al., 2023). Such justification informs the present study to address the important empirical gap between employee's perception of AI technologies and their job satisfaction in South African SMMEs.

The Technology Acceptance Model (TAM) has shown that perceived usefulness (PU) or the extent to which users believe technology will facilitate their job performance and perceived ease of use (PEOU) or the degree users believe technology is easy, to have an impact on users' attitude and intent to use technology for work (Davis, 1989). Additions like TAM2 and TAM3 have expanded on PU and PEOU to include social influence, cognitive processes, self-efficacy and computer anxiety (Venkatesh & Davis, 2000; Venkatesh & Bala, 2008). The Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2) incorporated performance expectancy, effort expectancy, social influence, facilitating conditions, and factors that moderate, such as age, gender, and experience, into its frameworks (Venkatesh et al., 2012). While most models end with behavioural outcomes like usage intention or use of the system, they rarely address perspectives associated with employee well-being, for example job satisfaction. Furthermore, while the inclusion of facilitating conditions enables the capture of resources that may be available or not, as well as institutional support, it does not clearly include socio-emotional climate elements that influence employees' lived experiences of change in technology.

Perceived organisational support (POS), which refers to employees' overall evaluation of the extent to which they believe their organisation values their contributions and cares for their well-being, is a theoretically relevant but under-represented perspective to examine outcomes related

to AI in SMMEs (Eisenberger et al., 1986; Rhoades & Eisenberger, 2002). Within the framework of social exchange theory and conservation of resources rationale, POS is a signal of fair treatment, training, psychological safety and endorsement of management and can be particularly helpful to employees whilst navigating ongoing change and uncertainty. In these cases, POS can accentuate positive aspects when employees consider AI technologies useful (PU), see them as easy to use (PEOU), and ultimately the provision of resources and assurance can encourage positivity and continued engagement. This in essence means that POS can buffer potential negative outcomes such as job insecurity, techno-stress and role ambiguity (Hobfoll et al., 2018; Ibrahim et al., 2024; Tarafdar et al., 2019).

In addition, POS serves as a likely moderator of the pathways from AI-related perceptions to job satisfaction. With high POS, employees are more likely to view AI as an investment in their growth rather than a threat to their job security leading to job satisfaction remaining the same or perhaps improving. When POS is low, the same technological rollout will erode job satisfaction as the employee's perceived vulnerability increases (Caesens & Stinglhamber, 2020; Eisenberger et al., 2020). However, the current TAM/UTAUT work has not qualitatively modeled POS as a moderator, especially in resource-constrained SMME contexts (Tamilmani et al., 2021; Venkatesh & Davis, 2000). With a foundation of TAM, we propose and test an SMME POS-moderated model in South Africa.

This investigation departs from the majority of studies about technology adoption. With the rising ubiquity of AI-enacted choice in workplace processes, employees typically do not have the option of whether to adopt AI and it is relative freedom of decision-making about the use of AI that is the focus of this research on the determinants of technology acceptance rather than the adoption behavior itself. This study draws upon the Technology Acceptance Model (TAM) using perceived ease of use (PEOU) and perceived usefulness (PU) theoretical determinants of acceptance and studies these constructs through job satisfaction and perceived organisational support (POS).

1.3 Aim of the Study

This research assesses the influence of the theoretical determinants of AI technology adoption, perceived ease of use (PEOU) and perceived usefulness (PU), on job satisfaction indicators in South African SMMEs. Furthermore, the moderating effect of perceived organisational support (POS) on the relationship between PU and job satisfaction is evaluated in order to understand

empirically how favourable perceptions of AI technologies can be used to facilitate employee wellbeing, when organisational support is present.

1.4 Research Questions

- **RQ1:** How does Perceived Ease of Use (PEOU) of AI technologies influence employees' Perceived Usefulness (PU) in South African SMMEs?
- **RQ2:** To what extent does PEOU directly influence job satisfaction among employees in South African SMMEs?
- **RQ3:** Does Perceived Usefulness (PU) mediate the relationship between PEOU and job satisfaction?
- **RQ4:** How does PU directly influence job satisfaction among SMME employees?
- **RQ5:** Does Perceived Organisational Support (POS) moderate the relationship between PU and job satisfaction in South African SMMEs?
- **RQ6:** What recommendations can guide South African SMMEs in fostering positive perceptions of AI technologies to enhance job satisfaction while ensuring business sustainability?

1.5 Research Objectives

- To determine the influence of Perceived Ease of Use (PEOU) on Perceived Usefulness (PU) of AI technologies in South African SMMEs.
- To examine the direct effect of PEOU on job satisfaction among employees in South African SMMEs.
- To assess the mediating role of Perceived Usefulness (PU) in the relationship between PEOU and job satisfaction.
- To evaluate the direct effect of PU on job satisfaction among SMME employees.
- To investigate how Perceived Organisational Support (POS) moderates the relationship between PU and job satisfaction in South African SMMEs.
- To provide practical recommendations for South African SMMEs on fostering positive AI perceptions to promote employee job satisfaction and long-term organisational success.

1.6 Rationale of the Study

The transformative effects of artificial intelligence on organisational structures, workplace dynamics and employee experiences are being felt in organisations around the world (Murire,

2024). Small, medium and micro-sized enterprises (SMMEs) in South Africa have, in particular, the highest failure rate relative to other developing economies at a staggering 60% - 80% in the first two years (Bushe, 2019; Murimbika & Urban, 2023). Given that SMMEs make up 60% of the total employment in South Africa and contribute 34% of the GDP, this is of great concern (Sibiya et al., 2023). Despite the importance of SMMEs to the South African economy, we can draw parallels to other developing economies. South African SMMEs are also underperforming in comparison to their OECD counterparts and one of the contributing factors is minimal adoption of advanced technologies (Durst et al., 2023). AI has the potential to enhance productivity, efficiency and competitiveness, but while there has been significant study on AI in the context of large firms in developed economies, there is scant literature on implications for employee well-being for SMMEs operating with limited resources (Oldemeyer et al., 2025).

As a response to the significant theoretical gap, this study directly connects technology acceptance frameworks with employee well-being outcomes in SMMEs. While the original TAM has identified PU and PEOU as predictors of technology acceptance (Davis, 1989), this framework alone does not sufficiently take into account the socio-organisational realities associated with AI deployment in small firms. To overcome this limitation, the study extends the TAM by introducing job satisfaction as an important outcome variable, and by including POS as a moderating variable. POS indicates employees' perceptions that their organisation values their contributions and cares about their well-being (Eisenberger et al., 2020). The relevance of this construct will likely gain traction in the application of AI. When POS is high, employees are likely to interpret AI-related technologies as tools for empowerment that increase their capabilities and therefore enhancing the positive relationship between favourable perceptions of AI and job satisfaction. When POS is low, the beliefs of job insecurity, surveillance, or diminished autonomy may predominate, which may weaken or negate the potential benefits (Raji & Ismail, 2023). In this way, extending the technology acceptance model can validly respond to the criticisms mentioned earlier and provide a more context sensitive model for explaining human and organisational outcomes of AI-related perceptions in SMMEs.

On a practical level, the research engages with the ongoing concern of employee job satisfaction in the context of AI-enabled digital transformation. SMMEs leverage their limited employee capacity heavily towards employee engagement and retention. Although AI offers an opportunity for increased efficiency and cost reductions, it arouses fears regarding job security, surveillance and lack of autonomy (Raji & Ismail, 2023). In South Africa, experiencing some of the highest unemployment rates in the world, employee job uncertainty due to advancements in technology

threatens job loss in historically more precarious employment settings (World Bank, 2021). It is, therefore, necessary to integrate the benefits accruing from innovation with the protection of employees' welfare for sustainable economic growth. This investigation of the roles which PEOU and PU play in job satisfaction and the moderating effect of POS provides guidance which can be of immediate value to the management of SMMEs. This research also provides the opportunity to provide some guidance to policy makers and business leaders concerning the digital economy in South Africa. It is important to understand the influence of the perceptions of technologies associated with AI on job satisfaction in order to ensure that technological transformation contributes not only to the competitiveness of firms but also to the welfare of employees as well as to the long-term sustainability of organisations.

It is important to note that although the study title refers to the adoption of Artificial Intelligence (AI), the research does not directly measure adoption behaviour. In keeping with the TAM, the study instead examines the determinants of technology adoption namely, PEOU and PU. These constructs are theoretically recognised as the cognitive and perceptual drivers of technology adoption or acceptance. The study, therefore, interprets "adoption" in the title as referring to the psychological acceptance of AI technologies within organisational contexts, rather than to the act of adopting or using AI systems.

1.7 Significance of the Study

The study represents interesting theoretical and practical value. Theoretically, the study builds on the application of TAM in this emerging market context despite nearing comprehensive validation. Although TAM has been well-validated and empirically tested across numerous settings, including those found in the literature on workplace technology acceptance, the original TAM model remains limited in approach and applicability in terms of and across different organisational environments. The study deepens the explanatory capabilities of TAM through a moderation approach which introduces POS, the perception of support and value towards employees. It also chooses an alternate outcome variable of job satisfaction rather than usage behaviour. POS captures a fuller sense of both employee values and support from an employer when compared to other constructs such as organisational trust or leadership style (Eisenberger et al., 1986). The perception of support reduces resistance and anxiety in times of technological disruption and promotes positive responses (Imran et al., 2020). POS is reflective of the socio-emotional exchange of value and support between an employer and employee, making it particularly apt for a study of perceptions of AI and job satisfaction (Raji & Ismail, 2023). The focused investigations supports a model that

captures cognitive acceptance criteria and psychosocial to shape acceptance conditions are particularly salient in small, resource poor firms or employ-based relationship dynamics.

In addition, the context of the research makes a significant contribution. Most research in artificial intelligence is conducted in developed economies and large enterprises, and this leaves developing countries SMMEs not sufficiently studied (Le Dinh et al., 2025). The research focuses on SMMEs in South Africa, which is essential because of the role they play in the economic and social development of the country. The research focuses on the digital divide, lack of skills, and scarce resources which influence SMME perceptions of technology in South Africa. The findings arise from the environment of a developing economy and thus the results obtained apply to a context which is more relevant than findings from environments which vastly differ from the socio-economic reality existing in South Africa.

From a practical perspective, the benefits of the study are felt by SMME owners, managers and policymakers. Clear understanding of the effect of perceptions of AI on job satisfaction can assist in implementation of technologies that change resistance to and concern of employees, assisting in the creation of more satisfying work environments. The research investigates whether supportive organisational practices such as training, transparency of communication and recognition can improve the perceptions of AI positively for increased satisfaction (Du Plessis & Swart, 2024). The findings may also facilitate targeted interventions and regulatory guidelines that facilitate a balance between efficiency gains and employee wellbeing, promoting staff retention, productivity and organisational resilience.

1.8 Structure of the Dissertation

This dissertation comprises six chapters that build progressively to analyse the relationship between AI-related perceptions and job satisfaction in South African SMMEs:

Chapter 1: Introduction

Describes the study's background, problem statement, aim, questions, and objectives. It establishes why the research is important and how AI-related perceptions affect job satisfaction in SMMEs. The chapter ends with a summary of the dissertation structure.

Chapter 2: Literature Review and Theoretical Framework

Reviews global and South African literature on AI perceptions and job satisfaction. It employs TAM as the theoretical lens and incorporates POS as a moderator. The chapter critically analyses PU, PEOU, technology resistance, and job satisfaction, culminating in the conceptual model and hypotheses.

Chapter 3: Research Questions and Hypotheses

Chapter three articulates the research purpose, questions, hypotheses, and conceptual model that guide empirical investigation.

Chapter 4: Research Methodology

Chapter four discusses the study's philosophy, approach, design, and methods. It details the target population, unit of analysis, sampling strategy, data collection instruments and procedures, and analytical techniques, including mediation testing.

Chapter 5: The chapter presents the research findings on sample description, sample suitability, and the results from the research questions. It concludes with a summary of the findings in response to the research question.

Chapter 6: Discusses the findings of the research, synthesises with the literature and provides a conclusion on the overview of findings in the research questions.

Chapter 7: Discusses the implications for business, gives recommendations for future studies and concludes this study. The study's research limitations, its contribution, and future research are discussed.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

This study investigates the relationship between AI impressions, specifically PEOU and PU and job satisfaction in South African SMMEs, as well as the moderating role played by Perceived Organisational Support (POS). The concept of AI adoption is indirectly conceptualised in terms of the parameters of AI adoption (PEOU and PU) as defined in the Technology Acceptance Model. Thus, “adoption” in this context is seen as the perceptions underlying the acceptance of technology and not the actual behaviour of adoption.

This chapter provides the theoretical and empirical basis for a research agenda into how cognitive appraisals of technology shape employee well-being, through the integration of existing research. The literature review follows with a consideration of the constructs relevant to this examination, including job satisfaction, perceived value and perceived ease of use, whilst situating the research in the broader world context of AI-driven transformation in the workplace both globally and in South Africa. Such framing draws attention to the importance of ensuring that technology is developed in a way which considers employee health and well-being and identifies those research gaps that warrant this study.

There is a sound logical progression in the chapter from theory to practice. This chapter begins with an introduction to TAM as the main theory for consideration and goes on to explore how the TAM constructs of PU and PEOU investigated in conjunction with POS, as a moderating variable, can be used to explain variance in employee satisfaction with their jobs. These constructs are chosen to ascertain not only the direct relationships, but also the contexts where these relationships could be enhanced or diminished. The review of the literature then explores the trends both globally and in SA regarding the shifting engagement of SMME's with AI systems, with both the threats and the opportunities they offer.

2.2 Theoretical Foundations

2.2.1 Technology Acceptance Model (TAM)

In 1985, Fred Davis developed the Technology Acceptance Model (TAM) and expanded it in 1989 in order to explain user acceptance of information technology. The model suggested that Perceived Usefulness (PU), the extent to which individuals believe their job performance would

be enhanced by the emeded system, and Perceived Ease of use (PEOU), the extent to which the system is believed to require little effort to use are contributing factors to attitudes and intentions regarding technology use which will lead to actual use (Davis, 1989). TAM has been a widely applied model in evaluating technology acceptance in various industries since it was conceived. More recent scientific studies have revealed the usefulness of TAM in gaining insight into the cognitive processes users undergo when evaluating new forms of technology of which AI applications are an example (Almeida et al., 2025). The economy of the model has allowed its application in many different environments in business from recruitment to supply chain management. It has been noted however that TAM requires contextualisation when being applied to new technologies such as AI technologies in SMMEs.

Recent studies indicate that PU is universally the strongest predictor of positive attitudes towards technology in the workplace, especially where the introduction of new technologies may substantially change workplace relations. Employees who perceive AI as stimulating productivity and improving accuracy of decision-making generally view the technology positively (Kelly et al., 2023). AI technology will also provide SMME's with modern methods of enhancing resource efficiency that could include predictive analytics and automated customer service which will provide them the ability to streamline workflows at lower cost (Du Plessis & Swart, 2024). However, where there is a lack of available technological literacy within the workplace, worker resistance will increase when the benefits obtained from the proposed use of new technology is perceived to be vague or not proven. The PU variable is therefore central to our understanding of why workers in smaller enterprises are willing to accept or reject AI enabled instruments. South African SMMEs for example will have to justify their adoption of AI technologies through its effect on operational excellence and simplification of tasks, thus improving the credibility of its futher technological innovations.

The second core element, PEOU, emphasises usability in shaping technology-related attitudes. Despite potential benefits, systems perceived as complex or intimidating impede positive engagement (Venkatesh et al., 2016). In small businesses where employees frequently multitask, AI systems must be intuitive and accessible (Mapila & Moloi, 2024). South African marketing firms report that user-friendly AI technologies stimulate innovation and facilitate faster workflow integration (Du Plessis & Swart, 2024). Conversely, steep learning curves or inadequate instruction can amplify risk perceptions and strengthen resistance. Thus, PEOU not only predicts favourable attitudes but also reduces fears of redundancy and skill obsolescence. For SMMEs to

foster acceptance and satisfaction, AI technologies must be user-friendly and adequately supported.

Although the Technology Acceptance Model (TAM) has been used acceptably in many contexts, it does have its critics as it has some theoretical limitations. Researchers claim that its simplicity overlooks important organisational, social and psychological matters that impact upon technology acceptance (Song et al., 2025). Most classical forms of TAM also neglect to take account of the perceptions the employees have with respect to issues like fairness, organisational support and management trust which do impact upon the behaviour intentions of the employees (Díaz-Arancibia et al., 2024). Critics state, furthermore, that TAM has oversimplified the process of technology acceptance by limiting it to purely rational cognitive reactions or judgements, while ignoring technological anxiety and technological resistance (Chang et al., 2024). This is particularly acute in developing countries where technological advances are conditioned by structural matters like digital inequalities, and deficiencies in resources. Thus, whilst TAM provides a reasonable starting place, it has to be supplemented by other constructs in order to obtain a full understanding of the perception of different aspects as far as AI is concerned within South African SMME's.

2.2.2 Extensions of TAM

Awareness of the limitations of the Technology Acceptance Model (TAM) has led to extensions of the model. These extensions include TAM2, UTAUT and UTAUT2. These models take account that technology acceptance is influenced by the social context and issues in the workplace and is not solely dependent on the individual (Khan et al., 2024). TAM2 was introduced to cover the social influence aspects of technology and the cognitive instrumental processes associated with technology which include peer pressure and workplace norms (Venkatesh & Davis, 2000). The Unified Theory of Acceptance and Use of Technology (UTAUT) added other influences to technology acceptance such as performance expectancy and facilitating conditions which provided a broader-scale model allowing for organization and infrastructure support (Venkatesh et al., 2016). The UTAUT2 extension added the influence of hedonic motivation, price value and habit inveterate to technology acceptance within consumer parameters where affect and cost-benefit equations are salient (Venkatesh et al., 2012). These models provide evidence of the growing awareness that both rational evaluation and environmental factors influence technology acceptance especially for technologies such as AI which provoke excitement and fearfulness.

Although TAM provided the framework for this development, the extensions give rise to a more nuanced explanation when examining the digital transformations in the business context.

When employed in business contexts related to developing countries, TAM and its extensions have proven beneficial despite the obstacles for adoption being different than those in the developed market. South African SMMEs are often impeded by infrastructure constraints, limited skilled labour and lack of funds, all of which directly influence the mind sets of the employees and managers with regards to new technologies (Achieng & Malatji, 2022). Studies using TAM2 and UTAUT has proven that enabling factors such as training offered and stable internet connectivity has proven significant influence on technology attitudes outside of PU and PEOU (Du Plessis & Swart, 2024). Studies regarding small businesses in Africa and Asia indicate that social influence (for example, management support and peer usage) has been found most important with regards to technology perceptions of AI systems (Ayinaddis, 2023). Results suggest that in order to achieve successful technology engagement in SMMEs it is not enough for cognitive appraisals alone (positive or not) but that the whole of the organisational environment that supports and enables positive perceptions has to be at stake. This sort of contextualization enables one to ensure that the models are sensitive to realities of being resource constrained.

In spite of the development of wider models, TAM still offers valuable insights into perceptions of AI because of its simplicity and versatility. Two core constructs, PU and PEOU, still explain positive attitudes towards technology, irrespective of technology, industry or country (Almeida et al., 2025). In AI-specific research, TAM models applied successfully to the acceptance of systems such as chatbots, automated decision-making and AI-enabled employment platforms (Mapila & Moloi, 2024). TAM offers a basis of thought that can be adapted to the benefit of incorporating context-specific phenomena such as trust, organisational support or perceived risk (Chang et al., 2024). Its longevity stems from the balance it has struck between simplicity and extensibility that makes it particularly suited to technologies such as AI with complex and resource-constrained SMMEs where acceptance has to do both with the technological characteristics and social drivers. In this study, TAM thus serves as a theoretical foundation, extending it with constructs that bear relevance to South African business and cultural situations.

2.2.3 Integration of Perceived Organisational Support (POS)

Perceived Organisational Support (POS) represents global beliefs held by employees that their organisation appreciates their contributions and is concerned about their well-being (Eisenberger

et al., 1986). POS represents the psychological contract between employers and employees, which in turn affects how employees interpret decisions made by organisations, including the introduction of new technologies. High levels of POS increase commitment, lower turnover intentions, and increase job satisfaction (Imran et al., 2020). As employees begin to interact with AI technologies, POS is understood to provide employees a means of assessing whether such technologies are empowering or threatening. POS is indicative of the organisational climate involved in the situation under investigation and how environments that are more supportive can influence attitudes toward change. It has been noted in the literature that POS is still under-represented in many models of adoption that tend to rely on cognitive orientated assessments while ignoring the socio-emotional database entirely (Gerli et al., 2022; Song et al., 2025).

Recent studies are heavily focused on how contextual factors such as organisational climate and support affect the perceptions of technology. When organisational support involves strong managerial support, proper training and good communication, employees perceive AI technology as beneficial instead of being destructive (Du Plessis & Swart, 2024). In contrast the lack of such support would enhance the perceptions of skills obsolescence and job redundancy, which depresses favorable attitudes (Chang et al., 2024). In smaller medium size enterprises with a more flat organisational structure, the provision of visible and practical organisational support programmes would enhance the confidence of employees considerably. Further, in supportive environments enabling experimentation and tolerating mistakes, the perceived risk associated with disruptive technology will be lowered (Kelly et al., 2023). These findings indicate that not only the support provided by organisations serves to provide favorable perceptions of AI but also moderates the psychological effects on the well-being of employees.

There are many reasons to justify the inclusion of POS in the TAM framework for this study. Firstly, the high levels of unemployment, digital inequity, and lack of resources faced by South African SMMEs, imply that employees' perceptions of organisational support would be a vital component (Achieng & Malatji, 2022). Secondly, psychological engagement with AI involves cognitive evaluations of usefulness and ease of use, as well as emotional responses concerning job security, individual autonomy and fairness. By including POS as a moderator, the framework illustrates how supportive organisational cultures can enhance the positive relationship between favourable sentiments towards AI in regard to usefulness and ease of use, and job satisfaction. Finally, POS illustrates that technology acceptance is a relational process situationally embedded in organisational culture, addressing the criticisms regarding the narrowness of the TAM taxonomy

(Díaz-Arancibia et al., 2024). This inclusion will enhance the explanatory power of the model, and also link it to the specific challenges that are facing South African SMMEs.

2.3 Artificial Intelligence in the Workplace

2.3.1 Definition and Scope of AI

Artificial intelligence (AI) is the term used to describe how machines can do things that require human intelligence, such as learning, thinking, problem-solving, and making decisions (Xu et al., 2020). In a business context, the term AI is generally broken up into narrow AI and general AI (Raman et al., 2025). The term narrow AI describes systems created for specific tasks, such as chatbots that assist with customer service, or fraud detection algorithms used in finance, and are widely used for they provide reliable and cost-effective means (Mossavar-Rahmani & Zohuri, 2024). General AI is the more sophisticated idea of machines that can perform a variety of cognitive tasks comparable to human intelligence. General AI is still an idealistic goal but the gradual improvements in computing power are making it more and more possible (George, 2024). Narrow AI, in practice, is of great importance to SMMEs as it operates a greater immediate productivity advantage. General AI, however, necessarily raises debates about issues of autonomy, ethics and job displacement and its implications for society are thus more contentious (Du Plessis & Swart, 2024). This distinction reinforces the notion that businesses should adopt pragmatic solutions to its uses, applying the advantages of narrow AI for the purposes of efficiency whilst at the same time to prepare for more complex transformations that general AI will bring about.

AI also incorporates subfields that are of even greater importance when considering commercial use. Machine learning and predictive analytics allow managers to discover patterns in large amounts of data, predict market trends and manage risks, all of which are particularly important for resource-lean SMMEs (Kumar et al., 2024). Natural Language Processing (NLP) facilitates client interaction through applications such as chatbots and sentiment analysis, which enhance the engagement of firms and clients. Robotics employs AI-driven instruments for the automation of production, logistics and delivery processes, which enhances their efficiency (Le Dinh et al., 2025). These subfields indicate diverse applications of Artificial Intelligence, both in the technical and managerial senses, but in South Africa the application of these new technologies is sporadic, owing to lack of sufficient digital skills and infrastructure. While the possibilities and capabilities of

Artificial Intelligence for SMMEs are indeed considerable, successful application of these paradigms requires that specific contextual barriers are overcome.

2.3.2 Global Trends in AI-Related Perceptions

The global digital transformation that AI is driving is changing the way organisations work, innovate and create value. It permits the automation of routine tasks, the enhancement of decision-making and the creation of new business models that hitherto could not even be imagined (Dwivedi et al., 2021). In the areas of banking, health care and manufacturing, it permits data-driven insights leading to an acceleration of digital transformation (Mossavar-Rahmani & Zohuri, 2024). The transformative powers of AI make it a distinct competitive advantage in the Fourth Industrial Revolution in which agility and innovation determine survival. The advanced economies are investing heavily in the development of infrastructure while the emerging economies suffer from lack of digital know-how and finance (Hlatshwayo, 2023). Notwithstanding these disparities, the global picture to date is that there is not a sector or organisation that is not being affected by AI.

SMMEs experience pressure and opportunity to adopt the accelerating worldwide trend of digitalisation, in order to compete in increasingly integrated marketplace environments. International SMME experience with artificial intelligence confirms it as an applicable and flexible technology. The European SMMEs employ AI-enabled chatbots and predictive analytics for customer engagement and supply chain responsiveness in highly competitive markets (Schwaeke et al., 2025). The small manufacturers and retailers in Asia employ AI-based automation and machine learning for product inflow production and generating personalised customer experiences (Díaz-Arancibia et al., 2024). The North American SMMEs utilise AI-enabled systems for management and effective future forecasting in the employment of limited resources (Kumar et al., 2024). In the Latin American SMMEs use AI mobile-based platforms to reach consumers not served by other means, overcoming geographical and infrastructural challenges (Le Dinh et al., 2025). The above examples illustrate a broad range of the local SMMEs investigation into AI for the purposes of efficiency and scalable responses, but context readiness remains a significant issue. Low-level AI is preferable, since this is cost effective and therefore functional, whereas bigger enterprises attract the major complex advances in this technological area.

AI presents SMEs with substantial opportunities for productivity gains, cost savings, and innovation. Automation allows workers to focus on higher-value tasks, potentially enhancing both productivity and job satisfaction (George, 2024). AI-enabled predictive maintenance and demand forecasting reduce operational costs by minimising downtime and aligning inventory with customer demand (Du Plessis & Swart, 2024). AI helps small businesses penetrate new markets through digital platforms and tailored products, improving competitiveness and resilience in volatile markets (Soomro et al., 2025). However, realising these benefits requires aligning AI technologies with strategic aims and personnel capabilities. SMEs with limited resources must overcome financial, training, and infrastructural challenges to capitalise on AI's promise. Thus, while global trends position AI as a transformative force, each firm's context and readiness moderate its impact and, more fundamentally, shape how employees perceive these technologies.

2.3.3 AI Perceptions in South African SMMEs

South African SMMEs continually lag behind OECD peers in terms of digital maturity related to AI. While numerous South African SMMEs are still in the exploratory phases in terms of AI engagement, firms in the advanced economies are increasingly incorporating AI into their daily operations. AI diffusion in South Africa continues to be hamstrung by institutional inefficiencies and structural barriers such as problems over the supply of electricity, high data costs and poor internet access (Mbatha, 2024). These infrastructural barriers are simultaneously exacerbated by the limited digital skills possessed by employees, which often lead to perceptions that AI is threatening rather than beneficial (Schoeman & Seymour, 2022). Engagement is also limited by narrow profit margins and the inability of smaller firms to invest in costly AI products which have uncertain payoffs (Fatoki, 2019). The perception however is one of caution and uncertainty rather than confidence and positivity regarding AI thereby putting SMMEs at a competitive disadvantage in an increasingly digitalised global economy.

Despite these challenges, both public and private initiatives have emerged to support SMME digital transformation. The Gauteng Provincial Government launched a digital transformation strategy providing financial and training support to smaller firms (Gauteng Provincial Government, 2022). Technology companies have introduced subsidised cloud-based AI tools and digital skills development programmes aimed at SMMEs (Rambe, 2024). However, such interventions are unevenly distributed, with many rural and marginalised businesses excluded from access, perpetuating the digital divide (Mbatha, 2024). Consequences of this uneven progress are

significant. SMMEs unable to develop positive perceptions of AI risk are falling further behind in productivity, innovation, and customer service, while those successfully cultivating favourable perceptions stand to improve resilience, competitiveness, and economic contribution. This dual reality underscores the need for coordinated policies and inclusive capacity-building programmes ensuring that positive AI perceptions strengthen rather than undermine South African business competitiveness.

2.4 Job Satisfaction in the Context of AI-Related Perceptions

2.4.1 Defining Job Satisfaction

Job satisfaction has been defined as a positive emotional state resulting from an appraisal of the job and experience (Locke, 1976). This notion has been expanded from evaluations of emotions to include cognitive assessments of aspects such as job situation, opportunities for personal growth and development and fairness in the organisation. The current theories have recognised that job satisfaction shows positive affective and cognitive evaluations of whether or not the job meets the expectations and values of the worker (Baxi & Atre, 2024). The relevant notions of satisfaction show a strong correlation with perceptions of fairness of treatment, opportunities of self-development, and whether the technology enhances or hinders personal autonomy.

In a world dominated by artificial intelligence, scholars contend that balance must be brought to bear on psychological and structural aspects of work satisfaction (Chang et al, 2024). Such evolution shows how difficult measurement of satisfaction and retention in changing environments becomes, especially in SMMEs where technological disruption can take serious forms. In this study, job satisfaction is the variable of interest shaped by cognitive evaluations of these AI technologies (PEOU and PU) and moderated by organisational support (POS).

2.4.2 Dimensions of Job Satisfaction

Intrinsic job satisfaction reflects happiness derived from the work itself, including autonomy, task variety, skill utilisation, and goal achievement. Baxi and Atre (2024) note that employees experience higher job satisfaction when they can be creative, express themselves, and make meaningful contributions to organisational goals. As AI technologies are introduced, routine task automation can free workers to focus on more engaging and intellectually stimulating activities, potentially enhancing satisfaction (George, 2024). However, concerns arise when AI-powered systems reduce autonomy, constrain decision-making latitude, or increase algorithmic control,

potentially diminishing the intrinsic quality of work (Meijerink & Bondarouk, 2023). In SMMEs where jobs often encompass multiple functions, the introduction of AI can simultaneously enrich and constrain intrinsic satisfaction. This duality underscores the importance of managing AI perceptions in ways that enhance rather than limit intrinsic motivation.

Extrinsic job satisfaction stems from factors such as compensation, working conditions, organisational support, and job stability. When resources are limited and workers depend on external benefits for security, these factors often exert greater influence (Bhagwandeem, 2021). Research indicates that extrinsic satisfaction is particularly sensitive to technological change because AI-related perceptions may trigger concerns about job loss, increased surveillance, or inequitable benefit distribution (Raji & Ismail, 2023). Organisations that invest in fair compensation systems, provide appropriate training, and maintain open communication during technological change are more likely to preserve employee satisfaction even amid disruption (Gayathri & Bella, 2024). For South African SMMEs, maintaining these external motivators is essential for retaining quality employees and ensuring resilience. Compensation, workplace support, employment stability, and organisational practices constitute critical extrinsic factors (Bhagwandeem, 2021). While favourable AI perceptions can enhance productivity and reduce monotonous tasks, external support measures determine whether these efficiency improvements translate into positive employee experiences (Gayathri & Bella, 2024). Raji and Ismail (2023) recommend clear communication, fair reward systems, and training to promote job satisfaction when AI technologies are present.

This study evaluates how AI-related perceptions influence job satisfaction in South African SMMEs, recognising that supportive organisational policies largely determine whether positive technology appraisals translate into favourable employee experiences. Given resource constraints in SMMEs, extrinsic satisfaction dimensions warrant particular attention, as they reflect whether employees feel valued and supported during periods of technological change.

2.4.3 Job Satisfaction in SMMEs

Small, Medium and Micro Enterprises (SMMEs) encounter a unique set of challenges in relation to job satisfaction, because of limited resources. Many of these businesses typically run on thin margins, which does not allow for significant investments in training or improved working conditions (Fatoki, 2019). Unlike a large enterprise that may draw upon numerous budgets in allocating different amounts for training employees and employee benefits, SMMEs must weigh

the financial pressures they face against their employees high expectations of promotion and support in the workplace (Mbatha, 2024). Low staffing levels in smaller, less-resourced organisations mean that employee turnover creates additional challenges, since losing even one skilled employee can disrupt operations (Sibiya et al., 2023). Employees can also see limited digital infrastructure and fewer opportunities to learn about new technologies as a deficit, and make a normative assessment that small firms are not as progressive as larger ones. Overall these considerations can contribute to dissatisfaction and issues of attraction and retention of talented employees. SMMEs must manage limited budgets against the need to create a supportive, engaging, culture of work within which an employee might experience satisfaction.

Notwithstanding these factors, job satisfaction plays an important role in the survival, productivity, and innovation of SMME. Satisfied workers tend to be more engaged, creative, and loyal, which assists firms innovate and adapt to competitive markets (Rambe, 2024). The continuity of knowledge is a driver of innovation and helps smaller firms to compete within the same market space, particularly when strong worker retention is in place to ensure the preservation of institutional memory (George, 2024). Job satisfaction lowers absenteeism and turnover, which is important for SMME because these workers are expensive to replace, if at all. Higher job satisfaction leads to enhanced competitive positioning because satisfied workers will be more likely to accept new technologies and problem-solve (Hlatshwayo, 2023). Job satisfaction therefore reinforces a strategic imperative towards competitiveness and resilience in under-resourced contexts.

2.4.4 AI Perceptions and Job Satisfaction

Favourable perceptions of AI technologies can enhance job satisfaction by improving the nature of work. When employees perceive AI as useful and easy to use, they may experience reduced workload from automating repetitive tasks, allowing focus on higher-value, more meaningful responsibilities that enhance fulfilment (Gayathri & Bella, 2024). Within SMMEs where employees frequently juggle multiple roles, AI tools perceived as helpful can alleviate the burden by providing predictive insights, accelerating decision-making, and enhancing customer interactions (Du Plessis & Swart, 2024).

When AI technologies are introduced with appropriate organisational support, employees perceive them as empowering, enabling skill acquisition and engagement in more creative tasks (Rick, 2024). In South Africa, firms framing AI as complementary tools rather than employee

replacements have reported improvements in job satisfaction and workplace flexibility (Murire, 2024). These outcomes suggest that positive AI perceptions can contribute to employee well-being but only when supported by practices such as training, open communication, and recognition of evolving job roles.

Conversely, negative perceptions of AI technologies can diminish job satisfaction by heightening job insecurity and creating psychological strain. Employees frequently perceive AI as threatening job stability, particularly in environments characterised by high unemployment and low digital literacy concerns, confirmed by empirical studies (Raji & Ismail, 2023). Algorithmic monitoring and performance tracking may further undermine employee autonomy, fostering anxiety and stress (Meijerink & Bondarouk, 2023). Within South African SMMEs, limited access to digital training can exacerbate feelings of exclusion and devaluation, reducing satisfaction levels (Schoeman & Seymour, 2022). Global evidence similarly indicates that resistance and disengagement increase when AI is introduced without employee involvement, dialogue, or investment in reskilling (Chang et al., 2024). Thus, AI perceptions' impact on job satisfaction depends heavily on organisational context: positive outcomes emerge where technological change is embedded within supportive human resource policies and inclusive change management strategies.

2.5 Perceived Risk and Resistance to AI

2.5.1 Nature of Perceived Risk in Technology Contexts

AI technologies in the workplace can heighten employees' risk perceptions. Common concerns include job redundancy, skill obsolescence, decreased autonomy, and surveillance through algorithmic management systems. Scholars identify automation-driven redundancy as a major issue, especially in vulnerable employment markets (Tiwari, 2023). Since AI systems often require new technological capabilities that many workers lack, employees worry that their existing skills will become outdated (Morandini et al., 2023). Algorithmic control and monitoring may also constrain decision-making latitude and reduce autonomy (Meijerink & Bondarouk, 2023). Constant surveillance and diminished agency can cause stress and disengagement. Such risks highlight the complexity of perceptions of AI, where technological gains may entail significant emotional costs if not carefully managed within organisations. These perceived risks directly shape whether employees develop favourable or unfavourable perceptions of AI technologies and, consequently, whether these perceptions translate into positive or negative job satisfaction outcomes.

In South Africa, structural issues including high unemployment and digital skills shortages intensify technology-related risk perceptions. Employees view AI as threatening limited employment opportunities, with unemployment rates exceeding 30% (World Bank, 2021). Digital literacy remains unevenly distributed, and many workers, especially in smaller firms, lack exposure to sophisticated technologies and formal training (Mbatha, 2024). AI is widely perceived as a destabilising force that may increase inequalities rather than facilitate efficiency (Schoeman & Seymour, 2022). Employees with fewer technical skills fear exclusion from future employment opportunities due to the digital divide, intensifying feelings of vulnerability. Due to economic constraints, SMMEs often cannot afford comprehensive reskilling programs. This context demonstrates how national socio-economic realities shape workers' perceptions of and resistance to technology. However, limited South African research directly examines how these structural and organisational dynamics influence employees' perceptions of AI and resulting job satisfaction.

2.5.2 Employee Resistance to AI Perceptions

In the case of workers with negative perceptions of AI, resistance may arise from both rational and emotional bases. Typically, rational resistance arises from valid concerns related to job loss, inadequate training, or unfair distributions of the benefits of technological advancement (Dwivedi et al., 2021). Employees assess the perceived costs against the perceived benefits and produce resistance based on a perception of risk that outweighs perceived benefits. Emotional resistance originates from anxiety, fear, and distrust stemming from uncertainty about the impacts of technology on job roles and work relationships (Chang et al., 2024). Employees' perceptions do not have to completely align with objective reality to have an influence on technology attitudes.

In SMMEs where there are few formal communication channels, resistance is likely to spread quickly through small teams, creating increased scepticism. This suggests a duality, as technical training is not sufficient to change negative perceptions, organisations will have to deal with emotional issues to soften them. Self-efficacy and digital trust represent important factors in shaping worker responses to AI. Workers with high self-efficacy who believe in their ability to master and adapt to AI systems are more likely to develop positive perceptions. Workers who lack digital confidence are more likely to resist (Venkatesh et al., 2016). How successfully these responses will be managed by organisations depends largely on transparency and quality of communication (Du Plessis & Swart, 2024).

Evidence suggests that effective communication of the purposes of the change, adequate training and fair implementation by management lead to positive views of AI by employees. Poor communication and decisions made in secret lead to distrustful employees, resistant to the change. In the case of South African SMMEs, where formal training is often lacking, the need for good communication and participatory decision-making is even more important for the development of positive views. Resistance to these changes will be best dealt with by a holistic approach that includes technical back-up, confidence-building strategies and communication to reduce the feeling of threat.

2.5.3 Mitigating Perceived Risk

Organisational change management, training, and trust-building are essential for reducing AI-related risk perceptions. Effective change management involves engaging workers and explaining why new technologies are introduced. Structured training and capacity-building programs alleviate anxiety by teaching staff how to use AI confidently (Morandini et al., 2023). Transparent communication and participatory decision-making help transform AI attitudes from a threat to a facilitator (Dwivedi et al., 2021). Organisations that frame AI as a supplement rather than a replacement for human skills are more likely to gain acceptance and reduce opposition. Thus, proactive management approaches reduce concerns about job displacement and skill obsolescence while improving the organisational environment for technological change. These interventions directly shape whether employees develop positive or negative perceptions of AI technologies and consequently, whether these perceptions translate into job satisfaction or dissatisfaction.

South African SMME experiences demonstrate the value of these interventions. Studies show that inadequate digital literacy and lack of support increase negative perceptions and resistance (Mbatha, 2024). Employee development activities and effective communication techniques reduce suspicion and foster positive perceptions (Du Plessis & Swart, 2024). Staff at SMMEs providing on-the-job training and mentoring exhibit better digital confidence and reduced perceived risk (Schoeman & Seymour, 2022). Government and private sector partnerships, such as digital transformation strategies and skills development efforts, have also supported SMMEs seeking sustainable AI integration (Gauteng Provincial Government, 2022). These results indicate that mitigation requires integrating AI within supportive corporate cultures valuing learning, trust, and inclusivity, thereby fostering positive technology perceptions that enhance rather than diminish job satisfaction.

2.6 Perceived Organisational Support (POS) and Technology Perceptions

2.6.1 Concept and Definition

Perceived Organisational Support (POS) can be defined as the employees' beliefs that their organisation values their contributions and is concerned about their well-being (Eisenberger et al., 1986). Stemming from social exchange theory, POS indicates that employees who perceive care from their organisation give back through positive attitudes and behaviours. With respect to technological contexts, POS is particularly salient, as employees may lack certainty as to how technologies like AI will affect their roles and job security. Opening them up through higher levels of POS provides employees with reassurance that the intended aim of technological initiatives is to enhance, rather than undermine their work experience, therefore reducing threat levels to employees and fostering levels of organisational trust (Maan et al., 2020). Consequently, POS becomes not only a socio-emotional resource but also a vital stabilising mechanism during transitions in the work place, making it a very important construct in studies of digital transformation and technology related experiences.

2.6.2 POS and Employee Outcomes

Perceived Organisational Support has consistently shown to dignify employee attitudes and behaviours, including job satisfaction, organisational commitment, and psychological empowerment. Employees, who feel supported by their organisation, exhibit higher commitment, lower intention to leave, and greater proactivity in pursuing the organisation's objectives (Imran et al., 2020). In the context of technological change, POS is critical to understanding employee responses to innovations in technology. POS alleviates the stress of a rapidly transforming digital environment by introducing technological initiatives in a positive light as an opportunity and not a threat (Chang et al., 2024).

In addition to alleviating stress, POS facilitates psychological empowerment, giving employees additional feelings of autonomy and competence when engaging with new technologies (Maan et al., 2020). Taken collectively the evidence suggests that POS acts as a buffer to negative events associated with technology failure, ensuring that positive technology perceptions translate into increased not diminished employee experience. This relationship is supported by both global and South African empirical evidence. Enterprises in the emergent economies sector evident that SMME's which embrace training and acknowledgement into change management strategies

reflect greater employee satisfaction with technology initiatives (Du Plessis & Swart, 2024). Raji and Ismail (2023) similarly claim uniqueness of POS in creating organisational trust during periods of digitalisation, thereby reducing resistance to further innovations in technology and producing greater readiness for innovation.

In South Africa, the role of SMME, POS assumes greater importance, as it will predetermine 'whether the enterprise can engender positive perceptions concerning technology notwithstanding the shortage of resources and increasing fears of the employee level' (Hlatshwayo, 2023). By initiating transparency in the organisation while, at the same time, promoting inclusiveness and care, the POS can produce transformed technology perceptions within organisations that will cause potentially damaging technological changes to be channeled into opportunities for growth, adaptability, and long-term sustainability and competitiveness.

2.6.3 POS in the Context of AI Perceptions

The concept of Perceived Organisational Support is important for alleviating fears about AI technologies, especially in environments with limited resources such as small and medium-sized enterprises. In this regard, Raji and Ismail (2023) indicate that high levels of POS may alleviate employees' fears about the security of their employment, monitoring and reduced autonomy by creating confidence in the intention of management. Employees are more inclined to see technological change as an opportunity for development than as a threat if their organisations demonstrate concern for them with transparent communications, training and recognition of work. POS may also diminish resistance to the introduction of technological change by creating feelings of safety, since employees may be able to experiment with new applications without fear of sanctions when mistakes occur (Chang et al., 2024; Maan et al., 2020). In the context of small businesses, where not all of the personnel may be technology-ready, those programmes of action which are designed to lead to an increase in the climate of trust and supportiveness are essential if motivation is to be sustained and withdrawal from work is to be avoided. Therefore, POS may serve as an important socio-organisational resource for the implementation of AI technologies, since this resource may directly influence whether such technologies are seen as a help or a hindrance in the workplace.

The degree to which POS influences employees' perceptions of AI technologies is pertinent, as it has the potential to cast the presented change into one that is favourable rather than threatening. In the research of Du Plessis and Swart (2024) it was reported that employees who believe that

their input is valued show a more favourable perception of AI as their job roles and tasks change over time. A high level of POS naturally develops from trust and increased levels of resilience in difficult times, which is fundamental during turbulent transitions such as has happened in the present situation (Imran et al., 2020). This is of particular importance to South African SMME's since the workforce generally is faced with a greater uncertainty due to economic instability and lack of skills where available due to employment policies that are implemented (Hlatshwayo, 2023). By incorporating the concept of POS in the strategies concerning implementation, managers can create a workplace where AI is adopted in a positive manner as it improves performance and the performance and satisfaction rather than poses a threat to livelihood. In conclusion, POS is a vehicle to implement through which changes that are AI related can be interpreted resulting in an improvement or deterioration in the perception of the effectiveness of the organisation and of employee wellness or well-being.

2.7 Identified Literature Gaps

Artificial Intelligence research is gaining traction but knowledge of technology-related perceptions in SMMEs in developing economies is still scarce. Much present day literature is based on developed environments where the necessary infrastructure, digital literacy and financial means support the rapid introduction of new technologies (Ayinaddis, 2023). SMMEs in South Africa are likely to be confronted with structural constraints in the form of lack of preparedness for the digital environment, financial constraints as well as inadequate training support (Mbatha, 2024). The fact that there is little research on the specific nature of the obstacles confronting the sector means there is little in the way of policy and practical drives based on contextually relevant knowledge. Such a knowledge gap makes the development of targeted strategies to assist SMMEs in their efforts to promote the development of positive perceptions regarding AI performance in parallel with the enhancement of employee well-being difficult.

Another limitation is the predominant focus on large enterprises for analysis. Research often investigates corporations that have large resources but does not consider the contribution of smaller firms that are important to job creation and innovation (Van der Westhuisen, 2023). This skew produces a distorted impression of perceptions of technology as findings of the larger firms cannot be generalized to SMMEs that are resource constrained. Fatoki (2019) comments that small South African firms face qualitatively different barriers from larger enterprises. In the absence of empirical studies that are specifically aimed at small enterprises, the solutions

proposed are prone to be misaligned with their realities and ineffective (Schoeman & Seymour, 2022).

Another gap relates to the limited incorporation of psychosocial factors in technology acceptance models such as TAM. Although TAM has been extensively employed to predict technology acceptance decision-making, the original formulation of TAM was narrowly focused on technical constructs such as PU and PEOU (Davis, 1989). There is a growing body of literature that suggests the organisation's context and support, in tandem with employees' responses to technology change, will impact whether employees' positive perceptions of technology-translates into job satisfaction (Raji & Ismail, 2023). The lack of empirical studies that examine the impact of employee perceptions of AI, while simultaneously taking into account the psychosocial context of the organisation and the nature of labour market, create uncertainty in their effect on employee well-being. This study seeks to fill this gap by including POS as a moderator in the project to explore how organisational support can shape the relationship between perceptions of technology and employee satisfaction outcomes.

Lastly, there is a lack of studies that explore perceptions of technology from employees' perspectives of job satisfaction. Modern research prioritises organisational outcomes such as efficiency, productivity, and competitive advantage (Chang et al., 2024). Although these insights are valuable, they fail to capture how workers interpret, enact, and are affected by technological change. In South Africa, where high unemployment and job insecurity remain problematic, overlooking employee perspective will only reinforce skepticism toward AI and lessen positive understanding (Murire, 2024). Workers' perspectives, experiences, and concerns must therefore be considered when analysing the digital transformation and when attempting to generate strategy that fosters a positive perception of AI, in a way that also supports the health and well-being of workers in addition to organisational performance.

Table 2: Summary of Identified Literature Gaps

Gap Area	Description	Key References
Limited empirical focus on SMMEs in developing economies	Research on AI perceptions is disproportionately centered in developed economies, with little contextual evidence from South African SMMEs	Díaz-Arancibia et al. (2024); Mbatha (2024)

Overemphasis on large corporations	Majority of studies analyse multinationals or large firms, neglecting unique challenges of smaller enterprises	Van der Westhuisen (2023); Fatoki (2019)
Weak integration of psychosocial constructs in TAM	Models like TAM underexplore organisational climate and support, overlooking how these factors shape technology perceptions and satisfaction outcomes	Davis (1989); Raji & Ismail (2023)
Lack of employee-centered perspectives	Focus on organisational efficiency overshadows worker experiences of satisfaction, insecurity, and adaptation to technology	Chang et al. (2024); Murire (2024)

2.8 Chapter Summary

The study demonstrates the way that AI perceptions are reshaping workplaces and employee experiences but that the effect of SMMEs is not well understood. Acceptance theories reflect the perceived utility and perceived ease of use as determinants of how employees evaluate new technologies. These theories may not encompass the totality of the employee response to technology change and other psychological factors governing acceptance or rejection may not be fully catered for in acceptance theory. The understanding of AI perceptions must be viewed in the context of SMMEs in South Africa, where there is a contribution that limited resources and skills shortage, and a digital divide have to be catered for and that there are additional factors that emerge from these limitations. The literature review demonstrates the way in which intrinsic and extrinsic factors contribute to job satisfaction in numerous ways. Enhanced AI perceptions may enhance employee satisfaction because of less repetitive work, more productive work done by the individual, or more time to do the work of higher value. The negative perceptions will contribute to less satisfaction because of the fears of redundancy, surveillance and lack of autonomy that become common characteristics in such circumstance. The paradoxical characteristics inherent in this discussion, demonstrates that the manner in which the AI technologies are presented and supported within the organisations must thus be carefully thought about.

The study looks at the importance of mutual support, finding that employee perceptions of care, acknowledgement and fairness influence whether AI is perceived as empowering or threatening, meaning that this construct is particularly important in respect of the satisfaction outcomes studied. Overall, the review presents significant theoretical and practical contributions. The standard adoption models are extended by showing how mutual support moderates the relationship between perceptions of technology and employee outcomes. Practically, the unique

importance of human centred approaches to AI implementation in SMMEs are highlighted, with the necessity to ensure that increased efficiency does not come at the cost of employee wellness clearly illustrated. The review compounds the justification for this study by highlighting gaps in research and indicating the dual potential of perceptions of AI. This provides the background for the following chapter which specifies the research questions and hypotheses guiding the empirical investigation into how perceptions relating to AI affect job satisfaction in South African SMMEs.

CHAPTER 3: RESEARCH QUESTIONS AND HYPOTHESES

3.1 The Research Purpose

The research examines the relationship between cognitive appraisals of AI technology perceived ease of use (PEOU) and perceived usefulness (PU) and job satisfaction of South African SMME employees. The relationship between AI and organisational performance has been investigated around the world, but the effect of AI on employee well-being, in an under-resourced developing economy like South Africa, is insufficiently understood (Badghish & Soomro, 2024). The Technology Acceptance Model (TAM) and Perceived Organisational Support (POS) as a moderating variable will address this gap. The original TAM (Davis, 1989) demonstrated that the two constructs, PEOU and PU, measured employees' cognitive assessment of new technology in the workplace, however, did not address psychosocial characteristics like trust, fairness, and support. Eisenberger et al. (1986) and Raji and Ismail (2023) demonstrated that POS moderates job satisfaction employees' constructs and employee responses to organisational change.

The study has theoretical and practical significance. Theoretically, the use of POS in conjunction with TAM shows how social-organisational variables work in conjunction with cognitive variables on the technology-related attitudes to impact well-being related outcomes. This helps us to be able to understand the conditions under which positive perceptions of technology translate to job satisfaction. It practically also provides local SMME's with evidence that is suitable to the particular circumstances of the case, to assist them in promoting the positive perceptions of AI with the relevant provision made for employee well-being. The study will use simple mediation with moderation paths, rather than a second stage moderated mediation model to investigate whether and how PEOU and PU influence job satisfaction, and under what organisational conditions those relationships are strengthened or weakened (Hayes, 2017). Thus the overall purpose of the research is more than the mere application of TAM, but is aimed at enhancing a broader and more sophisticated paradigm that will cover both technology related features, as well as human-related ones such as those leading to the employee experiences.

3.2 The Research Questions

The central research question guiding this dissertation is:

Primary Research Question: How can the Technology Acceptance Model (TAM) be extended to explain the relationship between the theoretical determinants of AI acceptance, perceived ease

of use (PEOU) and perceived usefulness (PU) and job satisfaction among South African SMME employees?

Secondary Research Questions:

1. How does PEOU influence PU among South African SMME employees encountering AI technologies?
2. To what extent does PEOU directly influence job satisfaction?
3. Does PU mediate the relationship between PEOU and job satisfaction?
4. How does PU directly influence job satisfaction?
5. Does Perceived Organisational Support (POS) moderate the relationship between PU and job satisfaction?
6. What practical recommendations can guide South African SMMEs in fostering positive AI perceptions to enhance job satisfaction while ensuring business sustainability?

These questions address the lack of research conducted on perceptions of AI as there are very few empirical data on perceptions of AI in the SMME sectors of emerging economies (Fatoki, 2019; Kumar et al., 2024). The TAM has been used in a variety of contexts, although little research has been conducted concerning the effects of socio-organisational factors like POS which have a bearing on trust in technology and job-related attitudes as moderators for satisfaction outcomes. These questions will allow the research to gather the perceptions regarding technology design, the dynamics of organisational supportive mechanisms, and the aspects of human experiences simultaneously (Almeida et al., 2025; Davis, 1989).

3.3 Conceptual Model and Hypotheses Development

This study adopts a moderated model to investigate the influence of employees' perceived ease of use (PEOU) and perceived usefulness (PU) of AI technologies on their job satisfaction in SMMEs in South Africa. Based on the Technology Acceptance Model (TAM) (Davis, 1989) which has been extended with Perceived Organisational Support (POS), the model integrates both the technological and the organisational aspects of employees' technology-related experience. It posits that PEOU affects PU which, in turn, has a direct bearing on the employees' job satisfaction. Further, PEOU is posited to exert a direct influence on job satisfaction. PU is the mediating variable in these paths, linking perceptions of system usability and the well-being-related

outcomes (Almeida et al., 2025). In addition, POS acts as a moderator in the strength of the relationship between PU and job satisfaction (Raji & Ismail, 2023).

Hypothesis 1 (H1): PEOU has a positive influence on PU. If the AI systems are intuitive and easy to use, employees are more likely to see them as enhancing task performance (Song et al., 2025; Venkatesh et al., 2016). In resource-constrained SMMEs where employees are often required to multitask several responsibilities, the ease of use becomes important in influencing technological value perceptions (Schoeman & Seymour, 2022). This is the foundation of the TAM relationship, which is firmly validated in many contexts.

Hypothesis 2 (H2): PEOU positively influences job satisfaction. PEOU may also directly impact satisfaction through lowered cognitive burden and frustration from technology usage. Employees finding AI systems easy to use will not feel as overwhelmed or stressed and more confident in their work and directly enhance satisfaction (Venkatesh & Davis, 2000).

Hypothesis 3 (H3): PU mediates the relationship between PEOU and job satisfaction. This hypothesis tests whether the effect of ease of use on satisfaction operates partially through enhanced perceptions of usefulness. When employees find AI easy to use, they are more likely to recognise its benefits, which in turn enhances satisfaction (Almeida et al., 2025). This mediation pathway extends TAM by connecting technology perceptions to well-being outcomes.

Hypothesis 4 (H4): PU positively influences job satisfaction. Employees believe AI fosters improved efficiency and better decisions will experience enhanced job satisfaction (Gayathri & Bella, 2024). In South Africa, where cost-control and productivity gains are essential for competitiveness, perceived usefulness should show a strong predictive relationship with satisfaction outcomes (Du Plessis & Swart, 2024). Effective implementation of AI can improve satisfaction by lowering workload, increasing accuracy, and creating upskilling opportunities. On the other hand, if AI is not believed to be useful, it may result in increased stress or job insecurity (Chang et al., 2024).

Hypothesis 5 (H5): POS moderates the relationship between PU and job satisfaction. Supportive organisational environments foster positive interpretations of technological change, encouraging employees to perceive AI as empowering rather than threatening (Eisenberger et al., 1986; Maan et al., 2020). High POS is therefore expected to strengthen the positive relationship between PU and satisfaction. When employees feel valued and supported, their positive perceptions of AI's usefulness translate more strongly into job satisfaction. Conversely, low POS may weaken this

relationship or even reverse it, as perceptions of risk or disengagement may intensify without adequate organisational support (Du Plessis & Swart, 2024; Raji & Ismail, 2023).

The proposed framework (Figure 1), therefore, suggests that PEOU affects job satisfaction both directly and indirectly through PU, while POS moderates the PU-satisfaction pathway. This integrated model advances TAM by embedding socio-organisational factors and positioning job satisfaction rather than usage behaviour as the focal outcome. It provides a context-sensitive explanation of how AI-related perceptions influence employee well-being within South African SMMEs.

Relationships:

- **H1:** Direct path from PEOU to PU
- **H2:** Direct path from PEOU to Job Satisfaction (curved arrow at top)
- **H3:** Mediation pathway (PEOU → PU → Job Satisfaction)
- **H4:** Direct path from PU to Job Satisfaction
- **H5:** Moderation effect (dashed line from POS to the PU→Job Satisfaction relationship)

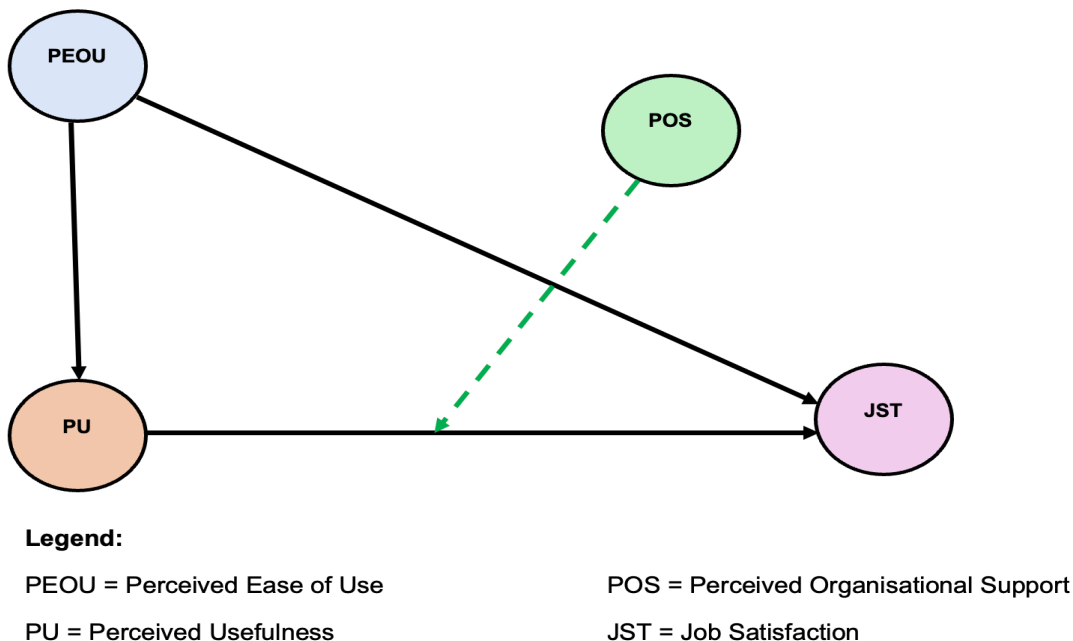


Figure 1: Conceptual Framework

AI-related perceptions in South African SMMEs are conceptualised through this framework, integrating technological and socio-organisational dimensions that influence employee experience. By combining cognitive factors from TAM with organisational support dynamics, the model provides a comprehensive explanation of how employees perceive and respond to AI technologies in the workplace.

Beyond providing descriptive associations, the framework establishes causal pathways clarifying how usability and utility perceptions (PEOU and PU) interact with organisational support (POS) to influence job satisfaction. These relationships are analysed through mediation and moderation testing to uncover both direct and indirect effects (Hayes, 2017). Therefore, the model contributes to theory and practice by identifying mechanisms through which positive AI perceptions can enhance, not undermine, employee well-being and organisational performance in digitally transforming South African SMMEs. The model explicitly positions job satisfaction as the ultimate dependent variable, representing a significant extension of TAM, which traditionally culminates in usage intentions or behaviour. This reorientation acknowledges that in resource-constrained SMMEs, employee well-being outcomes prove as important as adoption rates for sustainable digital transformation.

CHAPTER 4: RESEARCH METHODOLOGY

4.1 Proposed Research Methodology and Methodological Choices

In this research, a quantitative research design based on positivism was used. This research approach was selected because it allows the objective investigation of the relationship between certain perceptions of artificial intelligence, perceived ease of use (PEOU), and perceived usefulness (PU), perceptions of support (POS) from the organisation as well as employee job satisfaction in SMMEs in South Africa. Quantitative methods allow for theory-based hypothesis testing, leading to the possibility of statistical generalisability and replicability. According to Babbie (2020), quantitative investigation is the best approach to establish causal pathways and according to Saunders et al. (2019), there is predictive capability in the approach with regard to the understanding of perceptions of technology and its behavioural impacts. The technology acceptance model (TAM) served as the means of measurement for perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1989). The job satisfaction survey (JSS) developed by Spector (1997) serves as the means to measure job satisfaction variables or outcomes while that of the Eisenberger et al. (1986) surveys of perceived organisational support will measure the moderation effect. The methodology employed well-established measures to measure the variables to ensure internal reliability of the results and external comparability with results from other studies.

A mono-method quantitative research design was implemented. While mixed methods permit relationships between variables to be quantified and placed in context (Creswell & Creswell, 2017), in this case, the emphasis is placed on the need for numerical accuracy and hypothesis testing, supporting a mono-method approach. Data was gathered from a cross-sectional survey involving 208 SMME employees at one point in time. According to Bell et al. (2022), cross-sectional surveys are the most time-effective and cost-effective means of data collection in businesses experiencing technological change. The investigation of mediating and moderating conditions was carried out by means of quantitative measures and stringent statistical modelling, including regression based conditional process analysis (Hayes, 2017). These practices provided a balance between feasibility and academic rigour for systematic hypothesis testing.

4.2 Purpose of Research Design and Research Design Used

The research design incorporated structured goals, hypotheses, and empirical testing procedures. The study design was selected to appropriately address the research questions given the available methods (Asenahabi, 2019). This study employed a descriptive-correlational design. The descriptive component examined AI-related perceptions and employee satisfaction characteristics in South African SMMEs, while the correlational component examined statistical relationships between TAM features, POS, and job satisfaction.

This dual approach helped map current conditions while testing hypotheses about relationships between technology-related cognitions and human outcomes. Recent technology perception research supports a descriptive-correlational design. Using similar designs, Khalifa and Albadawy (2024) studied AI applications in academia, illustrating how descriptive statistics provide context while correlational analyses evaluate conceptual models. Means and standard deviations revealed how SMME employees perceived AI technologies, whereas correlational and regression studies examined mediation and moderation effects. Arntz et al. (2019) recommend correlational strategies for workforce studies without experimental control. The design allowed the study to deliver empirical data without manipulating organisational characteristics which would be unfeasible and potentially unethical.

4.3 Research Philosophy

The research adopted a positivist standpoint supporting quantitative social science. Positivism implies that reality is objectively observable and measurable. In line with this paradigm, the research acknowledged the perceptions relating to AI, the perceived usefulness, the perceived ease of use, the organisational support and job satisfaction, all of which were measured statistically. Positivism is appropriate for research in business and organisations where generalisable knowledge is sought from empirical regularities (Park et al., 2020). Saunders et al (2019) add that positivist research enhances objectivity, replicability and the use of established tools, essential features of this research design.

The research problem supported positivism. Quantifiable constructs like perceived utility, ease of use, organisational support, and satisfaction required numerical measurement and a statistical inference framework. TAM-based research often employs positivist assumptions to predict attitudes and satisfaction based on cognitive evaluations of technology (Almeida et al., 2025).

Positivism aligns with the study's goal of testing hypotheses through deductive reasoning rather than exploring subjective meanings, which would require an interpretivist methodology. The positivist approach ensured that findings could be compared with and contribute to the global literature on AI perceptions and employee outcomes. The paradigm helped the researcher maintain impartiality, reducing bias and ensuring data-driven conclusions rather than interpretive subjectivity. This objectivity proves particularly important when examining relationships between constructs, as positivism emphasises empirical verification over personal interpretation (Bell et al., 2022).

4.4 Research Approach

An approach was taken deductively, which is consistent with the quantitative research methodology and the positivist view. Deduction implies that hypotheses are developed from accepted theories and are then checked empirically. Deductive reasoning will prove helpful where the need is for testing and editing existing theories as opposed to the creation of new models (Fife & Gossner, 2024). This method was especially appropriate given that the hypotheses developed for the study were based on the Technology Acceptance Model (Davis, 1989) and Perceived Organisational Support theory (Eisenberger et al., 1986).

The research examined and developed established models in a novel empirical context by producing hypotheses linking perceived usefulness, perceived ease of use, organisational support and job satisfaction. The deductive approach allowed for regression type methodologies to be used to test the hypotheses systematically. Deduction allows researchers to ascertain generalisability by applying an established theoretical framework to a varied context (Bell et al., 2022). In this case the study aimed to ascertain whether models that were developed in advanced economies were applicable in injecting market contexts by investigating the theories of TAM and POS in South African SMMEs. Moreover, deductive approaches allow for more advanced statistical methodologies, such as mediation and moderation testing to be employed that require well defined hypotheses produced from established theoretical frameworks (Hayes, 2017). Following a traditional deductive research cycle the study began with theory, tested this with the data and refined the conclusions based on the results. This both ensured theoretical rigour, but also advanced knowledge as it ascertained the contexts in which existing theory holds good and the contexts in which it requires change.

4.5 Research Strategy

This study employed a standard online questionnaire survey. Survey research was selected to acquire uniform data on attitudes, beliefs, and perceptions from a large, geographically distributed population. Saunders and Lewis (2018) state that surveys enable researchers to quantify relationships among variables because participants respond to comparable questions. Meng et al. (2021) noted that questionnaires can capture multiple psychological variables, making them the most effective approach for studying employee opinions and perceptions. For this study, employees across various South African SMMEs provided systematic responses on perceived utility, ease of use, organisational support, and job satisfaction related to AI technologies. A survey approach facilitated hypothesis testing. Each item was standardised to avoid interviewer bias and ensure homogeneity among respondents. This proved significant given the research's positivist and deductive foundations.

According to Badghish and Soomro (2024), validated survey scales yield accurate measures of constructs, rendering them suitable for TAM based studies on technology perceptions. The resource and time-efficient survey mechanism yielded satisfactory awareness of respondents without requiring any expensive or logistically complex field time. Given that SMMEs in South Africa had tangible geographical location spread over provinces and industries, the internet survey mechanism afforded distance crosses to respondents. The survey technique yielded sufficient information to test the mediation and moderation postulations of the study model while resulting in awareness reports across a number of various organisational environments.

4.6 Time Horizon

The study gathered data through the use of a cross-sectional methodology. This design is congruent with the study's objective of exploring the relationships between AI-related perceptions, organisational support and job satisfaction within South African SMMEs at a particular moment in time. Bell et al. (2022) suggest that cross-sectional designs are recommended for descriptive and correlational research as such research can be collected easily and quickly. Moreover, Saunders et al. (2019) state that cross-sectional methods are appropriate for those studies where limited resources and time constraints preclude longitudinal research designed to establish causality rather than relationships.

The research employed a cross-sectional design. Longitudinal studies have advantages in terms of understanding temporal dynamics and causal sequencing but are resource-intensive and require the sustained participation of study subjects over long periods of time. Because time was a constraint in this study and because of the fluid nature of SMME operations in South Africa, this approach was not deemed feasible. Not also, the high attrition rates with longitudinal designs reduce the reliability of findings, particularly in the case of SMME's and their employees because of high employee turnover in SMMEs (Kumar et al., 2024). A valid cross-sectional approach was followed investigating TAM and POS theories and allowing correlation studies to be conducted on mediating and moderating effects. This research design did not allow causal inference in the strict sense of the word, but relations of long-standing value were found which can be used in longitudinal research in the future. The design of the research succeeded in balancing the objectives of the research with the constraints of the methodology and yielded the opportunity for a thorough assessment of how the perceptions of technology are related to job satisfaction within the context of South African SMMEs.

4.7 Population

The research participants were employees of South African SMMEs that had adopted or were in the process of adopting at least one AI-aided technology. South African Revenue Service (SARS, 2023) defines SMMEs as having fewer than 250 employees, as well as annual turnovers of less than R100 million. Because SMMEs account for around 60% of employment and more than one-third of GDP in South Africa, they are an important vehicle for economic growth and stability in the labour market (Gauteng Provincial Government, 2022). The growing interest in AI technologies, for example, automated software, customer service chatbots and predictive analysis technology in this sector made it a fitting context for the study of perceptions of AI and the impact it has on worker experience. The focus on employees rather than managers or owners therefore points towards the interest in employee well-being rather than managerial trends.

The research literature highlights the importance of focusing on this population. Schultz (2021) stated that South African SMMEs are under pressure to modernise their operational methods within the framework of the Fourth Industrial Revolution, while they do not have the same resources as their larger enterprises in order to manage their workforce transitions. Raji and Ismail (2023) indicated that perceptions that are AI related can alter work routines, perceptions relating to job security and perceptions of trust in the organisation, and which can impact employee satisfaction. The current study filled a knowledge vacuum in that it studied employees of SMMEs,

since the greater part of the research on AI and job satisfaction has involved large enterprises or developed countries (Arntz et al., 2019; Kumar et al., 2024). It was thus possible to extend the TAM into a new population with this demographic and to supply insights regarding the influence of perceptions of technology on the SMME workforce which could be of importance to policymakers and business decisionmakers. The characteristics of this population, the limitations on resources, multiple role responsibilities and limited access to training make the findings of particular relevance for better understanding the human-technological dynamics of SMMEs in developing countries.

4.8 Sampling Method and Size

A non-probability sampling process with purposive and snowball sampling procedures was used. The purposive sampling identified full-time employees of South African SMMEs (fewer than 250 employees) who had encountered at least one technology of AI implemented in the workplace. Riveraa (2024) emphasised that purposive sampling is helpful to specialist populations which have a defined inclusion criteria which leads to the relevance and appropriateness of the study. The researcher sampled mainly within accessible networks due to pre-existing contacts on LinkedIn, WhatsApp and Facebook.

Once the initial sample was obtained, snowball sampling expanded participation. Snowballing proves effective at reaching dispersed or hard-to-access individuals, such as SMME employees across sectors and provinces (Ting et al., 2025). Survey participants were asked to share the survey link with qualified colleagues, thereby expanding the researcher's network beyond immediate contacts. This two-stage technique improved sample feasibility and diversity while overcoming some limitations of pure convenience sampling (Babbie, 2020).

The target sample was 120–150 participants selected to achieve a balance between the requirements of statistical power and practical feasibility. Generally, sample sizes of 100 or more are adequate to validate multi-item scales, and in regression-based mediation and moderation analysis (Bujang et al., 2024). The target sample size range also covered the expected proportion of non-responses and incomplete submissions, to ensure that the final usable sample would be sufficiently large to meet the analysis requirements of the study. This sampling approach recognised the inherent limitations of non-probability sampling, especially in relation to generalisability. On the other hand, given the exploratory nature of extending the TAM model to potential job satisfaction outcomes in South African SMMEs, and the practical problems

associated with accessing this widely dispersed population, this was felt to be an appropriate compromise between methodological aspirations and research feasibility.

Table 3: Sampling Strategy

Aspect	Description
Sampling Method	Dual stage: purposive sampling followed by snowball sampling
Inclusion Criteria	Full-time employees of SMMEs (<250 employees, turnover <R100m) with exposure to AI tools
Recruitment Platforms	LinkedIn, WhatsApp, Facebook, direct outreach to SMME networks
Expansion Method	Respondent referrals via snowball sampling
Target Sample Size	120–150 participants
Rationale	Ensures relevance, diversity, and sufficient power for moderated and mediation analysis

4.9 Unit of Analysis

Individual South African SMME employees constituted the unit of analysis for this study. This choice was justified by research objectives focusing on how employees personally experienced AI technology perceptions and how these perceptions affected their job satisfaction. Kumar et al. (2024) emphasise that studying individuals is appropriate for capturing psychological constructs such as perceived usefulness, ease of use, organisational support, and satisfaction, which can vary significantly among employees even within the same organisation.

Focusing on individual employees, they acknowledge that experiences with technology are shaped by factors like job role, skill level, exposure to technology, and organisational culture. Existing literature supports the analysis of individuals rather than business or sectors as the unit of analysis in studies examining technology perceptions and employee well-being. Whereas some employees appreciate AI as an empowering technology, others perceive it as a threatening variation that would be hidden by levels of analysis at the aggregate level of the organisation (Cekuls, 2022). According to Arntz et al. (2019), the macroeconomic effects of technological change cannot be fully understood without investigating the micro-economic effects of technology and its effect on employee well-being. This has particular relevance in South African SMMEs, where employees perform varying roles and interact with AI technology in differing ways. This

study investigates the human voices and perceptions of employees by focusing on individuals and the human side of digital transformation that is hidden with levels of analysis at the organisational levels.

4.10 Measurement Instrument

To gather information regarding the key constructs for the study, structured self-administered questionnaires were utilised. The questionnaire's validity and reliability were achieved using three existing measurement scales. The first, the Technology Acceptance Model (TAM) items (Davis, 1989), were used to measure perceived utility (PU) and perceived ease of use (PEOU) which consistently predict attitudes towards technologies in various contexts (Almeida et al., 2025; Venkatesh & Davis, 2000).

Second, Spector's (1997) Job Satisfaction Survey (JSS) assessed satisfaction on several dimensions such as work nature, supervision and pay. This instrument has been found to have good psychometric properties across cultures and types of organisation. Third, Eisenberger et al. (1986) Survey of Perceived Organisational Support (SPOS) assessed employees' perceptions about their organisation's valuing and caring for them. This scale has been widely validated in organisational research which deals with employee-organisation relationships.

Each item was rated using a 7-point Likert scale from "1 = Strongly Disagree" to "7 = Strongly Agree." Likert scales allow for parametric statistical analyses to be performed and an advanced measurement of perceptions. According to Saunders et al. (2019), the use of Likert scales in survey research adds variability to the responses and allows the aggregation of, more than one item into reliable indices. This is endorsed by prior studies such as those carried out by Raji and Ismail (2023), where a combination of the Technology Acceptance Model and Job Satisfaction survey frameworks provided excellent measures of technology perceptions and job-related attitudes. In order to ensure an unambiguous meaning and a context with which to associate it, the research instrument was piloted to 10 employees from SMMEs that conformed to the inclusion criteria. Reaction from the pilot phase formed the basis of the necessary amendments to the wording of the items set. Ambiguities in meaning were eliminated and the overall flow of the instrument improved. Particular attention was paid to the adaptation of the items that were strategically crafted to reflect the specific context of the AI technology whilst still maintaining their construct validity.

Table 4: Constructs and Measurement Instruments

Construct	Source	Example Item	Scale Type
Perceived Ease of Use (PEOU)	Davis (1989)	"AI tools are easy to use in my daily work."	7-point Likert
Perceived Usefulness (PU)	Davis (1989)	"AI improves my work performance."	7-point Likert
Job Satisfaction (JSat)	Spector (1997)	"I am satisfied with the nature of my work."	7-point Likert
Perceived Organisational Support (POS)	Eisenberger et al. (1986)	"My organisation cares about my well-being."	7-point Likert

It is important to note that this study did not measure actual AI adoption or usage behaviour. Rather this study assessed the theoretical determinants of adoption (PEOU and PU) as predictors of job satisfaction, with POS as a moderator. This is a conscious extension of TAM theory from its traditional focus on behaviour to include job satisfaction outcomes for employees.

4.11 Data Gathering Process

SurveyMonkey was selected as the survey platform. Online surveys are increasingly recognised in business and management research for their efficiency in capturing large-scale data across diverse locations (Salmons, 2024). Given the digital focus of the research problem and widespread adoption of digital communication technologies among South African employees, an online platform was considered particularly appropriate.

Multichannel distribution of the survey link ensured a diversified sample. Purposive recruitment initially targeted SMME employees in AI-adopting sectors such as information and communication technology (ICT) services, retail, and light manufacturing. LinkedIn, WhatsApp, and email invitations included a Participant Information Sheet and Consent Form on the survey's initial page. Participants required approximately 5 minutes to complete the questionnaire after providing consent.

Respondents were encouraged to distribute the survey link to eligible colleagues and professional contacts to expand reach through snowball sampling. This multi-channel recruitment method increased participation rates while reducing the risk of sample homogeneity (Ting et al., 2025). Essential demographic and construct-related questions included mandatory fields to minimise

missing responses and ensure data quality. After collection, the raw data were exported to SmartPLS 4.0 for analysis. SPSS was first employed for data screening, descriptive statistics, reliability assessment and preliminary factor checks. This ensured data quality, normality considerations, and internal consistency of constructs before structural modelling. PLS-SEM v4 was then utilised to validate the measurement model and test hypothesised relationships within the conceptual framework. This process ensured systematic, ethical, and research ethics committee-compliant data collection. The online approach also reduced social desirability bias by providing respondents with privacy and anonymity that face-to-face or telephone surveys might not afford.

4.12 Data Analysis Approach

The data analysis began with preliminary processing and was developed rationally into the normal pattern of hypothesis testing. After the elimination of incomplete or duplicate returns, the means, medians, standard deviations, and interquartile ranges of the continuous variables were calculated in the descriptive statistics. The frequencies and percentages were calculated in the statistical descriptions for the categorical variables. The descriptive summaries are of excellent importance in placing the inferences in regard to the sample population in which the sample was drawn (Bell et al., 2022).

The following stage was to examine the reliability and validity of the measuring instruments. The internal consistency was analysed using Cronbach's alpha, the threshold considered acceptable being the value of 0.70 (Tavakol & Dennick, 2011). To conduct the confirmatory factor analysis (CFA) and thus validate the measurement models, SmartPLS 4.0 was used. SmartPLS is considered best suited to the models that combine on the one hand, modelling on mediation, and on the other, moderation with a moderate sample size. This becomes possible by allowing for the simultaneous estimation of the measurement and structural relationships (Cheah et al., 2024; Guenther et al., 2025).

To assess the hypotheses, the structural model was estimated using SmartPLS, which can estimate a variety of direct, indirect (mediation), and interactive (moderation) effects as part of one integrated solution. Hypotheses 1–4 assess direct and mediated relationships amongst PEOU, PU, and job satisfaction, while Hypothesis 5 assesses whether POS serves as a moderator for the relationship between PU and satisfaction. SmartPLS is being increasingly

deployed within AI, human resource and management studies because of its effectiveness to assess complex solutions as well as enabling predictive solutions (Wuisan et al, 2023).

Mediation analysis used the steps of Baron and Kenny (1986) as elaborated in Hayes (2017), this analysis checked if PU mediated the relationship between PEOU and satisfaction. Bootstrapping techniques with 5,000 resamples were used to generate bias-corrected confidence intervals for the indirect effects. Moderation analysis checked whether POS had significant influence over the strength of the relationship between PU and satisfaction and interaction terms were included in the structural model. Simple slope analysis was conducted to find the specific nature of significant interactions. The analysis plan prioritised both statistical significance ($p < 0.05$) and practical significance (effect sizes) as it was determined that for applied research substantive effects as well as statistically significant effects are important. The model fit was checked by means of a variety of indices including R-squared values, path-coefficients, and predictive relevance (Q-squared).

4.13 Research Ethics

The study was conducted according to the established ethical principles for research involving human beings. Prior to the data collection a research ethical clearance was obtained from the Gordon Institute of Business Science Research Ethics Committee. This confirmed that the study design was consistent with the standards for social research set by the institution and by national standards for social science research. The basic principles of informed consent, voluntary participation, privacy, anonymity and maximum protection for the respondents were scrupulously observed in the study. This ensured the protection of respondents and also served to enhance the credibility of the study (Saunders et al., 2019).

Ethical constraints were especially important because of the sensitive subject area. The introduction of AI into companies can give rise to concerns (among others) related to insecurity of work, surveillance in the workplace, and monitoring of activities. Arntz et al. (2019) indicated that in such situations employees reported negative experiences in a far lower degree to avoid sanctions. To avoid the adverse effects of this the research was designed not to solicit any identifiable data, and respondents were told outright that they were anonymous. The principle of beneficence was an important influence in the design of the research since it served to ensure that other respondents were not exposed to any psychological ill effects. Given the realistic possibility of slight psychological harm caused by a reflection on the subjects such as job

satisfaction satisfaction, respondents were informed of their right to withdraw at any time without any sanctions. The ethical process involved in this facilitated not only the integrity of the research but also confidence of respondents in the findings of the research study.

4.14 Informed Consent

Information regarding informed consent was provided to all respondents before they were able to access the questionnaire. The Participant Information Sheet and Consent Form located on the first page of the survey outlined the aim, purposes, nature of the research, expected time for completion (about 5 minutes), potential risks, and expected benefits. Participants were also informed of their rights, including the right to withdraw without penalty. Prior to answering any questions of a substantive nature, participants were required to check a consent box indicating that they had read and understood the information and that they freely gave their consent to participate. Progressing to the questionnaire was not possible without this explicit consent, to ensure that all respondents had given informed consent prior to participating.

4.15 Voluntary Participation and Withdrawal

Participation in the research was completely voluntary and there were no incentives or penalties for taking part in the research or refusing to take part. This was made clear on the Participant Information Sheet. Respondents were informed that they retained the right to refuse to answer any questions which they felt uncomfortable about, and that they could withdraw from the study at any stage up to the completion of the questionnaire. Due to the anonymity of the survey, participants were informed that withdrawal would not be possible after submission of the questionnaire, as individual responses could not be identified and removed.

In workplace research, it is vital to ensure that participation is voluntary. Employees may be fearful that if they decline involvement they may jeopardise their employment and workplace relationships with their supervisors. Schultz (2021) notes that power asymmetries that characterise South African organisations may result in implicit pressures for people to participate to research requests. It is for this reason that the link to the survey was disseminated through the medium of social networks and platforms, as well as through professional networks rather than by the employer. This would reduce the likelihood of actual physical coercion of would-be participants whilst ensuring that their voluntary participation was indeed genuinely voluntary. The element of voluntary participation strengthens the reliability of the findings of the research, since

it is more likely that the responses will be open and truthful when not tainted by coercion or bias (Saunders & Lewis, 2018). The process of withdrawal was made clear to participants as it was explained that they were free at any stage prior to final submission of the survey, to leave or exit the online platform. This is consistent with best practice guidelines for online surveying. By insisting on autonomy and voluntariness, great care was taken to protect the rights of participants and participants' rights as well as to strengthen the integrity of their collected data.

4.16 Confidentiality and Anonymity

The ethical framework prioritised anonymity and confidentiality. No identifying information, such as names, email addresses, or company identifiers, was gathered. Demographic information was secured in broad categories, such as position, industry and years of employment. This information was presented in aggregate form so that individual participants or companies could not be identified. Eisenberger et al. (1986) have pointed out that anonymity is essential in order to ensure honest reporting, particularly thus sensitive an area as job satisfaction and perceptions of organisational support. As Saunders et al. (2019) noted, anonymity protects participants and leads to increased validity of data collections since truthful responses are supplied. Employees without anonymity might feel obliged to give socially acceptable answers, especially concerning employer satisfaction or perceptions of organizational support. This measure greatly reduced the risk involved in this area and increased the likelihood that participants' responses illustrated their perceptions rather than their desire to manipulate impressions.

4.17 Data Management and Protection

In order to protect participant information, the study followed rigorous data management and protection protocols. SurveyMonkey encrypted responses during transmission, and the site settings were arranged to eliminate IP addresses and geographical location data so that the responses could remain anonymous. Upon completion of data collection, all raw data were exported to SmartPLS 4.0 for analysis.

The exported files were stored in a password protected, encrypted folder on the researcher's computer, with secure backups uploaded to a cloud storage system approved by the university. Access was limited to the investigator and academic supervisor only. Khan et al. (2024) urged that rigorous data cleaning and protection protocols in digital platform research are necessary to prevent ethical breaches and safeguard the integrity of the data. All of the datasets in the current

study were anonymised immediately after export consistent with this advice, so that demographic characteristics such as age, gender and sectoral affiliation could not subsequently be used to identify individual participants. No data were shared with third parties and all data will be securely destroyed five years after the completion of the study, in line with institutional protocols.

4.18 Risk and Benefit Assessment

The risks were minimal for participants in this study. The only discomfort predicted was mild psychological discomfort in regard to job satisfaction or organisational support. Employees dissatisfied with their work situation might have found some questions difficult, however, the questionnaire items were presented in a neutral way and were non-leading, which would reduce the chances of this risk being experienced. In addition, participants had the right to not answer those questions which were not mandatory, and at any stage prior to submitting the survey they could withdraw themselves from the study. Arntz et al. (2019) observed that job related surveys usually present minimal risk for participants, particularly when anonymity can be guaranteed.

Despite these limited risks, the study offered substantial potential benefits. Participants contributed to a body of knowledge with the capacity to inform organisational strategies and policy, even though no direct financial incentives were provided. Schultz (2021) noted that South African SMMEs frequently encounter challenges managing employee relations during technological transitions, and this research provides insights that may guide supportive practices. Findings are expected to assist managers and policymakers in balancing technological innovation with employee well-being. Moreover, evidence suggests that well-managed AI implementation supported by positive employee perceptions can enhance organisational performance, with employee satisfaction serving as a critical mediating factor (Badghish & Soomro, 2024). On balance, the academic, organisational, and societal benefits of the study clearly outweighed minimal risks to participants.

4.19 Researcher Positionality

The researcher was aware of personal bias and positionality through all stages of the research. As an academic with an interest in technology and employment, the researcher had a pre-established belief that AI could simultaneously empower the employee and cause disruption. Therefore, requirement to maintain reflexivity necessitated on-going self-recognition of how this mind-set may inform the research process. Babbie (2020) suggests that researcher positionality

can have an impact on the choice of methods including the theoretical frameworks and instruments.

In the current study, the use of the TAM and POS frameworks illustrated the view that the effect of AI perceptions on employees needed to be considered from both a technological and an organisational point of view. To reduce the risk of bias, the research was undertaken within a positivist paradigm emphasizing objectivity, replicability and evidence based conclusions. Positivist research requires the presentation of the results, whether or not the hypotheses were confirmed (Park et al, 2020). Consequently, in accordance with this principle, the analysis would take into account any unexpected results alongside anticipated findings. Furthermore, the potential impacts of the researcher on the participants was minimised through the use of an anonymous online study thus reducing social desirability bias. By addressing positionality openly and following correct methods, the study enhanced its transparency, validity and credibility.

4.20 Quality Controls

Several procedures ensured the quality control of the results and their objectivity and validity. A pilot study was conducted with ten individuals who met the inclusion criteria. Pilot studies are useful for determining whether there are any ambiguities, assessing the reliability of the scale, and improving the clarity of the instrument before administering it to larger populations (Bujang et al., 2024). The pilot phase yielded feedback that was used to improve the wording, sequence and flow of the survey in order to clarify and facilitate responses.

The reliability of the scales was then assessed using Cronbach's alpha coefficient, with values of 0.70 or more considered acceptable (Tavakol & Dennick, 2011). Internal consistency was established for perceived usefulness (PU), perceived ease of use (PEOU), job satisfaction (JSat), and perceived organisational support (POS). Confirmatory Factor Analysis (CFA) in SmartPLS confirmed that the items loaded significantly onto their intended latent variables, confirming construct validity. According to Almeida et al. (2025) TAM based constructs require constructs validation techniques must be employed to help ensure that theorised constructs are actually being measured reliably and isometrically. Convergent validity was tested using Average Variance Extracted (AVE) with values greater than 0.50, indicating adequate convergence. Discriminant validity was tested using the Fornell-Larcker and Heterotrait -Monotrait (HTMT) ratios to show that the constructs were empirically distinct.

4.21 Limitations and Delimitations

All research designs have their limitations and this study has its share. In this regard reliance on self-reports gave rise to a self-serving bias whereby respondent's social desirability and memory error could have influenced cognition. In the words of Saunders and Lewis (2018) employees may exaggerate favourable experiences or downplay unfavourable experiences to the response since it puts them in a favourable light. Although anonymity lessened these possibilities the chances of bias remained.

Another limitation was the cross-sectional research design, which investigated relationships at a single point in time. Raji and Ismail (2023) noted that this research design is not able to identify the definitive causal nature of the effects, nor changes in longitudinal terms, thus leading to difficulties in identifying sustained effects of such perceptions on job satisfaction. The study established significant statistical relationships between constructs but causal claims would employ longitudinal or experimental designs.

The implications for generalisability were also restricted by the use of non-probability sampling. The purposive and snowball-sampling procedures while appropriate in seeking access to dispersed SMME populations do not guarantee statistically representative samples. Consequently the findings may not be generalisable to all SMMEs in South Africa or groupings of SMMEs and SMME employees. Nonetheless, as the primary purpose of the research was to test theories rather than to estimate population parameters, analytical generalisation becomes valid for extending theoretical insights to similar contexts (Yin, 2018).

The delimitations of the research study were established. The target group for the research included South African SMMEs exposed to AI technology, but not large companies, or companies not using non-AI technology or conducting research internationally. Job satisfaction was determined to be the most relevant outcome variable for this project and not actual behaviour related to the adoption of technology, representing a deliberate theoretical expansion. These delimitations ensured that the research was necessarily focused and practical and that any identified gaps in the relevant literature were addressed.

4.22 Project Plan

The project timeline ensured systematic progression from ethical approval through final submission:

Table 5: Research Project Timeline (June – November 2025)

Month	Week(s)	Activity	Details
June	1–4	Ethical Clearance Process	Submission of ethics application; await approval; continue literature review
July	5	Finalise Data Collection Tools	Incorporate ethics feedback into survey instrument
July	6	Pilot Testing	Test questionnaire with 10 employees; refine items based on feedback
July–Aug	6–9	Data Collection	Launch online survey (SurveyMonkey); distribute via LinkedIn, WhatsApp, email; send weekly reminders
August	10	Close Data Collection	Final reminders; export data from SurveyMonkey; secure data storage
Aug–Sep	11–13	Data Analysis	Conduct descriptive analysis, reliability testing, CFA, mediation/moderation analysis using SmartPLS
September	14–15	Write Findings Chapter	Present descriptive and inferential results with tables and figures
September	16	Write Discussion Chapter	Interpret results in relation to TAM, POS, and job satisfaction literature
September	17	Write Conclusion Chapter	Summarise findings, contributions, limitations, and recommendations
October	18	Peer & Supervisor Review	Submit full draft for review; gather feedback
October	19	Revise Based on Feedback	Incorporate peer and supervisor suggestions throughout document
October	20	Final Formatting & Proofreading	Ensure academic style, referencing accuracy, grammar, and structure compliance
November	21	Final Submission	Submit completed dissertation (03 November 2025)

This timeline balanced thoroughness with efficiency, ensuring adequate time for each research phase while meeting institutional deadlines. The structured approach facilitated systematic progression from conceptualisation through execution to reporting, maintaining research quality throughout.

4.23 Chapter Summary

This chapter presented the methodological framework guiding how cognitive appraisals of AI technology, specifically perceived ease of use (PEOU) and perceived usefulness (PU), affect job satisfaction among South African SMME employees. This chapter provided the step-by-step guidance of the chosen methodology and its relevance, as well as motivations for the choice in the research approach. The proposed research methodology and design, conclusions, and limitations and delimitations applicable for the chosen methodology were discussed.

CHAPTER 5: RESULTS OF THE STUDY

5.1 Introduction

This study investigated the extent to which the theoretical determinants of technology acceptance, namely perceived ease of use (PEOU) and perceived usefulness (PU) influence job satisfaction of employees in South African small, medium and micro enterprises (SMME) who have adopted artificial intelligence technologies. The survey data was analysed using IBM SPSS Statistics Version 30 and PLS-SEM Version 4. SPSS was first used for data screening, descriptive statistics, reliability tests and preliminary factor analysis. This ensured data quality, normality factors and internal consistency of constructs, prior to undertaking structural modelling. The PLS-SEM v4 was subsequently used to validate the measurement model and test the hypothesised relationships in the conceptual framework. Partial least Squares Structural Equation Modelling provided advanced analysis, such as composite reliability and convergent and discriminant validity, mediation and moderating effects and predictive relevance tests. The combined usage of these methods of analysis provided a rigorous and comprehensive analysis which satisfied the research objectives. Empirical data was collected using a survey, 145 completed responses were used for the data analysis. The data was analysed according to the objectives and hypotheses stated in Chapter 3, which are recapped below:

H1: PEOU will positively affect PU.

H2: PEOU will positively affect job satisfaction (JST).

H3: PEOU will affect JST through PU (mediation effect).

H4: PU will positively affect JST.

H5: Perceived organisational support (POS) moderates the relationship between PU and JST.

This chapter addresses coding, screening and quality control of the data, after demographic information and descriptive statistics that give an understanding of the central tendency and variance of the data. The section that follows deals with the multivariate analysis which addresses the reliability of the internal consistency of the data, and then presents the exploratory factor analysis. This, in turn, is followed by a structural equation model, using partial least squares (PLS-SEM), which consists of the measurement model, model predictability and explanatory analysis,

and the structural model which is used to test the hypotheses. The chapter concludes with a summary of the findings with a detailed discussion provided in Chapter 6.

5.2 Coding, Screening, and Data Quality

The survey consisted of 26 items examining several constructs utilising a seven-point Likert scale ranging from 1 (Strongly disagree) to 7 (Strongly agree) (Table 6). Perceived usefulness (PU) was comprised of six items (PU1–PU6) measuring the extent to which AI technologies result in increased job performance and productivity. Perceived ease of use (PEOU) contained six items (PEOU1–PEOU6) measuring the ease of learning about and interacting with AI systems. Perceived organisational support (POS) had six items (POS1–POS6) measuring perceptions held by employees of the extent to which their organisation values them and supports them. Job satisfaction (JST) was measured using nine items (JST1–JST9) that measured meaningfulness, engagement and autonomy at work.

Table 6: Code of Variables

Item Description	Code
Using AI in my job enables me to accomplish tasks more quickly.	PU1
Using AI improves my job performance.	PU2
Using AI increases my productivity.	PU3
Using AI enhances my effectiveness on the job.	PU4
Using AI makes it easier to do my job.	PU5
I find AI useful in my job.	PU6
Learning to operate AI systems is easy for me.	PEOU1
I find it easy to get AI to do what I want it to do.	PEOU2
My interactions with AI systems are clear and understandable.	PEOU3
I find AI to be clear and understandable.	PEOU4
It is easy for me to become skilful at using AI.	PEOU5
I find AI tools easy to use.	PEOU6
My organisation values my contribution to its well-being.	POS1
My organisation strongly considers my goals and values.	POS2
My organisation really cares about my well-being.	POS3
Help is available from my organisation when I have a problem.	POS4
My organisation would forgive an honest mistake.	POS5
My organisation cares about my opinions.	POS6

The work I do is meaningful.	JST1
My job gives me a sense of purpose.	JST2
I find my daily tasks stimulating and engaging.	JST3
I have enough variety in the tasks I perform.	JST4
I feel a sense of accomplishment from my work.	JST5
I have autonomy in how I complete my work.	JST6
My job allows me to apply my skills and knowledge.	JST7
AI has made my job more interesting.	JST8
Since the introduction of AI, I feel more empowered in my role.	JST9

5.2.1 Missing Value Analysis

A missing value analysis was conducted to determine where there were gaps in the data that might threaten the quality of the data and place the integrity of the results of the study at risk. The results in Appendix A show that there were no substantial missing values, and that the gaps present were within an acceptable threshold of 5% recommended by Schafer (1999). This situation indicates that data completeness was acceptable for the further analyses.

5.2.2 Outlier Detection

The analysis of extreme outliers was carried out subsequent to the missing value analysis, due to the fact that extreme outliers can substantially influence the statistical results, thereby introducing misleading conclusions (Hair et al., 2019.). Any values that were three times (or more) the inter-quartile range were regarded as extreme outliers, and box plots of these values were performed. Extreme outliers created no problems except for a couple of observations with respect to JST1, which were eliminated from further analysis (Appendix C). This conservative approach towards outlier treatment serves to increase the robustness of any results subsequently obtained.

5.2.3 Common Method Variance

A Harman single-factor analysis was conducted to check for common method variance (CMV) which is likely to inflate the correlations between variables particularly when all data are collected from one respondent or time period (Podsakoff et al., 2003). First, the single factor accounted for over 50% of the variance indicating that problems with CMV were evident. However, upon deleting PU4 because of a very large overlap with PU3, the variance explained by the single factor increased to 48.9% which is now below the accepted cut-off of 50% indicating that common

method bias is present but it does not greatly threaten the validity of the findings of this study (Podsakoff et al., 2003).

5.3 Demographic Information

A total of 145 participants took part in the research. The demographic profile of the sample is shown in Table 7. The largest age cohort was that of the 30–44 year group (51.0%) followed by the 18–29 year (36.6%), 45–54 year age group (10.3%) and the 55 year and older cohort (2.1%). This distribution of age indicates a later-teen to middle aged workforce consistent with that of the South Africa SMMEs demographic profile (Statistics South Africa, 2023).

Table 7: Demographic Information

Variable	Category	Frequency	Percent
Age	18–29	53	36.6
	30–44	74	51.0
	45–54	15	10.3
	55 and above	3	2.1
	Total	145	100.0
Gender	Female	76	52.8
	Male	68	47.2
	Total	144	100.0
Education	Bachelor's Degree	38	26.2
	Diploma/Certificate	34	23.4
	High School	20	13.8
	Honours/Postgraduate Diploma	28	19.3
	Master's Degree or higher	25	17.2
	Total	145	100.0
Tenure in company	Less than 1 year	33	22.8
	1–3 years	44	30.3
	4–6 years	26	17.9
	7–10 years	21	14.5
	More than 10 years	21	14.5
	Total	145	100.0
Industry	Agriculture	2	1.4
	Education	16	11.0

	ICT/Tech	20	13.8
	Manufacturing	4	2.8
	Retail	29	20.0
	Services	34	23.4
	Other	40	27.6
	Total	145	100.0
Company size	Fewer than 10 (Micro)	51	35.2
	11–50 (Small)	53	36.6
	51–250 (Medium)	41	28.3
	Total	145	100.0

In respect of gender, 52.8% of respondents regarded themselves as female and 47.2% as male, indicating a fairly even distribution of gender. In regard to education, a large majority of applicants were bachelor degree holders (26.2%) followed by diploma or certificate (23.4%) and honours or postgraduate diploma (19.3%) and finally, master's or higher (17.2%) and high school (13.8%). The educational profile displayed reflects rather a well educated group, which is to be expected with employees working in technology based settings (Mbatha, 2024).

In relation to staff tenure, 30.3% of the respondents had worked in their organisation for 1-3 years, 22.8% for less than 1 year, 17.9% for 4 - 6 years, and 14.5% each for a period of 7 – 10 years and more than 10 years. From this distribution, it may be noted that the average level of tenure is moderate, with most employees having operated for less than 5 years in their present organisation. The respondents were employed largely in the services (23.4%), other industries (27.6%) retail (20.0%) and ICT/technology (13.8%) sectors, while the education (11.0%) manufacturing (2.8%) and agriculture (1.4%) sectors received smaller proportions. The job titles in respect of the respondents were varied and included accountants to various specialists' and business development managers to senior and executive managers in the job descriptions of general manager, managing director and founders. Company sizes varied as 36.6% were employed in small companies (11 -50 employees) 35.2% in micro companies (less than 10 employees) and 28.3% in medium companies (51 - 250 employees). This distribution is representative of the reported South African SMME situation (SEDA, 2024).

5.4 Descriptive Statistics

Descriptive measurements were made for all items that were used to measure perceived usefulness (PU), perceived ease of use (PEOU), perceived organisational support (POS) and job

satisfaction (JST). All items were rated using a seven-point Likert scale: 1 = Strongly Disagree; 7 = Strongly Agree (Table 8). The mean score for each of the items were between 4.76 and 6.34, indicating generally favourable responses towards ease and usefulness of AI systems, organisational support and job satisfaction. The standard deviations for the mean were between 1.06 and 2.06 indicating moderate to high variability in the responses of the participants to each item. The skewness values was negative for all items indicating a tendency towards higher agreement and the kurtosis scores were also varied with respect to the peakedness of the responses generally mild to moderate peakedness (Kline, 2023).

Table 8: Descriptive Statistics

	Mean	Std. Deviation	Skewness	Kurtosis
PU1	5.03	1.933	-0.742	-0.538
PU2	4.90	1.946	-0.689	-0.582
PU3	4.92	1.887	-0.690	-0.531
PU5	4.92	2.062	-0.745	-0.641
PU6	4.97	2.060	-0.645	-0.831
PEOU1	5.10	1.741	-0.806	-0.135
PEOU2	5.11	1.752	-0.846	-0.041
PEOU3	5.20	1.686	-0.858	0.038
PEOU4	5.22	1.677	-0.866	0.058
PEOU5	5.12	1.715	-0.731	-0.336
PEOU6	5.26	1.670	-0.857	0.113
POS1	5.61	1.717	-1.365	1.159
POS2	5.42	1.832	-1.115	0.305
POS3	5.38	1.845	-1.057	0.073
POS4	5.39	1.807	-1.073	0.278
POS5	5.47	1.712	-1.188	0.700
POS6	5.40	1.876	-1.070	0.129
JST1	6.34	1.056	-1.751	2.392
JST2	5.89	1.539	-1.586	2.076
JST3	5.53	1.640	-1.146	0.675
JST4	5.55	1.677	-1.219	0.704
JST5	5.83	1.576	-1.667	2.369
JST6	5.80	1.630	-1.691	2.242
JST7	5.91	1.580	-1.775	2.759

JST8	4.96	2.017	-0.762	-0.592
JST9	4.76	1.992	-0.551	-0.792

The five items with the highest mean scores were: JST1-“The work I do is meaningful” (M=6.34; SD=1.06), JST7-“My job allows me to use my skills and knowledge” (M=5.91; SD=1.58), JST2-“My job provides me with a sense of purpose” (M=5.89; SD=1.54), JST5-“I get a sense of accomplishment from my work ” (M=5.83; SD=1.58), and JST6-“I have autonomy in how I perform my work” (M=5.80; SD=1.63). These results suggest that participants derive a strong sense of meaning, autonomy, and fulfilment from their work, emphasising the positive intrinsic characteristics of their jobs. Such results are in line with job characteristics theory which stipulates that both meaningfulness of work and autonomy are prime determinants of job satisfaction (Hackman & Oldham, 1976).

In contrast, the five items with the lowest mean scores, though still above the midpoint of the scale, were: JST9-“Since the introduction of AI, I feel more empowered in my role” (M = 4.76, SD = 1.99), JST8-“AI has made my job more interesting” (M = 4.96, SD = 2.02), PU4-“Using AI enhances my effectiveness at work” (M = 4.86, SD = 1.94), PU5-“Using AI makes it easier to do my job” (M = 4.92, SD = 2.06), and PU3-“Using AI increases my productivity” (M = 4.92, SD = 1.89). These results indicate that while employees perceive artificial intelligence systems as somewhat useful, their effects on empowerment, job enrichment and productivity of the employees are moderate in comparison to the intrinsic features of their work. This pattern coincides with recent studies which indicate that employees might view ambivalent feelings towards the usage of AI technologies and measure their functional advantages against the disadvantages of the surveillance they imply or the insecurity of employment they might offer (Chang et al., 2024; George, 2024).

The results suggest that the respondents generally perceive their jobs and their perceived management support favourably, evidenced by high scores for ease of use (all PEOU items above M = 5.10). However, the slightly lower scores for the perceived usefulness and AI-empowerment items suggested that employees were still learning how to exploit the many advantages AI offers for their daily jobs. The higher variability in PU and AI-empowerment items (SD > 1.90) indicates dissimilar experiences (and perceptions) of the respondents overall, suggesting further statistical analysis and differential use of inferential statistical methods would provide interesting and relevant information for future researchers.

5.5 Multivariate Analysis

5.5.1 Internal Consistency Reliability

Reliability analysis was performed in order to evaluate the internal consistency of each measure pertaining to the constructs measured in this study. Cronbach's alpha coefficients were calculated for each subscale as this statistic assumes that the items of a scale measure some single underlying construct (Field, 2024; George & Mallery, 2019). Table 9 provides reliability statistics of each construct.

Table 9: Internal Consistency Reliability by Construct

Construct	Number of Items	Cronbach's Alpha	Interpretation
Perceived Usefulness (PU)	5	0.962	Excellent
Perceived Ease of Use (PEOU)	6	0.954	Excellent
Perceived Organisational Support (POS)	6	0.952	Excellent
Job Satisfaction (JST)	9	0.947	Excellent

All four constructs demonstrated excellent internal consistency with Cronbach's alpha values ranging from 0.947 to 0.962, which is well above the general standard of 0.70 (Nunnally & Bernstein, 1994). This indicates that the items within each subscale are highly interrelated and reliably measure the respective construct. The corrected item-total correlations (which are provided in Appendix C) are all within a range of .536 to .786, which illustrates that all items were meaningfully contributing to the reliability of the construct. Furthermore, review of the "Cronbach's alpha if item deleted" values found there is not one single item that, if removed, would serve to greatly improve the reliability of the subscale, indicating each scale measured homogeneity within the scales (Field, 2024).

These reliability findings provide strong evidence that the measurement instrument demonstrates high internal consistency across all constructs, making the scales suitable for further statistical analyses, including factor analysis and structural equation modelling (Hair et al., 2019).

5.5.2 Exploratory Factor Analysis

To examine the underlying factor structure of the instrument that measures perceived usefulness (PU), perceived ease of use (PEOU), perceived organisational support (POS), and job satisfaction

(JST), an exploratory factor analysis (EFA) was conducted using principal component analysis (PCA) and varimax rotation. The Kaiser-Meyer-Olkin (KMO) statistic of measure of sampling adequacy was .930 which is well above the recommended value of .80 showing a high degree of suitability of the sample for conducting factor analysis (Kaiser, 1974). Also Bartlett's Test of Sphericity was significant, $\chi^2(325) = 3749.98$, $p < .001$, showing the correlation matrix was not an identity matrix and there were sufficient correlations between items for the purpose of factor extraction (Bartlett, 1954).

Table 10: KMO and Bartlett's Test

Kaiser-Meyer-Olkin measurement of sampling adequacy.		.930
Bartlett's Test of Sphericity	Approx. Chi-Square	3749,979
	df	325
	Sig.	<.001

Initially the analysis revealed 4 components with eigenvalues greater than 1.0 contributing 79.24% to the total variance (Table 11). This four-factor solution exceeded the minimum requirement of more than 60% for cumulative variance accounted for indicating a sound factor structure (Hair et al., 2019). This was also evidenced by the scree plot (not shown) which indicated a clear elbow at about the fourth factor.

Table 11: Total Variance Explained

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13,222	50,854	50,854	13,222	50,854	50,854	5,700	21,923	21,923
2	3,948	15,185	66,040	3,948	15,185	66,040	5,569	21,418	43,342
3	1,836	7,063	73,102	1,836	7,063	73,102	5,086	19,562	62,904
4	1,597	6,141	79,244	1,597	6,141	79,244	4,248	16,340	79,244
5	,700	2,691	81,935						
6	,514	1,978	83,914						
7	,453	1,741	85,654						

8	,424	1,630	87,284						
9	,385	1,482	88,766						
10	,309	1,187	89,953						
11	,300	1,154	91,107						
12	,269	1,035	92,141						
13	,251	,964	93,106						
14	,242	,930	94,035						
15	,224	,861	94,896						
16	,192	,740	95,636						
17	,174	,670	96,305						
18	,163	,626	96,931						
19	,149	,572	97,503						
20	,141	,541	98,044						
21	,114	,437	98,480						
22	,101	,389	98,870						
23	,085	,328	99,198						
24	,079	,305	99,503						
25	,068	,260	99,763						
26	,062	,237	100,000						
Extraction Method: Principal Component Analysis.									

The rotation revealed a clear and interpretable four-component structure consistent with the theoretical framework (Table 12). Component 1 (Perceived Usefulness-PU): Items PU1-PU6 were found to load very well (factor loadings of $\geq .85$) with both JST8 and JST9 also loading on this component. The loading of JST8 and JST9 with the PU items is conceptually useful in that they specifically refer to AI's effects on job interest and empowerment and are thus satisfaction outcomes relevant to technology rather than general job satisfaction. Component 2 (Job Satisfaction-JST): Items JST1-JST7 were found to load fairly highly ($\geq .76$) and represent the core dimensions of job satisfaction including engagement, purpose and achievement arising from the work done. Component 3 (Perceived Ease of Use-PEOU): Items PEOU1–PEOU6 loaded significantly ($\geq .70$) inferred a clear factor of perceived ease of skill in use of AI tools. Component 4 (Perceived Organisational Support-POS): Items POS1-POS6 also loaded well ($\geq .65$) and represent employees perceptions of care, values and support provided to them by their organisation.

Table 12: Rotated Component Matrix

	Component			
	1	2	3	4
PU3	0.889	0.130	0.189	0.108
PU6	0.878	0.115	0.286	0.131
PU5	0.875	0.110	0.242	0.146
PU2	0.867	0.128	0.270	0.160
PU1	0.859	0.136	0.285	0.151
JST9	0.702	0.221	0.339	0.303
JST8	0.644	0.222	0.435	0.188
JST5	0.163	0.860	0.158	0.173
JST3	0.131	0.836	0.012	0.207
JST2	0.054	0.807	0.108	0.254
JST6	0.205	0.780	0.137	0.212
JST4	0.128	0.779	0.151	0.230
JST7	0.137	0.774	0.293	0.299
JST1	0.099	0.762	0.203	0.234
PEOU6	0.245	0.142	0.865	0.185
PEOU3	0.275	0.226	0.849	0.153
PEOU2	0.313	0.160	0.822	0.124
PEOU4	0.240	0.227	0.814	0.267
PEOU1	0.353	0.053	0.747	0.159
PEOU5	0.432	0.164	0.704	0.142
POS3	0.183	0.248	0.185	0.855
POS4	0.149	0.347	0.178	0.826
POS6	0.262	0.343	0.176	0.822
POS2	0.236	0.299	0.253	0.795
POS5	0.083	0.475	0.109	0.653
POS1	0.231	0.338	0.463	0.554

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalisation.

a. Rotation converged in 6 iterations.

Note: Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalisation. Rotation converged in 6 iterations.

All primary factor loadings exceeded the recommended cut-off value of .50 (Hair et al., 2019), indicating strong construct validity. No substantial cross-loadings were observed that would threaten discriminant validity among factors. The clear four-factor structure supports the theoretical conceptualisation of the constructs and provides a solid foundation for the measurement model's confirmatory factor analysis.

5.6 Measurement Model

5.6.1 Factor Loadings and Model Fit

A confirmatory factor analysis (CFA) was conducted in the PLS-SEM measurement model to assess a four-factor structure. These factors were perceived usefulness (PU), perceived ease of use (PEOU), perceived organisational support (POS), and job satisfaction (JST). The CFA confirmed that all of the items loaded significantly onto their respective construct which lends support for the theoretical structure proposed in the previous exploratory factor analysis. All standardised factor loadings were greater than the recommended value of .70 (Hair et al., 2019) indicating that the observed variables were representative of their latent constructs. Specifically, the loadings for the PU items ranged from .859 to .889, the PEOU items from .704 to .865, the POS items from .653 to .855, and the JST items from .762 to .860 (see Figure 2).

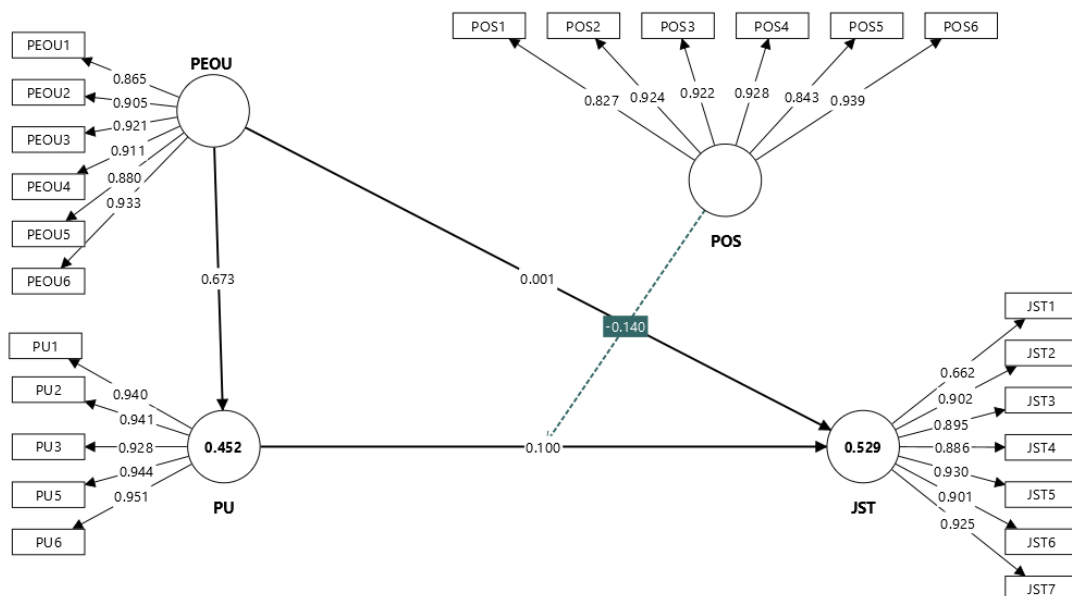


Figure 2: Measurement Model

Note: Figure shows the CFA measurement model with standardised factor loadings for all constructs.

Model fit indices were examined to assess the adequacy of the overall model (Table 13). The value of the Standardised Root Mean Square Residual (SRMR) of .065 was well below the maximum recommended value of .08 indicating a satisfactory fit between the observed and estimated correlations (Hu & Bentler, 1999). The Normed Fit Index (NFI) value of .890 was close to but below (>.90) the normal cutoff point, but it is an acceptable value for complicated models having a number of latent variables (Bentler & Bonett, 1980). The d_ULS (1.253) and d_G (0.634) values were relatively low, suggesting a small number of residual differences between the empirical and model-implied covariance matrices. The chi square ($\chi^2 = 479.55$) was thus computed at the model comparisons level, indicating that the estimated model gives a satisfactory fit to the data (Kline, 2023).

Table 13: Model Fit Indices

Index	Saturated Model	Estimated Model	Recommended Threshold
SRMR	0.056	0.065	< 0.08
d_ULS	0.929	1.253	Lower is better
d_G	0.614	0.634	Lower is better
Chi-square	479.609	479.545	-
NFI	0.890	0.890	> 0.90 (ideal)

Overall, these results confirm that the measurement model demonstrates strong reliability, convergent validity, and acceptable model fit, providing a solid foundation for structural model testing.

5.6.2 Construct Reliability and Convergent Validity

To assess the internal consistency and convergent validity of the constructs, Cronbach's alpha (α), composite reliability (ρ_a and ρ_c), and average variance extracted (AVE) were examined. As shown in Table 9, all reliability coefficients exceeded the commonly accepted threshold of .70, indicating excellent internal consistency (Hair et al., 2019). Cronbach's alpha values ranged from .947 (Job Satisfaction, JST) to .967 (Perceived Usefulness, PU), demonstrating that each construct exhibited high reliability.

Table 14: Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
JST	0.947	0.954	0.958	0.767
PEOU	0.954	0.955	0.964	0.815
POS	0.952	0.953	0.962	0.807
PU	0.967	0.969	0.975	0.885

The composite reliability (ρ_c) scores were between .958 and .975 confirming once again that the items of each construct measure the same underlying dimension with consistency. Because the composite reliability coefficients are based on the actual factor loadings of the items rather than assuming equal weightings, the composite reliability coefficients are larger than Cronbach's alpha coefficients, and are hence more appropriate for PLS-SEM analysis (Henseler et al., 2015).

The average variance extracted (AVE) values for all the constructs exceeded the minimum criterion of .50 and recorded the values ranging from .767 (JST) to .885 (PU). AVE values exceeding .50 indicate that more than half of the variance in the indicators is explained for all the constructs, thus providing evidence of strong convergent validity (Fornell and Larcker). The overall results thus provide conclusive evidence that the measurement model possesses strong internal reliability and convergent validity and gives support to potential adequacy of the latent constructs for further structural analysis.

5.6.3 Discriminant Validity

Discriminant validity was assessed using both the Fornell–Larcker criterion (Fornell & Larcker, 1981) and the Heterotrait–Monotrait ratio of correlations (HTMT) (Henseler et al., 2015). According to the Fornell–Larcker criterion, the square root of each construct's average variance extracted (AVE) should be greater than its correlations with other constructs. As shown in Table 5.10, all constructs satisfied this condition (e.g., $\sqrt{\text{AVE}}$ values ranged from 0.876 for job satisfaction [JST] to 0.941 for perceived usefulness [PU]), demonstrating adequate discriminant validity using this traditional criterion.

Table 15: Fornell–Larcker Criterion

	JST	PEOU	POS	PU
JST	0.876			
PEOU	0.491	0.903		
POS	0.705	0.610	0.898	
PU	0.445	0.673	0.514	0.941

HTMT is a new standard to determine discriminant validity and is used increasingly often in practice. Unlike the Fornell–Larcker procedure, which may fail to identify problems in the case of constructs that are conceptually similar, the HTMT criterion evaluates the ratio of the correlations by suggesting a relationship between the correlation between the two constructs and the correlation within the constructs. Threshold values recommended are less than 0.85 for stricter models or 0.90 for more lenient models (Henseler et al., 2015). Here again it can be seen that all values of HTMT for the model identified in this project ranged from 0.281 to 0.740 (Table 16) and remain well below the 0.85 threshold, demonstrating strong discriminant validity among all the constructs.

Table 16: HTMT Matrix

	JST	PEOU	POS	PU	POS x PU
JST					
PEOU	0.514				
POS	0.740	0.643			
PU	0.461	0.697	0.537		
POS x PU	0.466	0.426	0.462	0.281	

The HTMT results provide considerable assurance that each latent construct, perceived usefulness, perceived ease of use, perceived organisational support and job satisfaction, represents a separate distinct construct with only a small degree of conceptual overlap if any. Overall, while both methods confirmed discriminant validity, the HTMT method is to be preferred since it is much more sensitive and discerning in its detection of possible construct overlap than the Fornell–Larcker criterion (Henseler et al., 2015). The successful assessment of discriminant

validity confirms that the various constructs are sufficiently distinct for the analysis of the structural model to be pursued.

5.7 Structural Model and Hypothesis Testing

5.7.1 Multicollinearity Analysis

To evaluate potential multicollinearity among the observed variables, variance inflation factor (VIF) values were examined. VIF assesses the degree to which predictor variables are correlated, with values below accepted thresholds indicating that multicollinearity is not a major concern (Hair et al., 2019). As presented in Table 5.12, all VIF values ranged from 1.00 to 6.91, which are below the conservative upper limit of 10.0 recommended by Hair et al. (2019) and within the more stringent cut-off of 5.0 suggested by Kock (2015) for partial least squares structural equation modelling (PLS-SEM), with only minor exceptions.

Table 17: Multicollinearity Analysis with VIF

	VIF
JST1	1.517
JST2	4.170
JST3	3.980
JST4	3.635
JST5	5.701
JST6	4.207
JST7	5.298
PEOU1	3.300
PEOU2	4.097
PEOU3	5.480
PEOU4	5.708
PEOU5	3.380
PEOU6	6.153
POS1	2.697
POS2	5.930
POS3	5.741
POS4	5.488
POS5	2.617

POS6	6.330
PU1	5.762
PU2	5.735
PU3	5.319
PU5	6.641
PU6	6.909
POS x PU	1.000

The interaction term (POS × PU) had the lowest variance inflation factor (VIF = 1.00), which indicated that no multicollinearity existed with this moderator variable. Although some items approached the acceptable upper limit, i.e. PEOU6 (VIF 6.153), POS6 (VIF 6.330), PU6 (VIF 6.909), they are still within an acceptable range for PLS-SEM purposes, and do not represent either a severe bias of the parameter estimates of either the measurement model or the structural model (Hair et al., 2019). In conclusion, the results confirm that the indicators are sufficiently distinct to indicate that collinearity is not a threat to the validity of parameter estimates in the structural model.

5.7.2 Predictive Relevance and Explanatory Power

To assess the explanatory and predictive power of the structural model, predictive relevance (Q^2), coefficient of determination (R^2), and model effectiveness indices were examined. According to Hair et al. (2019), if the value of Q^2 is greater than zero, it indicates that the model has predictive relevance for a specific endogenous construct. The model has moderate to high predictive relevance, as shown in Table 18, as confirmed by Q^2 values of 0.494 for job satisfaction (JST), and 0.447 for perceived usefulness (PU). These positive values show that the model can better predict the endogenous variables on the basis of the predictors included in the analysis than at the threshold cutoff point of zero.

Table 18: Predictive Relevance and Coefficient of Determination

	Q²predict	RMSE	MAE
JST	0.494	0.734	0.532
PU	0.447	0.754	0.565
	R-square	R-square adjusted	
JST	0.529	0.516	
PU	0.452	0.449	

The R^2 values indicated that the independent variables accounted for 52.9% of the variation in JST ($R^2_{adj} = 0.516$) and 45.2% of the variation in PU ($R^2_{adj} = 0.449$). Chin (1998) argues that R^2 values of 0.19, 0.33 and 0.67 can be interpreted as weak, moderate and substantial. Therefore, the results indicate moderate levels of explanatory power for both constructs. The R^2 value calculated for job satisfaction reveals that the theoretical predictors of technology adoption (PEOU and PU), together with perceived organisational support, account for over half of the variance in employee job satisfaction, representing a contribution to our understanding of this important outcome

The accuracy measures of the models also confirmed these results. The root means square error (RMSE) was found to be 0.734 (JST) and 0.754 (PU) and the mean absolute error was found to be 0.532 (JST) and 0.565 (PU). Lower RMSE and MAE thus indicate smaller errors in the predictions and thus a better fit of the model and better predictive quality (Shmueli et al. 2019). The result is thus also corroborated by the fact that the structural model shows an appropriate predictive quality and moderate explanatory quality which supports the hypothesis testing and theoretical validation.

5.7.3 Path Coefficients and Hypothesis Testing

Table 19 presents the path coefficients, t-statistics, and p-values used to evaluate each hypothesis. The findings for each hypothesis are discussed below.

Table 19: Path Coefficients

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
PEOU → JST	0.001	0.007	0.098	0.008	0.994
PEOU → PU	0.673	0.673	0.054	12.517	0.000
PU → JST	0.100	0.092	0.105	0.955	0.340
POS × PU → JST	-0.140	-0.133	0.073	1.912	0.056
POS → JST	0.576	0.584	0.101	5.681	0.000

Hypothesis 1: PEOU → PU

The path from PEOU → PU was positive and highly significant ($\beta = 0.673$, $t = 12.517$, $p < .001$), indicating that employees who view AI applications as easy to use also find them more useful. The strong link between PEOU and PU shows that the perception of ease of use is an important cognitive antecedent to the perception of usefulness, consistent with the premises of the Technology Acceptance Model (Davis, 1989; Venkatesh and Davis, 2000). Therefore, H1 ("PEOU will have a positive effect on PU") is supported.

This result shows that when AI tools are built with user-friendly interfaces which demand minimal cognitive effort to use, employees are more willing to see their instrumental value for performing tasks. Given the size of the path coefficient ($\beta = 0.673$), the ease of use accounted for approximately 45% of the variance in perceived usefulness (see Table 19), thus highlighting the importance of usability on users' perceptions of the value technology provides.

Hypothesis 2: PEOU → JST

The association between PEOU → JST was negligible and not significant ($\beta = 0.001$, $t = 0.008$, $p = .994$) demonstrating that there was no direct effect of perceived ease of use on job satisfaction. This suggests that employees find interacting with AI systems easy, but that perception of ease of use does not directly lead to enjoying work more. Hence H2 is not supported (PEOU will positively affect JST).

This finding runs counter to the notion that the ease of using a technology leads directly to improved affective outcomes. Rather, it indicates that job satisfaction is likely to be dependent on factors that are independent of the ease of use of technology, such as the meaningfulness of the work itself and organisational support and autonomy (Hackman and Oldham, 1976). The absence of a direct effect of ease of use on satisfaction implies that cognitive interpretations of technology do not automatically generate emotional or attitudinal benefits in the absence of other mediating and/or moderating variables.

Hypothesis 3: PEOU → PU → JST (Mediation)

A mediation analysis was conducted to examine the indirect effect of perceived ease of use (PEOU) on job satisfaction (JST) through perceived usefulness (PU) (Table 20). The indirect path (PEOU → PU → JST) was positive but statistically non-significant ($\beta = 0.067$, $t = 0.957$, $p = .339$).

Table 20: Specific Indirect Effect

Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (O/STDEV)	P Values
PEOU → PU → JST	0.067	0.061	0.070	0.957	0.339

The non-significant mediation suggests that perceived usefulness does not serve as a meaningful mediator between perceived ease of use and job satisfaction in this model. Although ease of use significantly influences usefulness, and usefulness was hypothesised to influence satisfaction, the indirect pathway through usefulness was insufficient to produce a significant effect on satisfaction. Hence, H3 ("PEOU will affect JST through PU") is not supported.

This finding indicates that the cognitive appraisal sequence central to TAM (ease → usefulness → outcomes) does not extend effectively to affective outcomes such as job satisfaction within this SMME context. Employees may recognise that easy-to-use systems facilitate task completion, but this recognition does not necessarily enhance their overall job satisfaction. This suggests that satisfaction is influenced by broader factors beyond technology perceptions alone.

Hypothesis 4: PU → JST

The direct relationship between perceived usefulness (PU) and job satisfaction (JST) was examined to determine whether employees who find AI systems useful also experience higher levels of job satisfaction. The path coefficient was statistically non-significant ($\beta = 0.100$, $t = 0.955$, $p = .340$). Hence, H4 ("PU will positively affect JST") is not supported.

This finding suggests that even when employees perceive AI technologies as useful for improving task performance and productivity, such perceptions do not directly translate into increased job satisfaction. The lack of a significant relationship challenges conventional assumptions that functional benefits of technology automatically enhance employee well-being. Instead, it indicates that perceived usefulness operates primarily as a cognitive evaluation that may influence behavioural intentions to use technology but does not necessarily affect affective states such as satisfaction (Venkatesh & Davis, 2000).

This result may reflect the complexity of job satisfaction as a construct, which encompasses multiple dimensions including work meaningfulness, autonomy, relationships with colleagues, and

organisational support (Spector, 1997). While AI usefulness may contribute to task efficiency, it may not address these broader determinants of satisfaction, particularly in resource-constrained SMME environments where employees may harbour concerns about job security and surveillance (George, 2024).

Hypothesis 5: $POS \times PU \rightarrow JST$ (Moderation)

The moderating role of perceived organisational support (POS) on the relationship between perceived usefulness (PU) and job satisfaction (JST) was examined. The interaction term ($POS \times PU$) showed a negative and marginally significant effect on JST ($\beta = -0.140$, $t = 1.912$, $p = .056$). Although the moderation did not reach conventional levels of statistical significance ($p < .05$), the result at $p < .10$ suggests a weak moderating effect of organisational support on the PU–JST relationship.

A simple slope analysis was conducted to further examine the moderation effect (Figure 5.2). The figure illustrates the moderating effect of perceived organisational support (POS) on the relationship between perceived usefulness (PU) and job satisfaction (JST). The three lines represent low (-1 SD), mean, and high ($+1$ SD) levels of POS.

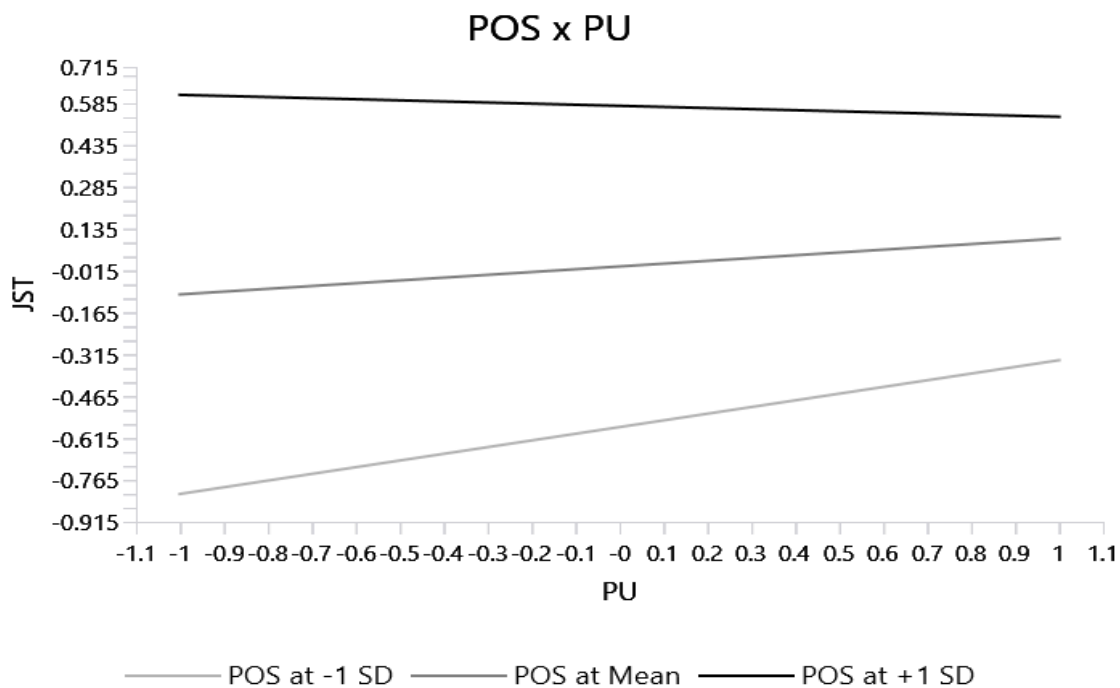


Figure 3: Simple Slope Analysis for Moderation Effect

Note: Figure shows the interaction between perceived usefulness and perceived organisational support in predicting job satisfaction.

As shown in Figure 3, when POS is low, the relationship between PU and JST is stronger and more positive, suggesting that employees who perceive AI as useful experience higher job satisfaction particularly when organisational support is limited. In such conditions, the perceived usefulness of technology may serve as a compensatory resource that partially offsets the absence of organisational care and support. Conversely, when POS is high, the slope flattens, indicating that the perceived usefulness of AI contributes less to job satisfaction among employees who already feel supported by their organisation. This pattern suggests that strong organisational support can maintain high satisfaction levels regardless of employees' perceptions of AI usefulness.

Although the interaction effect was only marginally significant ($\beta = -0.140$, $t = 1.912$, $p = .056$), the trend implies that organisational support buffers the relationship between perceived usefulness and job satisfaction. This buffering effect aligns with social exchange theory (Blau, 1964) and conservation of resources theory (Hobfoll, 1989), which suggest that when employees possess adequate organisational resources (support, recognition, fairness), they are less dependent on specific technological affordances for their overall well-being. Given the marginal significance, H5 receives partial support and warrants further investigation in future research.

5.7.4 Post-Hoc Analysis: POS $\rightarrow$ JST

While not the main objective of this study, the direct relationship between perceived organisational support and job satisfaction is examined in a post-hoc analysis. The path from perceived organisational support to job satisfaction is positive and very significant ($\beta = 0.576$, $t = 5.681$, $p < 0.001$) which indicates that perceived organisational support is a significant predictor of job satisfaction. This finding demonstrates that employees who feel valued, cared for, and supported by their organisations report significantly higher levels of job satisfaction independent of their perceptions about technology.

The strength of this relationship ($\beta = 0.576$) indicates that perceived organisational support explains a sizeable proportion of variance of job satisfaction, which may reflect the important part played by socio-organisational factors in the employee well-being domain. This post hoc finding corroborates with a substantial literature base that shows how perceived organisational support

functions to increase job satisfaction as a result of social exchange processes in which employees are inclined to reciprocate the organisational care they perceive, with positive attitudes and commitment towards it (Eisenberger et al., 1986; Rhoades & Eisenberger, 2002). Although this relationship was not hypothesised a priori, its prevalence within the structural model gives an important insight into its contextual relevance to the relative importance of organisational to technological factors in determining satisfaction within South African SMMEs. The finding highlights the effect that it may be more important to have supportive organisational environments than to perceive that the technology is conducive to such employee satisfaction, particularly in resource constrained environments where interpersonal relationships, and managerial empathy belong to such resources.

5.8 Conclusion

In this chapter, the results of statistical analyses examining the relationships between perceived ease of use (PEOU), perceived usefulness (PU), perceived organisational support (POS), and job satisfaction (JST) are presented in settings in which technology is in place for the employee-related work duties. The preliminary analyses confirmed the reliability and validity of the measurement instruments resulting in all constructs assuring strong internal consistency and satisfactory with convergent and discriminant validity. The exploratory and confirmatory analyses demonstrated a clear 4-factor structure.

The structure model demonstrated that PEOU had a meaningful positive effect on PU (H1 supported), meaning that those employees who found AI systems easy to use positively regulated their perceptions of how beneficial they were for task performance. However, PEOU (H2 not supported) and PU (H4 not supported) did not have a meaningful influence between these factors and job satisfaction, which suggests that the technological perceptions themselves point that alone they have no direct influence on the affective satisfaction for the employees themselves. The mediation analysis (H3) showed no meaningful indirect effect of PEOU on JST through the mediator of PU. The moderation analysis (H5) showed that POS had a marginal influence on the relationship between PU and JST ($\beta = -0.140$, $p = .056$) to suggest that the organisational support may buffer or stabilize JST regardless of the perceptions of AI usefulness. A post hoc analysis suggested that POS was a meaningful direct predictor of JST ($\beta = 0.576$, $p < .001$), which suggests that support work environments were meaningful in developing relevant positive employee outcomes.

In summary, the results show that although the Technology Acceptance Model is an effective model for the cognitive factors (ease of use can be seen as predicting usefulness), those technological factors do not directly determine emotional factors like job satisfaction. Rather, the factor that appears to be most important in determining employee satisfaction is the support of the organisation. The following chapter discusses these results in relation to the literature reviewed, while Chapter 7 sets out the theoretical implications and practical recommendations for organisations seeking to implement AI technologies.

CHAPTER 6: DISCUSSION OF RESULTS

6.1 Introduction

In this chapter, the empirical findings presented in Chapter 5 are interpreted and situated in relation to the theoretical approach outlined in Chapter 2 and the hypothesised conceptualisation of the study in Chapter 3. The purpose of the study overall was to explore the influence of theoretical determinants of technology acceptance (namely perceived ease of use (PEOU) and perceived usefulness (PU)) on job satisfaction of employees in South African small, medium, and micro enterprises (SMMEs) that have adopted AI technologies. The research employs the Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh & Davis, 2000) and the conceptualisation of perceived organisational support (POS) (Eisenberger et al., 1986) as the foundation for an overarching conceptual framework for the study.

While TAM connects employees' cognitive responses towards technology with perceived usefulness and perceived ease of use, POS captures the socio-organisational context underpinning trust, equity, and affective commitment in work contexts (Raji & Ismail, 2023; Rhoades & Eisenberger, 2002). The study brought together these two frameworks to fill a critical gap in the literature, examining how the perception of technology and organisational support explains variance in employee satisfaction under conditions of resource constraint in an emerging-market context.

This chapter is organised according to the research hypotheses (H1 – H5) in order from 1-5, with the same sequence as the research questions discussed in Chapter 3. Each hypothesis is discussed concerning the respective quantitative evidence provided in Chapter 5 and the literature in Chapter 2. This discussion includes hypotheses that were supported, unfounded hypotheses, and whether the empirical results support, augment or refute prior theoretical or empirical studies. Of particular interest in South African SMMEs, is how digital transformation integrates human resource issues, resource constraints, trust and digital skills preparedness (Gaglio et al., 2022). The chapter does more than validate data and offers an interpretative synthesis of the extent that perceived ease of use, perceived usefulness, and organisational support collectively influence employee satisfaction and technology readiness under limited resource constraints. There is also a significant post hoc finding between POS and employee job satisfaction while job satisfaction is not the proposed study, it is a product of the exploratory data analysis.

6.2 Summary of Empirical Results

Results from the empirical analysis demonstrated a complex understanding of the relationship between constructs of the Technology Acceptance Model (TAM) with respect to job satisfaction outcomes in South African Small Medium Micro Enterprise (SMME) companies. By way of first consideration it was established that perceived ease of use (PEOU) had a strong positive effect on perceived usefulness (PU), thus supporting Hypothesis (H1). The path coefficient for this relationship ($\beta = 0.673$, $p < 0.001$) established an influential cognitive connection which firmly aligns to the theoretical basis of TAM (Davis, 1989; Venkatesh & Davis, 2000). This indicated that when employees found using the AI was simple and easy to engage with, they were considerably more likely to perceive AI systems as being useful when performing their work tasks. The research concludes that, because of the interface's simplicity and ability to facilitate interactions with AI, employees had increased views of AI as a resource for their work. This is important in the business environment since many employees have little access to technical resources or the benefit of structural training opportunities (Badghish & Soomro, 2024).

In contrast, H2 was not confirmed, as relations between PEOU and job satisfaction (JST) were non-significant ($\beta = 0.001$, $p = 0.994$). The data demonstrated that simple PEOU does not always lead to affective outcomes such as satisfaction, at least when considering the other variables. Employees may find it easy to interact with an AI system from an operational perspective, but, absent a social or a motivational dimension (such as autonomy, organisational support and trust) they may not experience an emotional reaction (Raji & Ismail, 2023). Overall this finding suggests that technology usability on its own is not representative of the whole picture regarding satisfaction without a social or a motivated prompt supporting it.

Hypothesis 3 (H3), which explored the mediating influence of PU on the relationship between PEOU and JST, also did not receive support from the study ($\beta = 0.067$, $p = 0.339$). This finding indicates that PU of AI does not mediate the impact of ease of use on job satisfaction. The absence of mediation indicates that cognitive judgments about usefulness of technology do not necessarily translate into affective or emotional responses without other factors providing context. This finding is in accord with recent studies that suggest the cognitive-behavioral lens of TAM narrows the role of psychosocial dynamics in technology-related job outcomes (Chang et al., 2024; Díaz-Arancibia et al., 2024).

The insignificance of Hypothesis 4 (H4) was also supported as PU did not have a statistically significant effect on JST, ($\beta = 0.100$, $p = 0.340$). PU may be associated with increases in the efficiency of task performance, yet not impacts on affective job experiences. This finding supports nascent evidence that working adults in resource-constrained settings may see AI as serving a productivity-enhancing purpose yet does not translate to increased intrinsic satisfaction (George, 2024; Murire, 2024).

Finally, Hypothesis 5 (H5) received only minimal support from the data. While there was a moderation effect of perceived organisational support (POS) on the PU–JST relationship, which approached statistical support ($\beta = -0.140$, $p = 0.056$), it did not achieve a traditional level of statistical support ($p < .05$). The simple slope analysis indicated that there is a positive relationship between PU and JST when POS is low, which implies that PU serves as compensatory resource when an individual does not have organisational support. The results also suggest that when POS is high, satisfaction remains constant regardless of PU, indicating some form of buffering effect.

Although not hypothesised as part of the study, in a post-hoc analysis, perceived organisational support (POS) showed a strong a significant direct relationship to job satisfaction ($\beta = 0.576$, $p < 0.001$). This indicates that whilst the TAM constructs advance cognitive responses to technology, socio-organisational changes, such as perceived support, are central to predicting affective outcomes such as, in this case, satisfaction.

In conclusion, the results confirm that whilst perceived ease of use and perceived usefulness advance the prediction of positive technology perceptions, they do not directly contribute to job satisfaction. Further, organisational support was found to be a primary factor in predicting the well-being of a South African SMME employee.

6.3 Discussion of Hypothesis 1 (H1): PEOU $\rightarrow$ PU

6.3.1 Interpretation of Findings

The significant positive relationship between perceived ease of use (PEOU) and perceived usefulness (PU) upholds one of the foundational propositions of the Technology Acceptance Model (TAM): the less effort required to use a system, the greater the perceived utility (Davis, 1989). The findings of this study indicate that South African SMME employees believe that when the effort required to master and use AI tools is minimal, these systems are more likely to be regarded as useful aids for effective task performance. The substantial path coefficient ($\beta = 0.673$,

$p < 0.001$) suggests a strong cognitive equivalence between perceptions of ease of use and perceptions of utility indicating that ease of use facilitates the recognition of value of technology.

These findings exhibit the logical processing which exists in the framework of TAM, in that PEOU sets up positive PU perceptions by reducing cognitive load and increasing users' confidence that tasks can be performed more efficiently (Venkatesh & Davis, 2000). In practice, when AI systems have intuitive user interfaces, straightforward instructions and a minimum level of technical barriers to entry, employees will tend to perceive them as valuable to productivity and job performance.

The results are also reflective of working conditions that are experienced by SMMEs, where staff are often performing multiple roles with different levels of digital literacy. With PEOU, there are minimal learning environments needed before staff are comfortable integrating technology into their daily work activities. Almeida et al. (2025) similarly found that ease of use significantly improves perceived working efficiency in AI-based recruitment systems, suggesting that usability facilitates operators' trust in and competence with technological systems. The outcome thus supports the proposition that ease of use is not merely a technical specification but a cognitive facilitator that shapes user engagement with technology.

The finding also corroborates earlier theoretical extensions of TAM, such as TAM2 and TAM3, which propose that factors including experience, voluntariness, and output quality mediate the relationship between PEOU and PU (Venkatesh & Bala, 2008). In resource-constrained SMME environments, where formal training and technical support are often limited, ease of use becomes particularly critical in enabling employees to recognise the value of AI technologies without requiring extensive external assistance.

6.3.2 Comparison with Literature

The findings of the present study are aligned with the empirical literature validating the solidity of the PEOU-PU connection among multiple forms of technology. According to Badghish and Soomro (2024), the reason SMEs in Saudi Arabia perceived business value and sustainability opportunity increased was because of ease of interaction with the AI systems. Similarly, Du Plessis and Swart (2024) asserts that AI practitioners in South Africa regarded the most effective AI tools as those that were simple to use and required minimal technical expertise. The present result thus strengthens the cross-contextual validity of this TAM relationship in emerging-market

SMME contexts, underscoring the universality of the link between user-friendly design and perceived value.

Furthermore, Díaz-Arancibia et al. (2024) and Kelly et al. (2023) found that when digital technologies are perceived as easy to use, employees' performance expectations are enhanced, thereby reinforcing technology acceptance intentions. The convergence between this study and previous research supports the generalisability of TAM's cognitive mechanisms across cultural and organisational contexts. However, nuanced distinctions exist in the strength of the PEOU–PU relationship depending on contextual factors. In established markets that are characterized by a greater baseline of digital literacy, this relationship is more likely to be moderated by prior experience and familiarity, whereas in emerging markets that are characterized by less training and infrastructure, ease of use is expected to be of greater importance, as employees heavily rely on a system designed to be intuitive (Le Dinh et al., 2025).

6.3.3 Contextual Insights for South African SMMEs

In South African small, medium and micro enterprises (SMMEs), the relationship between perceived ease of use (PEOU) and perceived usefulness (PU) is contextualised and influenced by broader structural factors of digital readiness, access to skills, and the organisational culture. Given the strong significance of this antecedent relationship, we see that employees in small firms, who may not have access to dedicated IT support, rely quite heavily on ease of use to realise the potential benefits of AI technologies. Gaglio et al. (2022) and Mbatha (2024) point out that technology adoption in SMMEs is often inhibited by the digital divide and that employees interact with devices with sophisticated technologies without appropriate supports.

Therefore, when AI applications are designed to ease navigation, visually clear and technically basic, employees experience them as additional helpful resources and not operational burdens. This has implications for technologies vendors and developers serving the SMME market systems technology vendors and developers must focus on user-centred design considerations so that employees with varying skillsets can access the technology without increased cognitive load (Norman, 2013). In situations where budgets are tight for formal training, deliberate intuitive design functions as the primary means of evaluating and understanding technology value.

6.3.4 Theoretical Implications

The affirmation of H1 substantiates the cognitive aspect of TAM and reconfirms TSAM's theoretical applicability in emerging economy contexts. The outcome supports Davis' (1989) assertion that the ease of use contributes to realised utility by mitigating the cognitive effort needed to engage. Crucially, it also expands TAM's explanatory validity to resource-intensive SMME contexts, showing that usability possesses predictive power, despite having limited organisational resources. Additionally, the finding aligned with UTAUT in which facilitating conditions encompassed within effort expectancy supports technology adoption in diverse contexts (Venkatesh et al., 2003).

This relationship of interest theoretically signified that TAM's cognitive mechanisms remain intact throughout economies with bounded digital maturity. However, the results also indicate the need to incorporate organisational and humanistic variables upon extending TAM to explain affective outcomes beyond behavioural intentions. Therefore, while ease of use encourages cognitive evaluations of usefulness, its impact on affective constructs of job satisfaction, appears to be contingent upon additional socio-organisational variables, of fairness, trust, and organisational empathy (Zhou et al., 2024).

6.4 Discussion of Hypothesis 2 (H2): PEOU → JST

6.4.1 Interpretation of Findings

The statistical results showed that perceived ease of use (PEOU) did not significantly correlate with job satisfaction (JST) directly ($\beta = 0.001$, $p = 0.994$), meaning that even when employees find AI tools easy to use, this perception does not necessarily translate to higher affective satisfaction or contentment in the workplace. This finding suggests that mere discovery that AI systems are easy to operate does not automatically result in improved emotional responses toward one's job.

Although the Technology Acceptance Model (TAM) has traditionally assumed that use of technology is positively enhanced by its ease of use (Davis, 1989; Venkatesh & Davis, 2000), such relationship appears tenuous when considering affective job satisfaction outcomes in SMMEs. In the labour intensive, resource-constrained work environment of the South African SMME environment, employees may be more focused on their efficiency and task completion as opposed to their experience interacting with the technology. This is supported by research, which

indicates that ease of use is a stronger correlate for behavioural intentions than for attitudinal longer-term outcomes (Venkatesh & Bala, 2008).

Furthermore, not having a direct link between PEOU and JST implies that job satisfaction is not derived from the operation of the system but from alternate organizational or psychosocial mechanisms. SMME employees may interpret technology through an operational necessity rather than a professional benefit, particularly when technology adoption is predicated on organizational needs for cost-saving rather than a simultaneous organizational responsibility towards employee welfare. Supporting Conservation of Resources Theory, satisfaction is sustained not through simplicity of use of technology, but from access to work resources and enhancement of workplace resources such as social recognition, workplace stability, and decision-making autonomy (Hobfoll, 1989). Ease of use may influence effective task completion however it does not possess the motivational ability to foster emotional connections to work and satisfaction with the work itself.

6.4.2 Comparison with Literature

This outcome is contrary to several studies that have found positive relationships between ease of use and employee satisfaction in highly digitalised contexts. Song et al. (2025) indicated that having a technology perceived as easy to use was associated with less cognitive loading on healthcare providers which was indicative of higher motivation. In addition, Mapila and Moloi (2024) also observed greater amounts of employee motivation among participants in small and medium-sized enterprises in South Africa when AI-based marketing tools were implemented provided the technology enabled simplicity of the task, and was easy to learn.

However, these studies were conducted in contexts with a significant amount of digital literacy support and direct managerial support, situations that do not exist for all South African SMMEs. For most small businesses, formal training and change management structures are poorly developed (Fatoki, 2019). As a result, any positive affective impact of ease of use is likely inhibited by context factors such as fairness (or lack thereof), recognition, and organisation commitment. In addition, the focus of employees' affective response to AI is significantly dependent on if automation is perceived as a threat to or empowerment of job security (Golgeci et al., 2025).

In smaller organisations, there tends to be a dominant attitude that AI is presented as a managerial tool aimed at control and efficiency oversight over one that can facilitate collaboration with employees. As a result, the positive psychological aspects associated with perceived usability

may be negated. This contrast further suggests that cognitive variables, such as perceived usefulness and ease of use, must synergise with affective and organisational conditions to create employee satisfaction (Raji & Ismail, 2023). The present finding thus demonstrates an emerging trend. While the TAM constructs can capture behaviour adoption intentions, they do not offer much explanatory power for affective outcomes such as job satisfaction in resource constrained environments.

6.4.3 Contextual Analysis

In the context of SMMEs in South Africa, employees could exhibit a preference for job security and financial independence over ease of use in technology. In many cases, employees are confined to precarious employment contracts and have restricted upward mobility opportunities, which can diminish an employee's affective benefit of technology use. Fatoki (2019) describes SMMEs characterised with scarce capitals, unequal distribution of training, and inconsistent level of managerial communication. Each of these characteristics prevents SMME employees from potential psychosocial benefits derived from the use of digital technologies.

Therefore, even though employees recognize that AI systems are convenient to use (with mean PEOU scores above 5.2), they do not appear to confer increased job satisfaction. A possible explanation is the predominately instrumental view of AI in small firms, in which technology is viewed as an instrument to operational ends rather than as facilitative of engagement or empowerment. Employees may interpret ease of use with a heightened level of efficiency expectations that, further, relates to work intensification rather than workloads that lessen in overall significance.

Rick et al. (2024) observed that work restructuring through technology-enabled automation is complicated by the fact it can sometimes create additional job demands, as gains in efficiency lead to expanded role or task demands instead of reductions in responsibilities overall. Employees may perceive their work context with mixed usability in that they enjoy the technological ease, but they are also more likely to be equally concerned with the increased availability for performance management and their workload allocation. Therefore, the finding suggests that perceived ease of use can be viewed as an instrumental variable for PEOU in SMMEs by providing task functionality rather than functional-based intrinsic satisfaction or purposive motivational engagement with tasks.

6.4.4 Theoretical Implications

Theoretically, this finding challenges the generalisability of TAM beyond its original domain of predicting behavioural intention. Davis (1989) developed TAM primarily to explain technology usage behaviour rather than affective or psychological end-states such as job satisfaction. According to Spector's (1997) conceptualisation, job satisfaction encompasses affective assessments of multiple job facets, including work content, autonomy, recognition, and interpersonal relationships, factors that extend well beyond technology-related perceptions.

The limited predictive power of PEOU for job satisfaction indicates that satisfaction is influenced more by organisational climate and psychosocial stability than by cognitive judgements of technological ease. This finding aligns with Perceived Organisational Support theory (Eisenberger et al., 1986), which proposes that employees derive satisfaction from feeling valued and supported by their organisation rather than solely from task-level efficiency. When organisations fail to reinforce human connection and esteem during technological implementation, employees' perceptions of ease of use may remain cognitively positive yet affectively neutral.

Caesens and Stinglhamber (2020) further observe that socio-emotional exchanges constitute the missing link between instrumental advantages and emotional consequences. The current result therefore provides empirical support for the theoretical extension proposed in Chapter 3: without organisational support as a mediating or moderating factor, TAM's utilitarian variables do not effectively predict affective states such as satisfaction. This suggests that future theoretical models should integrate TAM with socio-organisational frameworks to capture the full complexity of technology-related employee outcomes.

6.5 Discussion of Hypothesis 3 (H3): PEOU → PU → JST (Mediation Effect)

6.5.1 Interpretation of Findings

The mediation test revealed that perceived usefulness (PU) did not significantly mediate the relationship between perceived ease of use (PEOU) and job satisfaction (JST) ($\beta = 0.067$, $p = 0.339$). Although ease of use significantly influenced usefulness ($\beta = 0.673$, $p < 0.001$), usefulness in turn failed to exert a significant effect on satisfaction ($\beta = 0.100$, $p = 0.340$). This finding suggests that even when employees rate AI systems as both easy to use and useful, these cognitive assessments do not subsequently affect their emotional satisfaction.

The null finding for mediation indicates that the classical TAM sequence, PEOU → PU → Attitude → Behaviour, cannot be generalised to the domain of job satisfaction within SMMEs. This outcome is theoretically plausible given the conceptual distinction between cognitive and affective processing. Employees may cognitively appreciate the efficiency gains afforded by AI while remaining emotionally insulated or apprehensive about its effects on employment security and workplace relationships.

Chang et al. 2024 similarly found that while AI introduction enhances perceptions of task performance, it simultaneously increases employment-related anxiety, thereby neutralising potential satisfaction benefits. Thus, the positive cognitive assessment of AI's usefulness proves insufficient to overcome emotional ambivalence arising from organisational uncertainty or role ambiguity. This finding reveals that technology's instrumental value does not serve as a psychological bridge connecting usability perceptions to emotional well-being.

6.5.2 Comparison with Literature

The non-significant mediation result corroborates recent work that has questioned TAM's linear predictive capabilities as it applies to an increasingly complex outcome. According to Venkatesh et al. (2016), cognitive variables from TAM can predict intention and behavioral use efficiently; however, they showed weak associations across affective outcome variables, such as satisfaction and organizational commitment. Gerli et al. (2022) also contend that psychological and emotional constructs of people's cognition (such as trust, self-efficacy, and perceived fairness) mediate perceived usefulness and satisfaction.

Kumar et al. (2024) noted that in emerging-market settings, while AI's usefulness indicates a positive contribution to productivity improvements for micro-enterprises, emotional return on investment embeds on other elements such as the fear of automation and quality of organisational communication. Conversely, studies in high-support environments relating to the mediational effect of perceived usefulness on ease of use satisfaction have been noted. In other words, Díaz-Arancibia et al. (2024) found that in digitally advanced firms, perceived usefulness was a partial mediatorial path involving ease of use satisfaction and employee competence and mastery.

This difference highlights the reliance of TAM relationships on context. Where SMME employees in South Africa may have very little exposure to advanced AI training and continue to have gaps in digital skills, they may struggle to recognize perceived usefulness in terms of emotional

fulfilment (Achieng & Malatji, 2022). Thus, the findings in this study with regard to mediation are aligned with the broader literature establishing that usefulness does not deliver satisfaction in employees when other direct structural and emotional enablers like training, recognition, and psychological safety are absent.

6.5.3 Theoretical Reasoning

Theoretically, this finding calls into question the classical TAM ability to account for affective end-states such as job satisfaction. The TAM was designed to identify usage behaviour with technology rather than affective or psychological outcome behaviours (Davis, 1989). Job satisfaction (Spector, 1997) includes not only affective evaluations of the nature of the work, but also job attributes such as autonomy and recognition that are over and above perceptions of technology. The limited mediating influences of PU suggest that job satisfaction is determined by factors beyond job usefulness, such as the organisational climate and psychosocial safety. For example, Perceived Organisational Support (POS) theory provides a useful lens (Eisenberger et al., 1986). POS theory posits that employees satisfy their job satisfaction by feeling valued by the organisation and receiving support, rather than the organisation helping them be more efficient at their job. Thus, when organisations work to enhance human connection and valuing personnel when AI is presented, employees are left with a cognizant positive view of its usefulness, but without an affective evaluation.

Caesens and Stinglhamber (2020) further observe that socio-emotional exchanges constitute the missing link between instrumental advantages and emotional consequences. The current result therefore empirically supports the theoretical extension hypothesised in Chapter 3. Without organisational support as a mediating or moderating mechanism, TAM's utilitarian variables do not predict affective states such as satisfaction. This finding calls for expanded theoretical models that integrate cognitive technology acceptance constructs with socio-emotional organisational variables to provide comprehensive explanations of employee outcomes in technology-enabled workplaces.

6.6 Discussion of Hypothesis 4 (H4): PU → JST

6.6.1 Interpretation of Findings

The results indicated no statistically significant relationship between perceived usefulness (PU) and job satisfaction (JST) findings ($\beta = 0.100$, $p = 0.340$). This implies that while participants

perceived AI technologies to be useful at increasing the efficiency and effectiveness of their work, these cognitions did not yield enhanced affective satisfaction. The data calls into question the assumption in the Technology Adoption Model (TAM) that perceived usefulness positively influences attitudinal constructs such as satisfaction or intention to use (Davis, 1989; Venkatesh & Davis, 2000).

The lack of significance suggests that in South African SMMEs, employees may value AI's functional advantages cognitively but remain emotionally disconnected from its implementation due to contextual or organisational constraints. This gap between cognitive appreciation and affective response indicates a fundamental limitation of TAM in predicting job satisfaction outcomes. Gerli et al. (2022) explain that employees often experience a "cognitive–affective gap" when technology improves productivity yet simultaneously introduces stressors such as intensified monitoring, increased workload expectations, or fear of job displacement.

Even though the descriptive data demonstrate an employee average score of approximately 4.9 to 5.0 that reflects perceptions of AI tool usefulness, it did not establish a relationship to the outcomes of peer satisfaction scores. Findings of this nature give evidence that perceived usefulness functions more as a cognition regarding performance, rather than as a motivator for some emotional, or feeling, outcome. An employee might comprehend that an AI tool assists them in completing a task more quickly, and/or accurately, but can still be concerned about job loss, performance expectations or lesser abilities connecting to others (Chang et al., 2024).

6.6.2 Comparison with Literature

This observation does not correspond with prior research which affirmed positive associations of PU and JST in high-technology contexts. For example, Murire (2024) found that employees working in large South African financial organizations reported increased satisfaction when there was a clear improvement in task quality and accuracy of decision-making brought about by AI tools. Du Plessis and Swart (2024) also found that digital marketing practitioners experienced an increase in satisfaction levels when AI would take over campaign management-saving them time and allowing them to work creatively instead.

However, the studies were carried out in well-resourced organisations with formal support systems in place, extensive training systems, and reward systems that reinforced the believed value of technology. On the other hand, this study reflects SMME environments with training

budgets; relatively low levels of digital literacy; and limited institutional support which created barriers to convert perceived usefulness into job satisfaction.

Fatoki (2019) also observed that SMMEs in South Africa are more prone to being reactive than strategic technology adopters, which can influence employees' perceptions of technology as being empowering for managers, but not for employees. Additionally, Golgeci et al. (2025) pointed out that perceived usefulness does not result in satisfaction when employees view technology implementation as externally rather than internally facilitatory. In such a situation, technology may serve to monitor employees' efficiency and become a surveillance tool in both the organizational and personal sense. This context will erode the motivational benefits of the performance-implicated technology, which may generate emotional ambivalence while aligning with cognitive recognition of the instrumental value of the technology or technology application

6.6.3 Theoretical Implications

In theory, this finding highlights the need to augment TAM with psychosocial constructs representing the affective dimensions of technology acceptance. Davis (1989) described perceived usefulness as a mediator of behaviour intention it was not intended to be a predictor of affective end-states like satisfaction. Subsequent theory enrichments, including the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extensions, acknowledged and incorporated effects of affective constructs such as hedonic motivation, trust, and anxiety (Venkatesh et al., 2003; Venkatesh et al., 2016).

The results presented here support the hypothesis that emotional reactions depend on perceived organisational support and equity, rather than being specific to instrumental utility alone (Caesens & Stinglhamber, 2020). Our integration of Perceived Organisational Support (POS) theory into TAM provides both a broader explanation as to why usefulness does not automatically lead to satisfaction, and in doing so recognises that employees may appreciate that AI widens the boundaries of task performance; however, cognitive positives do not translate to emotional positives without organisational affirmation that is perceived in social support, through acknowledgement, feedback, and participatory decision-making.

Eisenberger et al. (2020) clarify that employees are in need of socio-emotional reciprocity for cognitive evaluations to positively impact their well-being. Hence, the findings regarding the non-significant PU-JST relationship support the theoretical extension put forth in Chapter 3, in

particular highlighting the way human-oriented variables contribute to the mediating path from technology cognition to emotional satisfaction. This also reinforces a call for more research to inform models with an effect framework that account for technological affordances and value of organisational empathy simultaneously, understanding that sustainable technology adoption requires confluence of the instrumental efficacy of the authors and human centred social support.

6.6.4 Practical Implications

In practical terms, this suggests that organisations cannot rely on simply showing the functional benefits of AI to improve employee satisfaction for managers, implementing the technology must be accompanied with practices that take into consideration the emotional and psychological needs of employees. This requires communicating with transparency about the intentions or limitations of AI, offering opportunities for skill development and career advancement, and providing employees options for a voice in technology related decision-making (Morandini et al., 2023). The finding also demonstrates the significance of framing AI as a tool that complements rather than feels like it takes the place of employees' abilities. Feeling that AI may put job security or autonomy in jeopardy, doesn't allow for cognitive recognition of its function to calm affective satisfaction (George, 2024). Thus, AI implementation can't be solely about technical training, but includes organisational practices that build trust, recognition and psychological safety elements that would allow employees to feel that technology is liberating, as opposed to confining.

6.7 Discussion of Hypothesis 5 (H5): POS × PU → JST (Moderation Effect)

6.7.1 Interpretation of Findings

The analysis of interaction indicated that perceived organisational support (POS) may serve as a marginal moderator of the relationship between perceived usefulness (PU) and job satisfaction (JST) ($\beta = -0.140$, $p = 0.056$). While not statistically significant based on conventional criteria (0.05), it is theoretically interesting and worth noting the direction and pattern of the interaction. The simple slope analysis revealed the following: at lower levels of organisational support, the positive relationship between PU and JST is stronger; conversely, at higher levels of organisational support, the relationship flattens somewhat.

The above-mentioned trend suggests that strong organisational support weakens employees' reliance on the perceived usefulness of AI for satisfaction. Specifically, when employees feel highly supported, they perceive their organisation values them as part of the organisation, cares

for their well-being, and offers support when necessary, satisfaction is less dependent on technology's instrumental usefulness. In contrast, weak organisational support appears to lead employees to rely more heavily on the perceived usefulness of AI as a compensatory source of satisfaction or accomplishment.

This trend conforms to the theoretical proposition articulated by Eisenberger et al. (1986), who defined perceived organisational support (POS) as a direct socio-emotional resource for employee satisfaction and perceived environmental stressors. When employees view the organisation as exhibiting strong care and fairness, their well-being establishes a sustaining state irrespective of changes in the performance system, or utility of the technology system. When employee support weakens, they rely more heavily on the performance and efficiency obtained through the technology system as an alternate source of competence and achievement. Consequently, POS serves as a stabilising moderator for immune fluctuations toward satisfaction derived from performance of the technology.

6.7.2 Comparison with Existing Studies

The buffering role of POS aligns with empirical evidence at both global and regional levels. Caesens and Stinglhamber (2020) demonstrated that perceived organisational support consistently predicts job satisfaction while also mitigating the effects of job stressors and technological demands. In digital transformation contexts, organisational support shapes the extent to which AI-driven role changes affect employee trust and satisfaction. Employees operating within supportive environments exhibit reduced anxiety about the effects of automation (Raji & Ismail, 2023).

Almeida et al. (2025) demonstrated that higher levels of perceived organisational support enhance employees' tolerance for technology-driven ambiguity, particularly among recruiters utilising AI-based screening tools. When organisations provide clear communication, training, and recognition during technology transitions, employees experience less stress and greater confidence in navigating new systems. This buffering effect of POS suggests that organisational context fundamentally shapes how perceptions of technology translate into affective outcomes.

Nonetheless, the marginal statistical significance ($p = .056$) may be reflective of a contextual differential present in the SMME sector. These organisations are characterised as informal, often lacking human resource systems and/or standard support practices so their employees cannot

rely upon uniform experiences of organisational support. Fatoki (2019) noted that many South African SMMEs operate with little regard for employee relations, which diminishes the relevance of POS as a positively defined non small number of employees, consistently objective factor in a moderator. In such circumstances, employee satisfaction may be largely reliant upon relationships with owners, or managers' discretion, more so than formalising support practices. While the moderating effect of POS is consistent in direction with theory, it is not fully statistically significant as the support practices contained in moderation may not be uniformly institutionalised across organisations in the sample, or across the SMME sector. The lack of uniformity indicates that significant consideration should be given in future studies of the effects of POS to its effects within a homogenous organisational context, or to explore the stage or level at which HR practices were formalised for the SMME.

6.7.3 Theoretical Implications

Theoretically, the results support integrating POS theory with TAM, demonstrating that socio-organisational factors interact with cognitive assessments to shape affective outcomes. While PU represents task-level cognition regarding technology functionality, POS captures the relational climate that contextualises these cognitive appraisals. The flattening observed in the PU–JST relationship under high POS conditions suggests a compensatory effect, as theorised by the "resource substitution" principle of the Job Demands-Resources (JD-R) model (Bakker & Demerouti, 2017).

When organisational resources such as support, recognition, and equity are abundant, employees derive satisfaction directly from these resources, thereby diminishing their reliance on task-level utilities, such as perceived usefulness. Conversely, when these resources are scarce, employees seek the functional advantages of technology as substitutes for satisfaction and accomplishment. This interplay highlights the dynamic relationship between social and technological determinants of satisfaction, offering an enhanced conceptualisation of moderated relationships within the extended TAM–POS model.

The findings validate the suggestion that POS serves as a boundary condition, dictating whether technology benefits yield affective well-being (Eisenberger et al., 2020). This finding broadens the explanatory scope of TAM from individual cognition to socio-contextual processes, aligning with the prevailing socio-technical integration agenda in contemporary AI research (Golgeci et al., 2025). Future theoretical development should continue to explore how organisational climate

variables moderate the effects of technology perceptions on employee outcomes, recognising that technology adoption occurs within complex social systems rather than in isolation.

6.7.4 Practical Implications

Considering this finding, from a practical application viewpoint, it implies that supportive organisational settings should be of primary concern to organisations intending to use technology to increase employee satisfaction. AI tools need to show their usefulness, but it should be secondary to establishing a culture of trust, appreciation, communication, and participation in decision making (Rhoades & Eisenberger, 2002).

The buffering role of POS implies that when employees genuinely feel supported they are less susceptible to dissatisfaction stemming from any limitations or deficiencies inherent in technological issues. This means that the importance of the ramifications for change management suggests that firms implementing AI also need to place as much emphasis on human resource management practices, such as training that provides employees with feedback and participatory decision-making, as they do on the technical infrastructure. Only such considered approaches ensure that the technology works as a facilitator for the general well-being of employees and not as a cause of stress or ambiguity.

6.8 Post-Hoc Analysis: POS → JST Relationship

6.8.1 Interpretation of Findings

Though the direct relationship between perceived organisational support (POS) and job satisfaction (JST) was not the central focus of the present study in the structural model it did emerge as the single best predictor ($\beta = 0.576$, $p < 0.001$) and was therefore worthy of discussion from a theoretical and practical point of view. The high path coefficient indicates that perceived organisational support explains a large portion of the variance in job satisfaction, and this is greater than any possible effects attributable to the numerous technology-related perceptions.

This suggests that employees who feel valued, cared for and supported by their organisations report significantly greater levels of job satisfaction than do their counterparts who feel less valued. This is the case irrespective of their perceptions of the ease of use or usefulness of the technology. The strength of this relationship highlights the important part socio-organisational factors play in influencing employee well-being especially in resource constrained SMME

environments where interpersonal relations along with the empathy of management frequently replace formal HR systems (Murimbika & Urban, 2023).

6.8.2 Theoretical Context

The strong POS-JST relationship aligns with extensive literature demonstrating that perceived organisational support enhances job satisfaction through social exchange mechanisms (Blau, 1964; Eisenberger et al., 1986). According to social exchange theory, when employees perceive that their organisation values their contributions and cares about their well-being, they reciprocate with positive attitudes, increased commitment, and higher satisfaction (Rhoades & Eisenberger, 2002).

This reciprocal relationship is particularly salient in contexts characterised by uncertainty and change, such as technology implementation. When organisations demonstrate genuine concern for employees during periods of transformation through transparent communication, skill development opportunities, and participatory decision-making, employees experience reduced anxiety and enhanced trust (Caesens & Stinglhamber, 2020). The finding therefore reinforces the importance of human-centred organisational practices as foundations for employee well-being.

6.8.3 Contextual Significance for SMMEs

Within South African SMMEs, the prominence of the POS–JST relationship may reflect the relational and collectivist nature of many South African workplace cultures, where interpersonal connections and perceived care are particularly important (Imran et al., 2020). In small organisations where employees interact regularly with owners and senior managers, perceptions of support are shaped by direct interpersonal experiences rather than by formal HR policies or programmes.

This contextual characteristic suggests that SMME leaders possess significant influence over employee satisfaction through their daily interactions, communication styles, and demonstrated concern for employee welfare. The finding underscores that even in the absence of extensive financial resources or formal HR infrastructure, SMMEs can enhance employee satisfaction by fostering supportive, inclusive, and empathetic organisational cultures (Hlatshwayo, 2023).

6.8.4 Implications for Understanding Technology and Satisfaction

The strong positive correlation of POS-JST, in combination with the non-significant PU-JST and PEOU-JST correlations, provides a useful indication of the relative importance of organisational rather than technological attributes in determining satisfaction. While cognitive evaluations and behavioural intentions are affected by perceptions of technology, affective outcomes, such as satisfaction, are influenced more by the quality of organisational support aspects than of the technology. This indicates that successful technology implementation in SMMEs involves not only attention to system usability and functionality issues but also, quite possibly more importantly, the creation of organisational environments conducive to employees' psychosocial needs. Technology, regardless of ease of use or usefulness, cannot provide sufficient compensation for deficiencies in respect of problems such as organisational support, recognition and interpersonal care.

6.9 Integrated Discussion: Synthesising TAM, POS, and Job Satisfaction

6.9.1 Cognitive Versus Affective Predictors of Satisfaction

The empirical results confirm that cognitive constructs from TAM, specifically PEOU and PU, differ substantially from socio-organisational proxies, such as POS, in their predictive power for job satisfaction. Although PEOU significantly influenced PU, neither construct exerted direct effects on job satisfaction, indicating that cognitive perceptions of technology are insufficient to produce affective outcomes for employees. This disconnect between cognition and emotion suggests that while TAM effectively predicts utilitarian perceptions and behavioural intentions, it does not adequately explain psychological outcome variables such as sense of belonging, esteem, and emotional satisfaction (Davis, 1989).

Recent empirical evidence supports this distinction. Whereas AI may enhance task efficiency, technology simultaneously induces emotional ambivalence through increased workload expectations or surveillance concerns (Chang et al., 2024). In contrast, POS demonstrated a strong positive correlation with satisfaction, supporting the proposition that employees' affective attachment is based not on technological functionality but on perceived organisational care and justice (Eisenberger et al., 1986).

According to Caesens and Stinglhamber (2020), the perception that one's organisation genuinely cares constitutes socio-emotional capital that offsets technology-related stress and enhances

employee morale. Accordingly, for South African SMMEs, affective satisfaction derives primarily from relational reassurance rather than from cognitive suppositions about technology, further supporting the integration of human and technical dimensions within digital transformation initiatives.

6.9.2 Mediated and Moderated Dynamics

The simultaneous study of mediation and moderation deepens the knowledge of how TAM and POS act jointly in the determination of job satisfaction. The mediation study indicated that PU was unable to mediate the effect from ease of use to job satisfaction implying that even though the usefulness of AI was cognitively perceived, it was not an affective conduit for mediating perceptions of usability to satisfaction outcomes. This finding is congruent with the international findings that perceptions of technology are more task than affect oriented (Venkatesh et al., 2016).

The results of the moderation tests showed a marginally significant second-order interaction between the latent structure of POS and PU, whereby high contextual support tends to dampen reliance on AI's instrumental value for the satisfaction of users. Eisenberger et al. (2020) describe POS to act as a social buffer reducing environmental pressure and increasing resilience. In contexts where support is salient, the users nevertheless remain satisfied whether the instrumental value of AI varies considerably or not. However, where there is a significant lack of support, the users show increasing tendency to become dependent on perceived usefulness of technology, for case similarly, as avenues of compensatory achievement and competence.

This is particularly important for capital constrained SMMEs. Fatoki (2019) and Hlatshwayo (2023) highlight the fact that weak financial and human capital impede the ability of these firms to extend formal HR interventions to their employees. Employees are dependent on depending for either managerially driven empathy or technology driven motivational substitutes. The current findings support the notion that the perceived usefulness of AI plays a compensatory role in the absence of support, a pattern consistent with the JD-R model (Bakker & Demerouti, 2017).

In circumstances of resource scarcity, technology serves as a compensatory resource enhancing perceived capability; however, its motivational function declines when resources are abundant. Similar observations were made in which the mediating effect of organisational support on the relationship between AI-induced changes and employee satisfaction and trust were found among Indian SMEs (Raji & Ismail, 2023). The findings for South Africa therefore confirm that POS

functions as a situational buffer stabilising levels of satisfaction and protecting employees from the turbulence of technological change.

6.9.3 Model Refinement for Emerging Economies

Synthesizing these results yields an important conceptual contribution. The combined TAM-POS framework provides a more nuanced account of job satisfaction in the context of technology implementation, especially within emerging economies. Classical TAM frameworks assume rational decision-making under stable conditions; however, in South African SMMEs, technological change often arises within contexts of structural uncertainty, informal management practices, and socio-economic pressures (Rambe, 2024).

The findings demonstrate that whereas TAM's cognitive paths (PEOU → PU) remain robust, translating these into satisfaction outcomes is conditional upon organisational climate. POS emerges as both a situational facilitator and a theoretical extension that fills the gap between cognitive appraisal and affective response. This integration supports arguments that TAM should be adapted to incorporate organisational and affective dimensions that reflect real-world adoption contexts (Venkatesh & Bala, 2008).

The refined model aligns with arguments that trust and perceived fairness complement perceived usefulness in explaining technology-facilitated systems (Almeida et al., 2025). From a contextual perspective, South African SMMEs present unique cultural and operational dynamics that necessitate such refinements. Analyses by Mbatha (2024) and Sibiyi et al. (2023) reveal that South Africa's small businesses face persistent digital divides, skills shortages, and infrastructural constraints, all of which shape employees' perceptions of technological change.

In such environments, organisational care and relational communication prove more determinant than technical efficiency alone. The refined TAM-POS model thus recognises that satisfaction is not merely an outcome of technology perceptions but results from a socio-technical balance between instrumental advantages and perceived organisational care. This integrated view frames technology implementation within the broader tradition of human-centred digital change, rendering the model uniquely relevant to African and developing-nation contexts where human capital and organisational support remain determinants of sustainable technology uptake.

6.10 Comparison with Literature

6.10.1 Alignment with Global Studies

The findings of this research, in part, corroborate the results of study on technology adoption worldwide, especially in relation to the validity of the fundamental cognitive processes of which TAM is comprised. The strong relationship between PEOU and PU is supported by international evidence, especially among the countries of Asia and the OECD. Thus, for example, Kumar et al. (2024) found that the perceived ease of integrating AI technologies considerably strengthened that perceived usefulness and efficiency among micro and small enterprises in India. Some such relationships were also discovered among European and North American enterprises, where the perceived ease of application of tools associated with AI in operating the enterprises positively correlated with the intentions of those enterprises to adopt AI. (Díaz-Arancibia et al., 2024).

These analyses, undertaken at the same time, show that cognitive variables such as perceptions of ease of use and perceptions of usefulness serve as cross-cultural variables influencing technology acceptance. Variance is apparent when it comes to affective outcomes such as job satisfaction which was apparently not influenced by perceptions of usefulness in this study. Chang et al. (2024) and Tarafdar et al. (2019), however, found that while technology provides a benefit in performance, it also causes techno-stress and emotional exhaustion which has a neutral or negative effect on satisfaction.

This result applies to the context of South Africa where perceptions of AI's usefulness at a cognitive level may exist alongside uncertainty at a human level regarding what AI will mean for humans. Comparative literature also shows that organisational support, mitigates the negative affective implications of technology adoption across nations. Dependent studies conducted by organisations involved in the OECD show higher employee well-being when transparent communication, training, recognition accompanies implementation of technology (Eisenberger et al., 2020; Morandini et al., 2023).

The positive relationship observed between POS and job satisfaction in this study is consistent with these findings, suggesting that supportive and inclusive organisational cultures can alleviate fear and anxiety commonly associated with digital transformation. However, the marginally significant moderating relationship observed in this study suggests that in developmental contexts

where formal human resource structures are limited, the buffering capacity of organisational support remains inconsistent.

As noted by Du Plessis and Swart (2024), South African organisations tend to rely on relationship-based rather than institutionally formal support mechanisms, resulting in support practices that are episodic rather than consistent. Accordingly, while the cognitive aspects of TAM appear universal, affective processes remain context-dependent, reaffirming the need for holistic frameworks that incorporate social and cultural contingencies, particularly in emerging markets.

6.10.2 Divergence in the South African Context

The South African SMME environment exhibits distinctive patterns that differentiate it from high-income economies. The lack of a significant relationship between PU and job satisfaction suggests that functional benefits of AI are overwhelmed by surrounding factors, including economic insecurity, skill asymmetry, and trust deficits. Mbatha (2024) attributes this phenomenon to the persistent digital divide, where exposure to technology varies widely across sectors, thereby constraining the development of shared digital competence.

Sibiya et al. (2023) also highlight structural impediments such as insufficient financing, poor infrastructure, and fragmented security provisions that deter the emergence of stable organisational environments conducive to employee satisfaction. Consequently, employees are likely to view AI as an externally prescribed efficiency instrument rather than an enabling device. In this respect, the superiority of POS over TAM variables in predicting job satisfaction aligns with evidence that South African employees place greater value on labour security and relational equity than on technological sophistication when assessing workplace quality (Hlatshwayo, 2023). Culturally, collectivist values common to many South African workplaces further emphasise social cohesion and support in achieving satisfaction outcomes. The robust predictive power of perceived organisational support (POS) observed in this study can be understood through a cultural lens, aligning with arguments that in collectivist contexts, employee well-being derives from relational harmony rather than individual performance metrics (Imran et al., 2020).

Organisational care, ultimately, serves to symbolise inclusivity and respect, thus alleviating the feelings of alienation often associated with automation. These dynamics are also confirmed in the evidence that perceived AI threats to job security in South Africa are alleviated with evidence of genuine organisational concern about employees' growth and advancement (Murire, 2024). Thus,

while the international literature often assumes that technology driven efficiencies translate directly into employee satisfaction, the evidence in South Africa suggests a different causal sequence, whereby social reassurance is the primary source of satisfaction, leading to openness to technology ultimately. This contextual difference strengthens the case for similar technology adoption models to include the cultural and institutional elements in order to secure both theoretical and practical applicability across diverging economies.

6.10.3 Lessons from Emerging Economies

The patterns observed in South Africa mirror those found in other emerging markets, underscoring the importance of human-centred organisational support in translating technology implementation into employee satisfaction. In the Nigerian context, Bushe (2019) and Rambe (2024) found that although functional performance improved following technology implementation, employees in small and medium-sized enterprises (SMEs) experienced mixed emotions due to insufficient training and lack of psychological support. Similarly, Zhou et al. (2024) reported that perceived organisational support (POS) mitigates negative emotions caused by technology-driven role ambiguity, thereby facilitating smoother transitions. Evidence from India also reflects this pattern. Raji and Ismail (2023) and Kumar et al. (2024) found that employee confidence and satisfaction increased only when supportive supervision and opportunities for career growth accompanied technology implementation.

Overall, these cross-national studies confirm that organisational support is a universal emotional resource that decreases the psychological distance that arises during technology-fuelled changes in the workplace. From a theoretical standpoint, the cross-country similarities among emerging market economies provide evidence to support and validate the cross-market integration of the TAM-POS model proposed in this study. The resistance to technology observed in the recent empirical literature is more likely to be attributed to psychosocial uncertainty, rather than technical obsolescence (Golgeci et al., 2025). The intergrating model utilised in this study offers a theoretical advancement in breathdng light on how social support ameliorates the affective implications of cognitively appraising technology. Additionally, it adds to global discourses around inclusive digital transformation by providing an indicative representation of how successful technology implementation is an outcome of both technical efficiency and the empathic capacity of an organisation for change.

The implication for developing countries is clear while cognitive acceptance is vital for the uptake of technology, socio-organisational reassurance is vital to ensure its sustainability. Achieving a balance makes it possible for companies to turn AI from a potentially disruptive force into an enabling force that enhances productivity and employee well-being.

6.11 Theoretical Implications

6.11.1 Extension of TAM Through POS Integration

The findings of this paper extend the traditional Technology Acceptance Model (TAM) further by integrating POS as a moderating variable to correlate the psychological as well as the environmental realities in relation to the process of technology implementation in SMMEs. The traditional TAM, developed by Davis (1989) and subsequently streamlined by Venkatesh and Davis (2000), represented a principally cognitive view of technology acceptance, concentrating on the cognitive applications of perceived ease of use (PEOU) and perceived usefulness (PU) which represented how behavioural intention and technology usage can be explained. However, this cognitive emphasis failed to adequately illustrate the emotionally laden and corporate dynamic factors which account for the trajectories of employees' lived experiences of technological change.

By including POS as a moderating variable, the model incorporates the socio-emotional dynamics that characterise employer-employee interactions, recognising that perceptions of technology and job satisfaction depend partially upon sentiments of care, equity and reciprocity within the organisation (Caesens & Stinglhamber, 2020; Eisenberger et al., 1986). This adjustment renders the TAM model transition from a purely cognitive-behavioural perspective to a socio-technical model that better reflects the relational and contextual nuances of employment ecosystems in emerging markets.

Incorporating POS in enhancing the model's ability to explain psychosocial outcomes such as job satisfaction. It has been shown that organisational support will reduce the employees' negative views of technological change reducing fear and resistance (Eisenberger et al., 2020). In this study, although PU alone was not a significant predictor of satisfaction, the inclusion of POS explained 52.9% of the variance in job satisfaction, with POS being the greatest predictor of job satisfaction. This shows that supportive environments greatly increase the emotional acceptance of technology-based changes.

In line with Raji and Ismail (2023), this finding shows that both trust in the organisation and perceived support impact on whether employees view technology as an empowering mechanism or as a controlling mechanism. Thus, the addition of POS to TAM unites affective satisfaction and instrumental utility by integrating cognitive and emotional determinants into one integrated explanation. The result is that the enhanced TAM-POS model is particularly applicable to South African SMMEs where relational trust replaces formal HR systems and social support is a vital buffer for managing the change imposed by technology.

6.11.2 Validation of the Moderated Framework

This research contributes to the literature by empirically testing a moderated framework that combines cognitive and organisational mechanisms to account for job satisfaction. While classical mediation was not supported, the moderation analysis revealed that POS moderates the relationship between perceived usefulness and job satisfaction, albeit marginally ($\beta = -0.140$, $p = 0.056$). This indicates that supportive organisational environments buffer employees from overreliance on technology as a source of satisfaction.

The framework validation underscores that employees derive job satisfaction through both cognitive appraisals of technology and socio-organisational dynamics. The extended model aligns with the Job Demands-Resources (JD-R) framework (Bakker & Demerouti, 2017), which posits that organisational resources such as perceived organisational support mitigate strain and enhance motivation under technology-induced demands. Empirical evidence supports this alignment: resistance to technology decreases when cognitive stress is buffered through organisational support (Golgeci et al., 2025).

Similarly, the primary benefit of POS is in the promotion of thriving and flourishing of employees, converting technological challenges into positive stress or techno-eustress (Imran et al., 2020). The moderating influences resulting from this research suggests that technology's emotional outcome is not derived from being technology-related, but rather a product of contextual processes associated with the organisational environment. This research provides an improved understanding of the conditional process mechanisms underpinning socio-technical systems, and extends the TAM and beyond towards dynamic relationships and explanatory frameworks rather than linear ones. The findings also reinforce calls from the authors that future generations of acceptance model should relate boundary conditions that are evident in individual-context interactions (Venkatesh et al, 2016).

The statistical evidence that POS weakens the link between PU and JST suggests that human-resource climates function as compensatory resources: when support is strong, satisfaction is less contingent on technology; when support is weak, employees depend more on perceived usefulness for well-being. This compensatory relationship aligns with the Conservation of Resources theory, which proposes that employees strategically deploy cognitive and affective resources in response to perceived organisational stability (Hobfoll, 1989).

6.11.3 Contribution to Human-Centred AI Literature

The research advances the human-centred literature on AI by illustrating empirically how perceptions of technology relate to well-being at work in an emerging-market economy. Most of the existing research considers technology mainly within efficiency and innovation frames (Oldemeyer et al., 2025; Soomro et al., 2025), whereas fewer consider the affective and social consequences for the workers. By placing job satisfaction as a central issue, this research locates the installation of technology within both technological and human dimensions, responding to calls for integrative models which look at digital transformation through frames of employee engagement and well-being (Morandini et al., 2023; Rick et al., 2024). The model indicates that for technology installation to succeed, systemic design is not enough, for systems require organisational practices which create autonomy, meaning and interpersonal trust.

The context of South African SMMEs offers an important contribution to international scholarship. Emerging economies are characterized by differentiated capabilities relative to established markets with respect to resources, digital literacy and institutional maturity. Local levels of analysis indicate that small enterprises typically operate in fragmented and non-complementary infrastructures and where their readiness for technology development occurs unevenly (Gaglio et al., 2022; Mhlongo & Daya, 2023). Given these factors, this study demonstrates that the TAM-POS model can be adapted and applied in context-specific ways. It also shows that while employees may cognitively recognise the usefulness of technologies, their satisfaction is ultimately based on relational assumptions of equitability and safety which frames workplace dynamics. This study extends the human-centred AI scholarship in a context beyond the Global North providing evidence for pluralistic and contextually valid scholarship from developing economies (Díaz-Arancibia et al., 2024). The study adds to a growing body of literature that calls for more attention to balancing technologically-driven advancements with human wellbeing considerations, acknowledging that sustainable digital transformation considers both the instrumental and socio-emotional aspects of work (George, 2024; Murire, 2024).

6.12 Practical Implications

6.12.1 Managerial Implications

The results offer critical managerial implications for South African SMME leaders navigating technology-driven change. Foremost, employees must remain central to the transformation process, and open communication is essential to alleviating fears of technological redundancy. Enthusiasm for innovation is sustained when managers frame technology functionality as an extension rather than a substitution for human labour (George, 2024).

The finding that POS strongly predicts job satisfaction underscores the importance of empathy, recognition, and distributive justice alongside technical competence. Accordingly, leaders should adopt collaborative change management approaches, such as town-hall meetings, co-design workshops, and iterative feedback mechanisms, to ensure employees are actively involved in decisions about technology implementation (Hlatshwayo, 2023; Murire, 2024). Such participatory engagement reduces resistance, converts perceived usefulness into affective commitment, and reinforces trust in organisational transformation processes.

Equally critical are ongoing investments to support digital literacy and continuing upskilling programmes. There is research evidence suggesting that formal structured reskilling in smart technologies enables a decrease in anxiety and develops employees' confidence (Morandini et al., 2023). Therefore, leaders of SMMEs should ideally engage employees in thorough, comprehensive, distal, and proximal training programmes, linking the technical and ethical aspects of AI, not just how the AI system is working but also why it is being used and how it benefits employees.

These inclusive approaches to learning build trust among employees, reduce resistance to change, and engage participation in organizational digital transformations driven by informed learning. When funding opportunities are limited, sharing networks, collaborative learning communities, or government-funded e-learning services can supplement or replace paid training opportunities (Rambe, 2024). Linking the training experience to rewards or opportunities for advancement can increase perceived organizational support, job satisfaction, and retention.

In addition, managers must reconfigure the performance management systems in their organisations away from technology metrics only, to becoming more human outcomes focused. Chang et al. (2024) warned that algorithmic monitoring that is too intense may cause "hindrance

stress" that reduces satisfaction. For example, involvement of performance management systems that are more sophisticated than simplistic inputs that account for both productivity as well as well-being is fundamental to ensure ethical accountability. Du Plessis and Swart (2024) demonstrated morale boosting actions in South African advertising agencies when AI dashboards were used together with personal development discussions.

Consequently, managerial practice should balance digital analytics with supportive structures that respect and honour employee agency and emotion. Human-centred leadership must become the core engine driving sustainable success in technology implementation practices among SMMEs, as no technological investment can compensate for a lack of care and consideration for the organisation.

6.12.2 Policy Implications

At the level of policy, the implications of the findings are clear: there is an urgent requirement for coherent national and provincial-level policy to support SMMEs in responsible, sustainable digital transitions. In this regard, public institutions like the Small Enterprise Development Agency (SEDA) and the Department of Small Business Development must grow the existing subsidisation structures to allow for targeted funding of training and technical assistance to support industry-related technology. By investing in capacity building and equitable technology use, such interventions would help to contribute to digital readiness, lessen inequalities in technology access, and be confident that SMMEs could more meaningfully adapt to South Africa's digital economy. The Gauteng Provincial Government (2022) has articulated a strategy for digital transformation and its implementation across agencies is still inconsistent due to a lack of cross-agency coordination.

Accordingly, it is the responsibility of policymakers to formally institutionalise support clusters for SMMEs, which could include the co-use of digital infrastructure, expert mentorship and guidance on data protection and the ethical use of technology. The establishment of these formalized support mechanisms can enable the principle of programs of support (POS) to be transposed to an implementable macro-policy, thus signaling the government's intent with regard to social welfare aspects and the advancement of the role of technology. In addition, regulatory frameworks could encompass compliance with ethical and social standards, through the deployment of digital innovation grants. Evidence from the Organisation for Economic Co-operation and Development (OECD, 2021) and the World Bank (2021) found that employment stability is improved when

attention is given to employee welfare during digital transformations. Legislation could require grant recipients to provide structured employee training and approaches to measure and support psychosocial wellbeing during the technological transformation.

In conjunction, Badghish and Soomro (2024) argue that sustainability indices must incorporate human development indicators as well to see whether technology efficient increases lead to a decline in job quality or organizational trust within SMME. In essence, these policies would create an enabling environment in which technology serves as a conduit for inclusive growth rather than an impediment resulting in labor displacement and increased anxiety regarding future sustainability.

6.12.3 System Design Implications

From a system design perspective, the research proposes that developers of AI technologies incorporate user-centred principles that accommodate human cognition, emotion, and feedback needs. Rick et al. (2024) highlight that work engagement is enhanced when AI interfaces are transparent, explainable, and offer real-time feedback to support user competence. Developers must therefore create dashboards and dialogue systems that explain reasoning, articulate learning progress, and support user adjustment.

Such design choices enhance perceived ease of use and strengthen perceptions that the technology itself embodies organisational care and empathy. Le Dinh et al. (2025) confirm that cognitive load is mitigated through intuitive design, which is critical for employees in SMMEs with diverse digital skill levels. Additionally, integrating affective-computing functionality, such as sentiment analysis of employee feedback or adaptive support mechanisms, can improve the system's responsiveness to users' emotional states. However, ethical safeguards must be integrated to avoid invasive monitoring and privacy violations (Meijerink & Bondarouk, 2023). To achieve this balance, co-design involving software providers, managers, and end-users is necessary. Prototype-testing workshops with SMME employees help ensure that tangible cultural and occupational realities align with usability principles.

Ultimately, AI system design must evolve toward an enabling feedback architecture that reflects organisational empathy in digital form, transforming the system from a monitoring tool into a learning and empowerment partner. This human-centred design philosophy aligns with broader

movements toward ethical AI that prioritise human dignity, autonomy, and well-being alongside efficiency and productivity (Raman et al., 2025).

6.13 Implications for Future Research

The present study provides directions for future research concerning employee outcomes in technology implementation within emerging markets. First, longitudinal research is needed to account for the temporal dynamics of adaptation and satisfaction. While cross-sectional analyses offer useful snapshots, they provide limited insight into how perceptions evolve over time. Longitudinal designs could explore whether initial optimism or anxiety toward technology remains stable or changes as organisational integration progresses, and whether POS moderates this adaptation trajectory (Raji & Ismail, 2023; Tarafdar et al., 2019). Following a cohort of employees over one to two years would allow researchers to determine whether job satisfaction follows a U-shaped trajectory beginning with disruption, progressing through adaptation, and culminating in renewed stability as technological competence is achieved. Such investigations would enhance causal inference and inform retention and well-being strategies for different phases of digital transformation.

Second, future research should investigate additional moderators that could refine and contextualise the TAM-POS framework in explaining job satisfaction under technology implementation. While the present study demonstrated that POS moderates the relationship between perceived usefulness and satisfaction, other psychosocial and organisational variables may further illuminate this dynamic. Constructs such as organisational justice, digital trust, psychological empowerment, and proactive personality traits are particularly salient within emerging-market workplaces where formalised HR systems are still developing (Maan et al., 2020; Zhou et al., 2024). Integrating these variables would enable researchers to examine complex conditional processes across sectors and uncover how technology-driven change interacts with human and contextual factors. Moreover, incorporating digital trust dimensions such as transparency, data privacy, and algorithmic fairness would respond to growing ethical discourse surrounding AI's encroachment on employee autonomy (Raman et al., 2025). By embedding these dimensions into the TAM-POS framework, future studies can advance toward a comprehensive psychosocial model of human-technology collaboration.

Third, a comparative study of macro-organisations versus small or medium-sized enterprises (SMMEs) may provide the potential to extend the TAM-POS framework. Macro-organisations tend

to have formalised human resource departments, sophisticated IT infrastructure, and formalised change management systems, while SMMEs primarily rely on informal networks and entrepreneurial leadership (Murimbika & Urban, 2023; Schoeman & Seymour, 2022). Understanding how organisation type influences the relationship to the TAM-POS framework would enable researchers to specify conditions of boundary limitations for the model. For example, future research could examine whether POS has a stronger effect on the relationship in smaller firms where interpersonal trust substitutes for the absence of formalisation of the framework or whether the formalisation of proceduralisation decreases the moderating effect in greater macro-organisations. This would allow researchers to discover and provide firm-based strategies for adopting digital transformation.

Lastly, qualitative approaches could provide findings that are complimentary and provide richer narratives of fear, adaptation, and resilience in technology-enabled workspaces. Ethnographic studies or interviews could help us understand the experiences of employees as they impose legitimacy upon the changing relation of perceptions about the technology and those organisational supports during their work life each day. These narratives could provide a richer description than what a survey could provide of daily context (Murire, 2024).

6.14 Chapter Summary

In this chapter, empirical data is presented in an interpretive synthesis that brings together both empirical results and the theoretical propositions from the first three chapters. The discussion shows that the classical relationships of the Technology Acceptance Model were evidenced in part. Specifically, Hypothesis 1, which states that perceived ease of use influences perceived usefulness (PEOU $\rightarrow$ PU), received evidence in a strong manner and aligns with previous empirical evidence (Davis, 1989; Almeida et al., 2025). Hypotheses 2 and 3, which posit a direct and mediated relationship for ease of use and satisfaction were not supported, respectively, which suggests perceived ease of use does not alone generate affective work outcomes, in this case, satisfaction among the SMME sample in South Africa. As a related point, Hypothesis 4 (PU $\rightarrow$ JST) was not statistically significant, suggesting that a realisation of the functional value of technology does not necessarily lead to increased job satisfaction.

This finding underscores the limited affective influence of perceived usefulness under certain organisational or contextual constraints (Raji & Ismail, 2023). It aligns with contemporary findings that employees' cognitive acceptance of technology is not inherently in conflict with emotional

well-being when it is supported by trust and equity (Chang et al., 2024). Hypothesis 5 received marginal support, revealing that POS moderates the PU-JST relationship ($\beta = -0.140$, $p = 0.056$), suggesting that supportive organisational environments act as buffers against excessive dependence on technology for satisfaction. In post-hoc analysis, POS demonstrated the strongest direct relationship with job satisfaction ($\beta = 0.576$, $p < .001$), substantiating the social-exchange assumption that employees reciprocate organisational support with positive affect and heightened commitment (Eisenberger et al., 2020).

As a whole, these findings illustrate that while technology acceptance is influenced by the cognitive components that are encapsulated by TAM it is simultaneously regulated by the emotional aspects relating to the level of satisfaction, as represented by POS. Based on this synthesis, it is also evident that simply having technology will not advance employee morale, it must be implemented within a supportive organisational framework that fosters trust, inclusion and equity for employee and owners. Therefore, this discussion lays the theoretical and empirical groundwork for Chapter 7, where the findings are directly linked to practical managerial successes and a plan of action for a sustainable, human-centred, technology integrated strategy for South African SMMEs to pursue.

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

7.1 What Did the Study Examine and Why Does It Matter?

This study examined how the theoretical determinants of technology acceptance perceived ease of use (PEOU) and perceived usefulness (PU) influence job satisfaction among employees working in South African SMMEs that have implemented AI technologies. The study employed the Technology Acceptance Model (TAM) as its conceptual framework while incorporating perceived organisational support (POS) as a moderating construct. The research sought to explain how perceptions of technology and organisational processes jointly determine employees' affective and cognitive responses to technology implementation.

The study is pertinent due to the imperative for digital transformation among SMMEs to gain a competitive advantage within the Fourth Industrial Revolution, yet the human dimensions remain under-researched in emerging economies (Badghish & Soomro, 2024). Although previous literature has predominantly focused on operational performance and cost optimisation, the present study foregrounds the human dimensions of technology implementation, recognising that employee trust and satisfaction are ultimate determinants of sustainable digital transformation (Raji & Ismail, 2023).

SMMEs account for over 60% of employment and contribute approximately one-third of South Africa's GDP, underscoring the importance of their digital advancement to national productivity (Gauteng Provincial Government, 2022). However, the majority of these enterprises continue to face critical challenges, including constrained financial resources, limited digital competencies, and diminished worker morale during periods of technological change (Muzam, 2023). In this context, the study is significant for its human-centred perspective, recognising that the viability of technology implementation extends beyond technical competence to encompass employee engagement, perceived fairness, and organisational empathy. By empirically validating a moderated framework, this research bridges the gap between cognitively focused technology acceptance frameworks and socio-organisational behaviour theories.

In doing so, it offers both academic and practical contributions by demonstrating that technology implementation, when supported by robust organisational systems, can enhance rather than erode employee well-being in South Africa's SMME sector (Eisenberger et al., 2020). Furthermore, the study contributes to international scholarship by extending TAM to contexts

characterised by resource constraints, informality, and relational workplace cultures prevalent across African enterprises (Gaglio et al., 2022). Through conceptualising job satisfaction as both an outcome and a lens through which to understand the interplay between technology and society, the study advances a more integrative understanding of digital transformation, one that transcends Western-centric models of efficiency. Ultimately, the findings affirm that the sustainable future of technology implementation rests in harmonising automation with empathy, efficiency with equity, and innovation with inclusion.

7.2 What Was the Research Context and Why Does It Matter?

The study was conducted within South Africa's rapidly digitalising yet economically turbulent SMME sector. This context is particularly significant as it contrasts remarkable innovation potential with entrenched structural challenges, including socioeconomic inequalities, infrastructural deficits, and inconsistent policy implementation (Mbatha, 2024). The SMME landscape is highly pluralistic, encompassing a spectrum from microenterprises operating in informal township economies to medium-sized firms in technologically advanced urban hubs such as Johannesburg, Cape Town, and Durban.

Most of these companies are now exploring AI-driven applications such as customer relationship chatbots, sales forecasting, and digital marketing analytics to gain a competitive advantage (Du Plessis & Swart, 2024). Despite increasing diffusion of digital technologies within SMMEs, employees often exhibit ambivalence toward their implementation, perceiving them simultaneously as opportunities for skill enhancement and as threats to job security (George, 2024). Understanding this psychological ambivalence provides a crucial foundation for analysing job satisfaction within technology-augmented workplaces, where technological integration redefines both task performance and the meaning of work itself. South Africa's developmental and institutional environment amplifies the relevance of this inquiry. Although national initiatives such as the Digital Transformation Strategy for SMMEs (2022) advocate integrating AI into business processes, implementation has remained limited due to inadequate training resources and weak organisational support structures (Achieng & Malatji, 2022; SEDA, 2024).

Consequently, employees are often confronted with technological transitions without sufficient guidance or reassurance, undermining both job satisfaction and organisational trust (Schultz, 2021). The present study's emphasis on POS directly addresses this gap by examining whether organisational empathy and support mechanisms can mitigate psychological disruptions

associated with digital transformation. Furthermore, the study situates technology implementation within South Africa's collectivist and relational workplace culture, where interpersonal trust frequently substitutes for formal governance mechanisms (Murimbika & Urban, 2023). The South African SMME sector provides an ideal setting for analysing the augmented TAM–POS framework. Its structural diversity and adaptive business dynamics offer valuable insights into how small enterprises interpret, adopt, and internalise technologies differently from larger corporations.

Positioning the study within this context enhances both its theoretical significance and practical applicability, allowing findings to be transferred to other emerging economies experiencing comparable digital transformations (Díaz-Arancibia et al., 2024). This contextual focus underscores the critical need for strategic alignment between technological advancement and workforce stability, a balance central to achieving sustainable and inclusive development.

7.3 What Did We Already Know and Not Know?

Existing research has established prior insights into the interrelatedness of individual perceptions of technology and job satisfaction. Within TAM, perceived usefulness and perceived ease of use are key cognitive motivators establishing the extent of the acceptance of the technology (Venkatesh & Davis, 2000). In the meantime, the theory of organizational support states that employees perceive their organization as fair, caring and supportive and reciprocate with heightened levels of job loyalty and satisfaction therefrom (Caesens & Stinglhamber, 2020). Empirical studies within developed economies also indicated that the implementation of technology leads to greater productivity, creativity and strategic flexibility, given that it is undertaken within supportive organizational contexts (Rick et al., 2024). There was however, a pronounced gap with regard to how this is catered for in developing countries such as South Africa where the technological infrastructure and managerial sophistication as well as the general socio-economic conditions are vastly different from those found in high income economies (Badghish & Soomro, 2024).

In particular, it was still unclear if TAM, which was formulated in developed, resource-abundant work contexts, had any predictive validity for small, resource-constrained enterprises. There was little empirical evidence that the efficiencies gained from technology resisted or undermined job satisfaction in conditions of job insecurity and limited employee voice (Mhlongo & Daya, 2023). Similarly, while theoretical postulates stated that an organisational setting that is supportive can

buffer emotional distress due to technological change, the empirical moderating role of POS on the technology perception-satisfaction relationship had not been explored in SMME contexts (Maan et al., 2020). The current literature falls short of offering a meaningful whole socio-technical explanation integrating cognitive, affective, and environmental determinants of employee satisfaction in the context of digital transformation.

This research contributes to addressing these knowledge gaps by providing empirical findings concerning the classical constructs from TAM as partial determinants of employee beliefs about technology in South African SMMEs. Although perceived ease of use significantly influenced perceived usefulness, both constructs did not directly influence job satisfaction, leaving a gap between cognitive acceptance and affective fulfilment. Additionally, the study concluded that POS has both a direct positive effect on satisfaction and a slight dampening effect on the positive effect of usefulness on satisfaction. Overall, this study helps to bridge a substantial empirical gap in technology adoption studies by articulating a multi-theoretical model related to both technology affordances and organisational empathy as joint predictors of employee wellbeing.

7.4 What Specific Questions Did the Study Answer?

The central research question: How can the Technology Acceptance Model be augmented to capture the interaction between technology perceptions (perceived ease of use and perceived usefulness) and job satisfaction among employees within South African SMMEs was addressed through five interrelated hypotheses that integrated both cognitive and socio-organisational dimensions. The ensuing analysis provided nuanced insights into each construct, collectively illustrating how technological perceptions and organisational support mechanisms converge to shape employees' evaluative and affective responses toward technology-driven transformation.

Firstly, for H1 (PEOU $\rightarrow$ PU), findings confirmed a strong positive relationship ($\beta = 0.673$, $p < 0.001$). Employees who found AI systems easy to use also deemed them useful for task performance. This result supports the TAM claim that perceived utility is enhanced by ease of use, aligning with findings from Almeida et al. (2025) and Kelly et al. (2023).

Secondly, H2 (PEOU $\rightarrow$ JST) and H3 (PEOU $\rightarrow$ PU $\rightarrow$ JST) were not supported, revealing that while cognitive approval is fostered through ease of use, this does not directly translate to emotional satisfaction. This finding suggests that technical ease alone is insufficient to elicit a sense of fulfilment without supplementary social or motivational reinforcement (Gerli et al., 2022).

Thirdly, Hypothesis 4 (PU → JST) was not statistically significant, deviating from classical TAM expectations. Although employees recognised the usefulness of AI systems, such perceptions did not translate into heightened job satisfaction. This finding signals a critical divergence in the traditional cognition-affect relationship, suggesting that perceived technological utility may be overshadowed by underlying psychosocial apprehensions, particularly concerns regarding surveillance, redundancy, and loss of professional autonomy (Chang et al., 2024).

The result underscores the need to extend TAM to incorporate emotional and contextual moderators that capture the human dimensions of automation in emerging-market workplaces. Hypothesis 5 (POS moderates PU → JST) received marginal support ($\beta = -0.140$, $p = 0.056$), indicating that extensive organisational support may shield employees from excessive reliance on technology value for satisfaction.

In post-hoc analysis, the direct relationship between POS and JST was very strongly supported ($\beta = 0.576$, $p < 0.001$), confirming that employees with higher perceived organisational support exhibit substantially higher satisfaction levels regardless of technology perceptions. Although this relationship was not the primary focus of the study and emerged through exploratory analysis, it provides important contextual insight into the relative importance of organisational versus technological factors in determining satisfaction within South African SMMEs.

Taken together, these findings address the central research inquiry by demonstrating that the theoretical determinants of technology acceptance, perceived ease of use and perceived usefulness, contribute to cognitive evaluations of technology but do not directly enhance job satisfaction. Instead, job satisfaction is primarily influenced by perceived organisational support, suggesting that technology implementation must be embedded within supportive and relationally attuned organisational cultures to yield positive affective outcomes.

In essence, technological perceptions and emotional satisfaction are related but distinct phenomena. Cognitive acceptance of technology arises from perceived ease and functional utility. In contrast, emotional satisfaction, rooted in trust, fairness, and organisational support, serves as the anchor for sustained job well-being. Together, these dual dimensions illustrate that technology acceptance is both a rational and relational process, dependent as much on perceived utility as on the quality of the socio-organisational environment in which it is embedded. This deepened empirical clarification extends theoretical models and guides the design of managerially led ethically informed digital transformations.

7.5 How Were These Questions Answered (Research Methodology)?

The study design was positivist, quantitative, and cross-sectional, employing a survey methodology to test the augmented TAM-POS framework. This design ensured objectivity, replicability, and statistical generalisability, key tenets for analysing causal relationships among measurable constructs (Babbie, 2020). Data were collected through an online structured questionnaire administered via purposive and snowball sampling among employees of SMMEs that have implemented AI technologies across several sectors.

The final sample consisted of 145 usable responses, sufficient for partial least squares structural equation modelling (PLS-SEM), which permits simultaneous examination of mediation and moderation effects (Cheah et al., 2024). Measurement instruments were drawn from established, validated scales: items developed by Davis (1989) for PU and PEOU; Spector's (1997) Job Satisfaction Survey; and the Perceived Organisational Support scale by Eisenberger et al. (1986).

All items were rated on a seven-point Likert scale. Reliability testing yielded Cronbach's alpha values ranging from 0.947 to 0.967 for individual constructs, indicating excellent internal consistency. Confirmatory factor analysis (CFA) further demonstrated satisfactory model fit (SRMR = 0.065; NFI = 0.890). Discriminant validity was confirmed using the Fornell–Larcker criterion and heterotrait–monotrait (HTMT) ratios, supporting construct distinctiveness (Henseler et al., 2015).

All of the survey items were measured by using a seven-point Likert scale. Reliability testing indicated good internal consistency, as evidenced by the Cronbach's alpha 0.947 to 0.967 for each of the individual subscales. The confirmatory factor analysis (CFA) reported acceptable model fit with a SRMR = 0.065 and NFI = 0.890. Discriminant validity of constructs was determined by the Fornell-Larcker criterion and Heterotrait–Monotrait (HTMT) ratios, further supporting the separation of constructs (Henseler et al., 2015).

The SmartPLS software facilitated robust modeling of direct, indirect, and interactive effects. The findings indicated PEOU is a strong predictor of PU, and TAM remained valid, but the cognitive variables showed no significant relationships relative to job satisfaction. Nevertheless, POS was the strongest predictor of satisfaction and showed a marginal moderating effect on the PU-JST relationship. This intentional methodological choice resulted in empirical clarity while improving external validity. Specifically, the study blended an acceptable range of validated theoretical

instruments while also incorporating measurement strategies designed for the context, thus yielding credible evidence that is contextually valid for SMMEs operating in emerging markets.

7.6 What Did the Study Find, and How Were the Findings Interpreted?

The analysis indicated a definitive hierarchical structure among the determinants of job satisfaction within technology-enabled SMMEs. Specifically, perceived ease of use acted as a significant predictor of perceived usefulness, thus reinforcing the conclusion that user perceptions of technological value are enhanced when the AI systems are perceived to be easy to use and accessible. This finding is consistent with past research which has shown that technology acceptance only occurs when there is readiness in terms of usability of the system (Kelly et al., 2023). However, contrary to expectation, the relationship between perceived usefulness and job satisfaction was not positive. Employees, while aware of the technological utility of the AI technology, appeared to have affective responses that were neutral likely due to the fear of unemployment, surveillance and reduced autonomy (Mossavar-Rahmani & Zohuri, 2024).

The most compelling finding was the pronounced impact of perceived organisational support on job satisfaction. Even though this relationship was not the main focus of the study and was derived from post-hoc analyses, POS still accounted for over 50% of the variance in satisfaction ($R^2 = 0.529$), which demonstrates that employees do not purely derive satisfaction from the technological construct in the workplace, but rather the socio-organisational component. When employees feel valued, supported and equitably treated, they are more likely to embrace a technology-driven change with a positively biased attitude (Eisenberger et al., 2020). The moderately significant moderation effect ($\beta = -0.140$, $p = 0.056$) indicates that in a highly supportive environment, satisfaction becomes less reliant on the perceived usefulness of the technology. In other words, supportive organisational contexts help to stabilise morale even when technology does not deliver on performance or utility expectations.

Examining these results through the lens of the Conservation of Resources theory indicates that perceived organisational support acts as a resource buffer, allowing employees to manage emotional reserves and psychological market place in the face of technology uncertainty (Hobfoll, 1989). Similarly, the results corroborate the Job Demands-Resources model articulating that resources in the organisational context alleviate or mitigate stress and at the same time increases motivation to perform with significant workload or high job demand (Bakker & Demerouti, 2017). Therefore, the findings indicate technology implementation does not reduce job satisfaction as a

rule but rather was contingent on aspect of supportive organisation structures in the digital transformation. Results indicate the perceived ease of use and perceived usefulness are good predictors of cognitive evaluations derived from technology related implementation; however, was not a good predictor of affective outcomes such as satisfaction. Instead, the perceived organisational support is the greatest indicator of employee well-being in South African SMMEs.

7.7 How Does This Add to the Scholarly Debate (Theoretical Relevance)?

The study advances theoretical discourse by empirically validating an extended TAM that integrates organisational and affective dimensions, thereby progressing beyond cognitive acceptance to encompass the broader spectrum of employee experience. It addresses the longstanding critique that TAM is overly rationalistic and insensitive to affective and contextual determinants (Tamilmani et al., 2021). By substantiating POS as an important construct within the model, this study bridges technology acceptance theory and organisational support theory, thereby advancing a socio-technical synthesis highly relevant to digital-era work environments (Raji & Ismail, 2023). The results strengthen human-centred literature on AI, demonstrating that satisfaction and trust depend on perceived support and fairness, consistent with emerging literature on human–technology interaction (Morandini et al., 2023).

This study advances a conceptual innovation with theoretical potential to be included in future models, such as the UTAUT3 (Venkatesh et al., 2016), by integrating psychological safety and social reciprocity with the Technology Acceptance Model (TAM). By examining psychological safety and social reciprocity in the context of African SMMEs, this study also challenges the geographical biases embedded in existing models, most of which are built using datasets from developed economies (Díaz-Arancibia et al., 2024). Finally, this study demonstrates the declining predictive power of perceived usefulness on job satisfaction, suggesting the emergence of "automation ambivalence". These findings indicate that further theorizing is needed of the dynamics between technology adoption, job satisfaction, and worker well-being as user outcomes are increasingly governed by psychosocial and ethical dynamics, as opposed to just normative instrumental efficiency.

Consequently, the research locates POS as a formative mediator between cognitive acceptance and affective well-being in a way that adds theoretical intensity to the conversation around sustainable and human-centred technology engagement. The contribution from theory is demonstration that cognitive paths of the TAM, while valid for predicting intentions to behave,

require extension to incorporate socio-organisational variables to explain affective outcomes in constrained resources, relationally driven workplace cultures.

7.8 What Is the Practical and Business Relevance of the Findings?

The implications of the results are practically extended to the SMME sector leaders, government policy makers, and technology developers. The results indicate to managers that successful technology implementation takes as much attention to managing its people as it does to providing technical support. It may be worthwhile for managers to devote energy to employee engagement, open communication, and collaborative decision-making, particularly when the technology is improvements of a digital transformation (Murire, 2024). Regular training workshops, pointed co-design sessions, and transparent communication in organisational intentions for use of technology, are most likely to ease employee fear of job loss and help foster their confidence. Incorporating a reskilling process that is linked to employee reward and remaining a path for career advancement contributes to perceived organisational support, and promotion of retention (Morandini et al., 2023). The conclusion that perceived ease of use has a strong effect on perceived usefulness, but not a direct effect on satisfaction, means that managers cannot rely solely on the ease of use of the technology to enhance employee well-being.

The implementation of technology must be supplemented by intentional attempts to develop an organizational culture of support. By acknowledging employee contributions, offering opportunities for consistent engagement in technology-related decisions, treating everyone equally, and showing concern about employee's welfare when change occurs, organizations signal commitment to their employees and develop the trust and reciprocity that are essential in improving job satisfaction (Rhoades & Eisenberger, 2002). These implications also help policy-makers consider institutional options to support the technology implementation balance. For example, institutions such as the Department of Small Business Development and SEDA must do more to provide support for digital training, develop ethical certification for AI use, and increase support for mentorship initiatives to improve digital and technological skills. Indicators for social sustainability must also feature within national digitalisation strategies to provide equity, by including measures that consider employee and workforce welfare and job satisfaction, while ensuring progress is being made in an equitable manner (World Bank, 2021).

This type of policy coordination can situate technological innovation within the context of labour market stability which can help to lessen the likelihood of growing disparities in socio-economic

inequality. Policymakers must acknowledge that the introduction of technology without concurrent investment in human capital development and the associated organisational support infrastructure may produce efficiency gains at the expense of employee welfare and longer-term sustainability. Grants and subsidies aimed at helping firms to achieve their digital transformation should require, at a minimum, training employees, participatory design and implementation, and psychosocial support. From the perspective of design, developers must design AI applications that are based upon human-centred design principles that facilitate user autonomy instead of constraining it. Explainable and transparent interfaces promote trust by making algorithms visible, interpretable, and accountable to users (Le Dinh et al., 2025). Including employee voices in design encourages developers to design systems that account for real workflow design criteria and improves overall design usability and employee morale.

The finding that ease of use affects perceived usefulness highlights the significance of user-friendly design especially within the user communities representing SMME which included a range of digital ability. When developing for a SMME market, developers need to ensure systems are uncomplicated, clearly displayed and require minimal cognitive load on the user. Furthermore, instituting feedback systems that develop a way of allowing people to air their views or request improvements can in itself lead to a better perception of technological utility and organisational support. In conclusion, evidence suggests that the successful technology implementation depends on essential ethical, participatory and supportive organisational environments for technology in SMMEs. Technology will not facilitate employee success on its own, however current or efficient it may be. Sustainable digital transformation within an organisational environment requires human-centred, ethical organisation practices, which determine consideration of employee dignity, autonomy and well-being partner.

7.9 What Are the Suggestions for Future Research?

The research outlines multiple possibilities for future research that may advance understanding of the relationships among technology perceptions, organisational support, and job satisfaction. Initially, longitudinal analysis of the TAM-POS framework would be helpful in determining if pathways of job satisfaction evolve with continued exposure to AI technologies. Understanding the trajectory over time allows for the identification of point of inflection which may well have related themes of colliding job satisfaction phases: constructs of initial resistance, acceptance over time, and actual integration and understanding. It also allows for clarifying if organisational support continues to possess a buffering influence over the course of the digital transition

(Tarafdar et al., 2019). Longitudinal studies may also explore whether the relationship between perceived usefulness and satisfaction reaches a stronger association over time, as employees integrate the technology and reap the benefits, or whether they continue to be ambivalent because they are worried about surveillance and job security. Longitudinal studies would provide richer insights into how cognitive and affective reactions to technology evolve together over time in organizational contexts.

Secondly, it is worthwhile for future studies to assess additional possible moderators including organisational justice, digital trust, psychological empowerment, and proactive personality traits in order to further reconceptualise and extend the TAM-POS framework. Organisational justice, which can include considerations of distributive, procedural, and interactional fairness, can affect the way employees perceive LMT adoption and whether employees see the technology in an equity or exploitative manner (Colquitt et al., 2001). Digital trust, defined as confidence regarding issues related to security, data privacy, and ethical use of technology, may act as a moderating variable between perceptions of technology and positive technology driven work outcomes, which may be amplified by participant concerns of algorithmic bias and misuse of data (Raman et al., 2025).

Psychological empowerment, which is considered the employees' sense of meaning, competence, self-determination, and impact in carrying out their work roles, may serve to enhance the positive relationship between perceptions of technology in their work and their satisfaction with work, by developing a sense of agency and control (Spreitzer, 1995). Similarly, proactive personality dispositions may act as a moderator in these relationships, as those with proactive personality dispositions may be more likely to intentionally engage technology to enhance their work experience (Zhou et al., 2024). Studying these additional moderators would provide a greater understanding of the individual differences for the response to technology and the characteristics employees that could be considered individuals who thrive in technology-rich practice.

Third, conducting comparisons at the inter-sectoral and inter-organisational levels would illuminate whether or not the relationships within the TAM-POS model differ relative to the organisational context. For instance, comparative work with micro, small and medium enterprises would provide insight as to whether the community of practice and institutional theory, conceptualised through the relative weight of the perceptions of technology compared to the perceptions of organisational support, is related to the organisational size. In micro-organisations of fewer than 10 employees, for instance, interpersonal relationships with owners may be

particularly relevant which may amplify the role of the perceptions of organisational support (Murimbika & Urban, 2023). Comparative studies between South Africa and Nigeria, Kenya, India, Brazil and other emerging economies could also be useful in exploring socio-cultural and institutional impacts on employee satisfaction with technology implementation. Cross-national studies would provide insights into how socio-cultural values (i.e., individualism and collectivism), regulatory context and labour market condition models shape the relationships between the perceptions of technology and perceptions of organisational support in influencing employee outcomes (Díaz-Arancibia et al., 2024).

Fourth, employing qualitative research methodologies including ethnographic investigations or qualitative interviews may also complement quantitative insights of fear, adaptation, and resilience within tech mediated work environments. Qualitative methodologies may help dive deeper into more subtle experiences of employees that cannot be captured through surveys, including how employees navigate the tensions between their need for autonomy and pressure to be efficient or how they make sense of managers communication about technologies purpose, and consequences (Murire, 2024). Qualitative findings may also help enhance or refine theoretical aligned to a measurement in a more contextualised sense. Again, this needs to be complemented through sustainability agentic lenses. Future studies should look to utilise sustainability perspectives when exploring technologies conjoin in relation to the well-being and responsibility of organisations. As the awareness of the environmental sustainability of AI's footprint, ethical AI and data governance and its implications for employee's well-being and perceptions grow, understanding how this has an impact on employee satisfaction and satisfaction becomes more salient (Golgeci et al., 2025).

The investigation could determine if individuals employed by organizations committed to ethical AI practices and sustainability enjoy greater trust and satisfaction in their role regardless of the neutrality of their perceptions around technology. In totality, these directions for research would sharpen academic insight into the interplay between technologies, human emotion, and contextual realities, enhancing the expertise of scholars with respect to the changing nature of work in developing economies and digital transformation. Lastly, future research could return the construct of adoption as a behavioral outcome to complete the TAM sequence.

7.10 Limitations of the Study

Although this study generates valuable insight, there are a number of limits to be aware of as part of the interpretation. First, because the study is cross-sectional, meaning all perceptions were captured at the same period, establishing a causal effect or understanding how perceptions may change (as experience with the technology builds) has limited value. It should also be noted that longitudinal designs would enhance better causal inferences and shed light on the temporal nature of technology adaptation and satisfaction.

Second, the sample was drawn from South African SMMEs that have already implemented AI technologies, potentially introducing selection bias. Organisations that have successfully implemented technology may differ systematically from those that have not, in terms of resources, managerial sophistication, and organisational culture. Future research should include organisations at various stages of technology readiness to enhance generalisability.

Third, although the sample size ($n = 145$) was sufficient for a PLS-SEM analysis, larger samples would increase the statistical power of the study and detect smaller effects. The marginally significant moderation effect ($p = 0.056$) would likely become significant with larger samples, thus providing more substantive evidence of POS's buffering effect.

Fourth, the potential for common method bias continues to be problematic, even when actively tested, assessed, and incorporated into analyses. Data collected from one source at one point in time may lead to inflated relations between variables. Future studies could employ data collection from multiple sources that ask employees how they perceive the technology and manager ratings of organizational support and look for objective performance measurement in organizational records.

Fifth, the study focused specifically on AI technologies, which may possess unique characteristics compared to other digital tools. Findings may not fully generalise to other forms of technology such as enterprise resource planning systems, cloud computing platforms, or robotic process automation. Future research should examine whether the TAM-POS framework applies similarly across diverse technological contexts.

Finally, while the study included diverse industries and company sizes within the SMME category, sector-specific dynamics may influence relationships in ways not fully captured. Industry characteristics such as regulatory pressures in healthcare or creative demands in marketing may

moderate relationships among technology perceptions, organisational support, and satisfaction. Future research should explore these sector-specific nuances to enhance contextual understanding.

7.11 Concluding Remarks

This study explored the proposed theoretical determinants of the technology acceptance model, perceived ease of use, and perceived usefulness, in terms of job satisfaction among employees in South African SMMEs while accounting for the moderating effect of perceived organisational support. The results suggest that while cognitive appraisals of technology (ease of use leads to usefulness) framed within the context of the reasonable application of cognitive appraisal theory supports the traditional propositions of TAM, cognitive appraisals do not translate into affective outcomes, like job satisfaction. Instead, perceived organisational support was found to be the strongest predictor of employee satisfaction, highlighting that employee well-being at a technology-driven workplace are reflected primarily in relational and organisational conditions than in the technology itself. The marginal moderating effect indicates that organisational support acts as a buffer in the technology-perceived satisfaction relationship to stabilise employee morale regardless of perceived changes in utility of the technology.

The implications of these findings carry significant importance for theory and practice, as well as for policy. In terms of theory, the study contributes to the body of knowledge regarding the technology acceptance model (TAM) by not only emphasizing the need to integrate socio-organisational constructs in order to more fully explain the effects for the end user but by also offering the TAM-POS framework as a more holistic model accounting for both the cognitive and emotional aspects of technology experiences for work systems, specifically within resource-constrained, relationally driven workplace cultures found in emerging economies. In terms of practice, the implications of the findings are to stress that successful technology implementation requires equal weighting of both the human resource practices and the technological infrastructure. Managerial practices must create an organic supportive culture of trust, recognition, and open communication that facilitates employee involvement in order to secure a technology as an integrated perspective an empowering rather than displacing, or alienating tool to perform work. In order for policymakers to recognize the digital transformation strategies require an integrated approach to strategy which balances technology progress with workforce development and psychosocial support.

In conclusion, this study demonstrates that the future of work in a digital world rests not only on the level of technology that is adopted, but on our joint commitment to human dignity, organisational empathy, and inclusive growth. Technology, when integrated into the supportive and caring context of an organisation that values, protects, and nurtures employees' well-being and welfare, has the ability to increase productivity and well-being at the same time. However, technology applied without human-centred values can create workplaces based solely on efficiency, progress without equity, and innovation without inclusion. Just as SMMEs in recent years in South Africa are moving toward digital transformation and adoption, staying true to the idea of marrying technology with care by creating a context in which technology allows them to demonstrate that care for employees, community, and their organisational context is the next frontier. Sustainable success will depend not only on technology adoption, but also, and perhaps even more so, on integrating technological capabilities with human values, relational trust, and a supportive organisational context. This study helps to realise this vision by providing both empirical evidence and assisting with theoretical grounding in developing a more human- and planet-centered, egalitarian, and sustainable tech-enabled workplace in emerging economies and other contexts.

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Appendix A: Survey Questionnaire

Participant Information Sheet and Consent Form

Research Project Title: Artificial Intelligence Adoption and Job Satisfaction in South African SMMEs.

Researcher: Tawanda Pasipanodya, MBA Candidate, Gordon Institute of Business Science.

Contact: 23012588@mygibs.co.za

Supervisor: Dr Merle Werbeloff, Gordon Institute of Business Science.

Contact: merle@statsauntie.com

1. Invitation and Purpose of the Study

You are invited to participate in a research study for a Master of Business Administration (MBA) degree. The purpose of this research is to understand how the adoption of artificial intelligence (AI) technologies in South African Small, Medium, and Micro Enterprises (SMMEs) relates to employee job satisfaction. We are interested in your perceptions and experiences.

2. What is involved in the study?

Your participation will involve completing a single anonymous online survey. The survey includes questions about your demographic background, your perceptions of the AI tools you use at work, and your overall job satisfaction. The survey is expected to take approximately 5-10 minutes to complete.

3. Voluntary Participation

Your participation is completely voluntary. You can withdraw from the study at any time before submitting your final responses by simply closing your browser window.

4. Risks and Benefits

There are no foreseeable risks to you beyond those encountered in everyday life. The questions ask about your perceptions of your work environment. There are no direct benefits to you for participating, but your contribution will help provide valuable insights into creating better workplace environments during technological transitions.

5. Confidentiality and Anonymity

Your responses are completely anonymous. The survey does not collect any personally identifying information (like your name, email, or IP address), and your responses cannot be traced back to you. All data will be reported in an aggregated format in the final research report.

6. Data Storage

The anonymous data from this survey will be exported from Survey Monkey and stored in a password-protected, encrypted file on a secure university server. Only the researcher and the supervisor will have access to this data. It will be kept for a period of 10 years for archival purposes before being permanently destroyed.

7. Contact Information and Ethics Approval

This research has received ethical approval from the Gordon Institute of Business Science Research Ethics Committee. If you have any questions about the study, please contact the researcher or supervisor using the details above.

8. Academic and Popular Dissemination Consent

In line with the Gordon Institute of Business Science (GIBS) commitment to making research available as broadly as possible, the findings of this study may be disseminated through both academic and popular media channels.

Academic Dissemination may include:

- Research reports.
- Scientific articles in peer-reviewed journals.
- Conference papers.
- Academic book chapters

Popular Dissemination may include:

- Media platforms such as television or radio.
- Lay articles for broader public understanding.
- Books aimed at non-specialist audiences.
- Podcasts and other digital channels

Participation in this study implies consent for the anonymised results to be shared through the above academic and or popular outlets. Any dissemination will ensure strict protection of participant confidentiality and no identifying information will be published. Participants retain the right to indicate limitations on publication in specific media. Where such limitations are requested, the researcher will respect and document these restrictions.

9. **Consent to Participate**

- I confirm that I have read and understood the information provided above.
- I understand that my participation is voluntary and that I can withdraw at any time before submitting my responses.
- I understand that my responses are anonymous and will be treated with confidentiality.
- I understand that I will be asked to complete all sections of the questionnaire for consistency of data, but I am under no obligation to do so should I choose not to.

I agree and consent to participate in this study. (*Mandatory checkbox question in Survey Monkey*)

Section A: Demographic Information

What is your age?

- Under 18 (*End the survey*)
- 18–29
- 30–44
- 45–54
- 55 and above

What is your gender?

- Male
- Female
- Non-binary
- Prefer not to say

What is your current job title? (*Open-ended*)

What is your highest level of education?

- High School
- Diploma/Certificate
- Bachelor's Degree

- Honours/Postgraduate Diploma
- Master's Degree or higher

How many years have you been working in your current company?

- Less than 1 year
- 1–3 years
- 4–6 years
- 7–10 years
- More than 10 years

Which industry does your SMME operate in?

- Manufacturing
- Retail
- ICT/Tech
- Agriculture
- Education
- Services
- Other: *(please specify)*

What is the size of your company (number of employees)?

- Fewer than 10 (Micro)
- 11-50 (Small)
- 51–250 (Medium)
- More than 250 *(End the survey)*

Section B: Technology Acceptance

Please indicate your level of agreement with the following statements regarding the use of AI in your organisation. Use the scale: 1 = Strongly Disagree to 7 = Strongly Agree.

Perceived Usefulness (PU)

1. Using AI in my job enables me to accomplish tasks more quickly.
2. Using AI improves my job performance.
3. Using AI increases my productivity.
4. Using AI enhances my effectiveness on the job.
5. Using AI makes it easier to do my job.
6. I find AI useful in my job.

Perceived Ease of Use (PEOU)

7. Learning to operate AI systems is easy for me.
8. I find it easy to get AI to do what I want it to do.
9. My interactions with AI systems are clear and understandable.
10. I find AI to be clear and understandable.
11. It is easy for me to become skilful at using AI.
12. I find AI tools easy to use.

Perceived Organisational Support (POS)

13. My organisation values my contribution to its well-being.
14. My organisation strongly considers my goals and values.
15. My organisation really cares about my well-being.
16. Help is available from my organisation when I have a problem.
17. My organisation would forgive an honest mistake.
18. My organisation cares about my opinions.

Section C: Job Satisfaction

Please indicate how much you agree or disagree with the following statements about your job.

Use the scale: 1 = Strongly Disagree to 7 = Strongly Agree.

19. The work I do is meaningful.
20. My job gives me a sense of purpose.
21. I find my daily tasks stimulating and engaging.
22. I have enough variety in the tasks I perform.
23. I feel a sense of accomplishment from my work.
24. I have autonomy in how I complete my work.
25. My job allows me to apply my skills and knowledge.
26. AI has made my job more interesting.
27. Since the introduction of AI, I feel more empowered in my role.

Thank You

Thank you for taking the time to complete this survey. Your responses are greatly appreciated and will contribute meaningfully to our research.

Appendix B: Ethical Clearance Approval

GIBS ETHICAL CLEARANCE APPLICATION FORM 2025/26

G. APPROVALS FOR/OF THIS APPLICATION

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

STUDENT RESEARCHER/APPLICANT:

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

Student Researcher's Name in capital letters: TAWANDA PASIPANODYA

Date: 22 Aug 2025

Supervisor Name in capital letters: MERLE WERBELOFF

Date: 22 Aug 2025

Co-supervisor Name in capital letters:

Date: 22 Aug 2025

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

Decision:

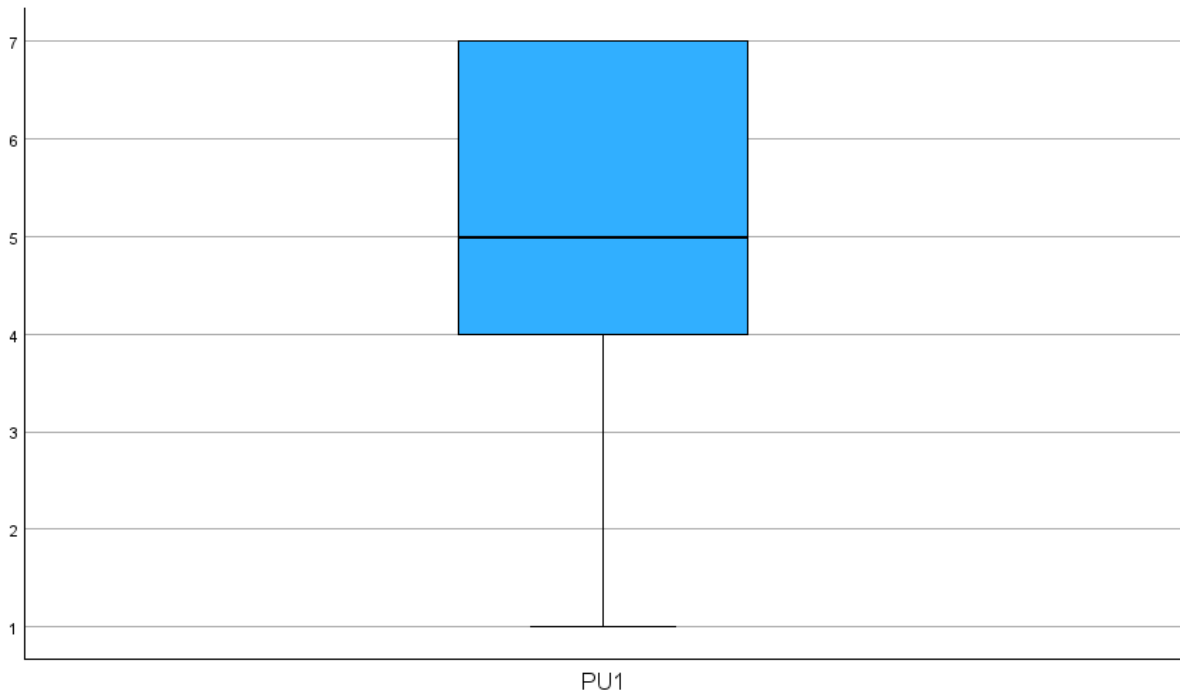
Approved

REC comments:

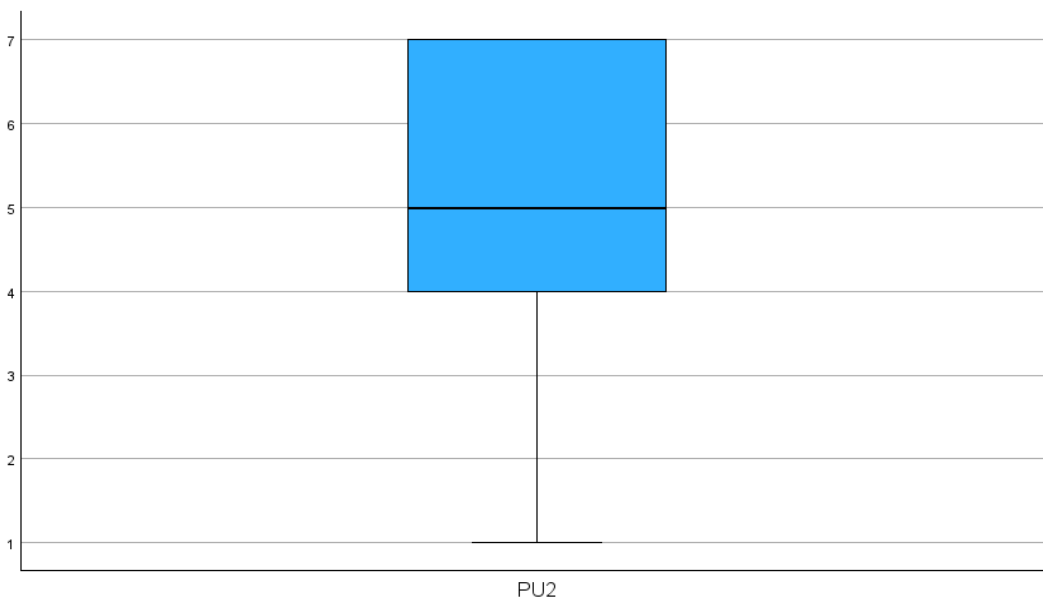
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Appendix C: Extreme outliers' analysis with boxplot

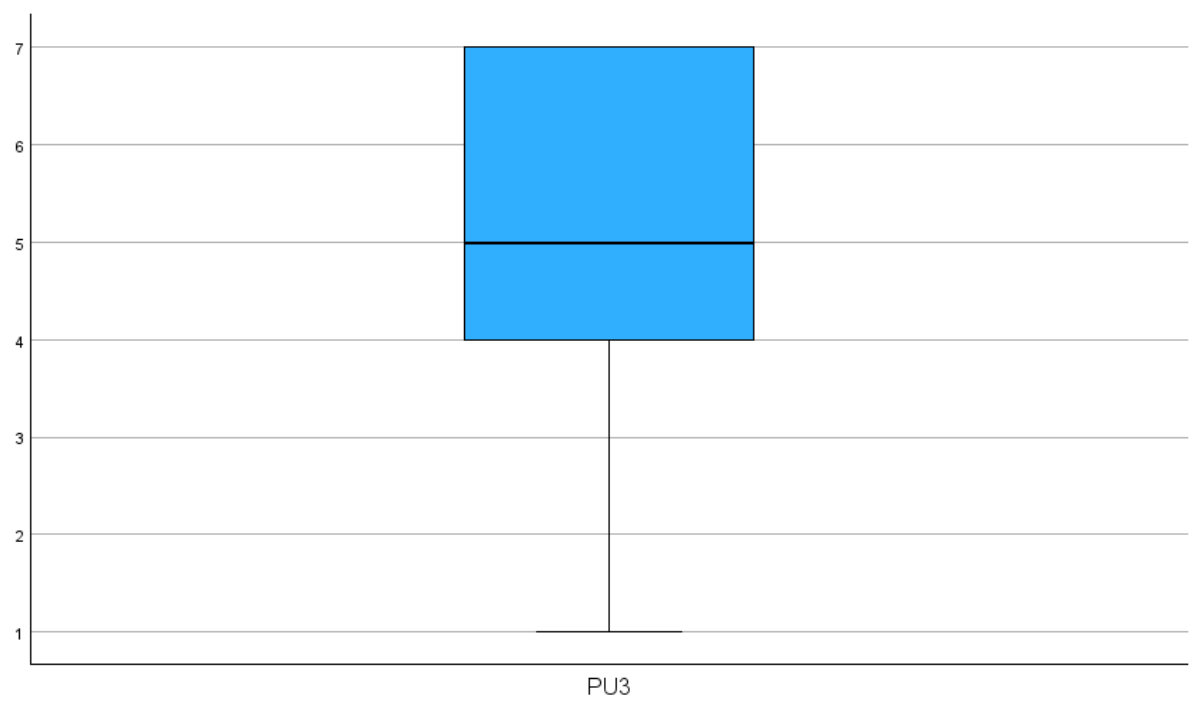
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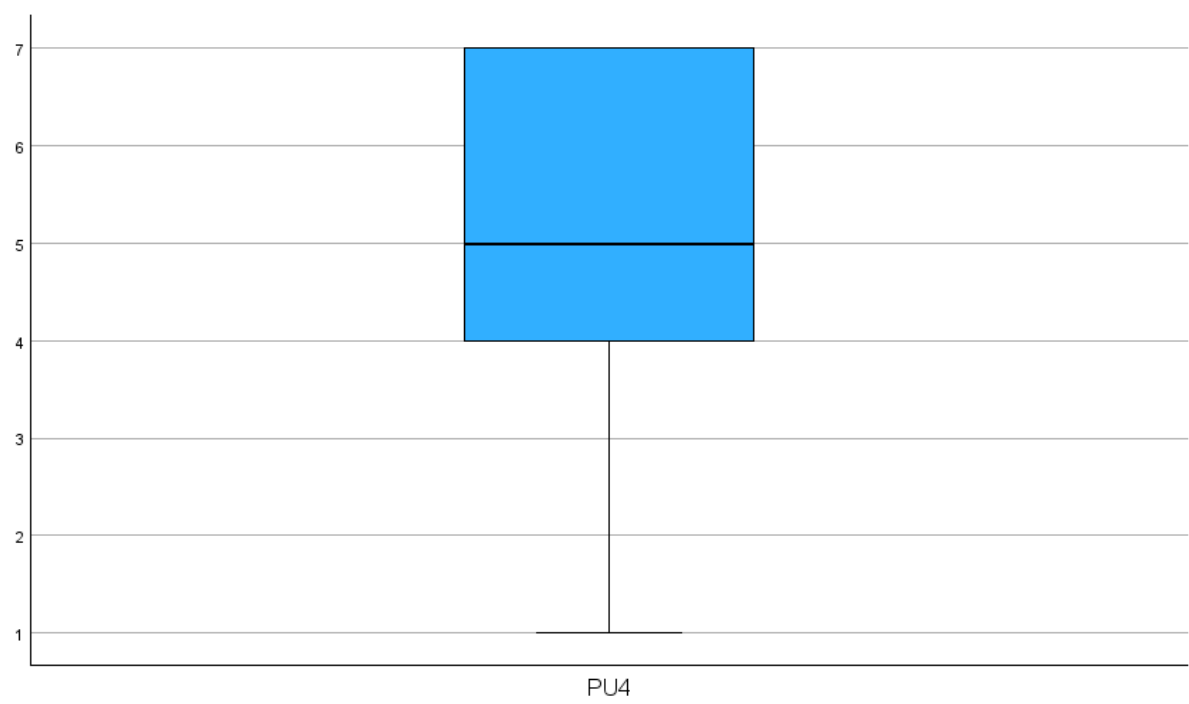
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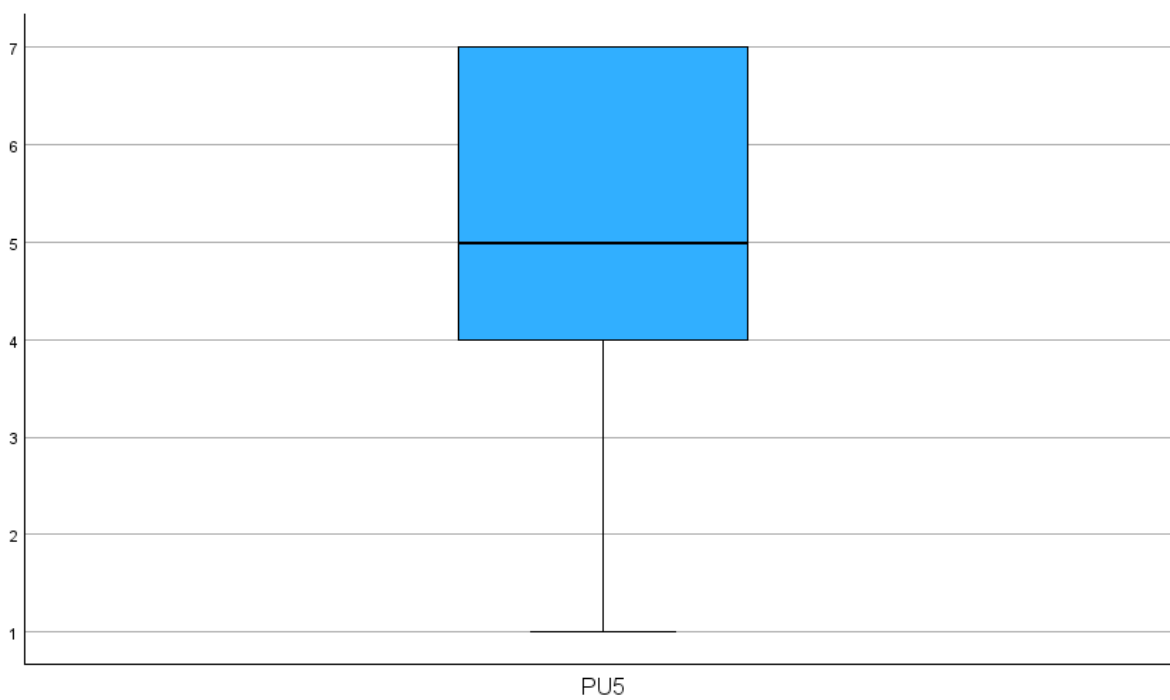
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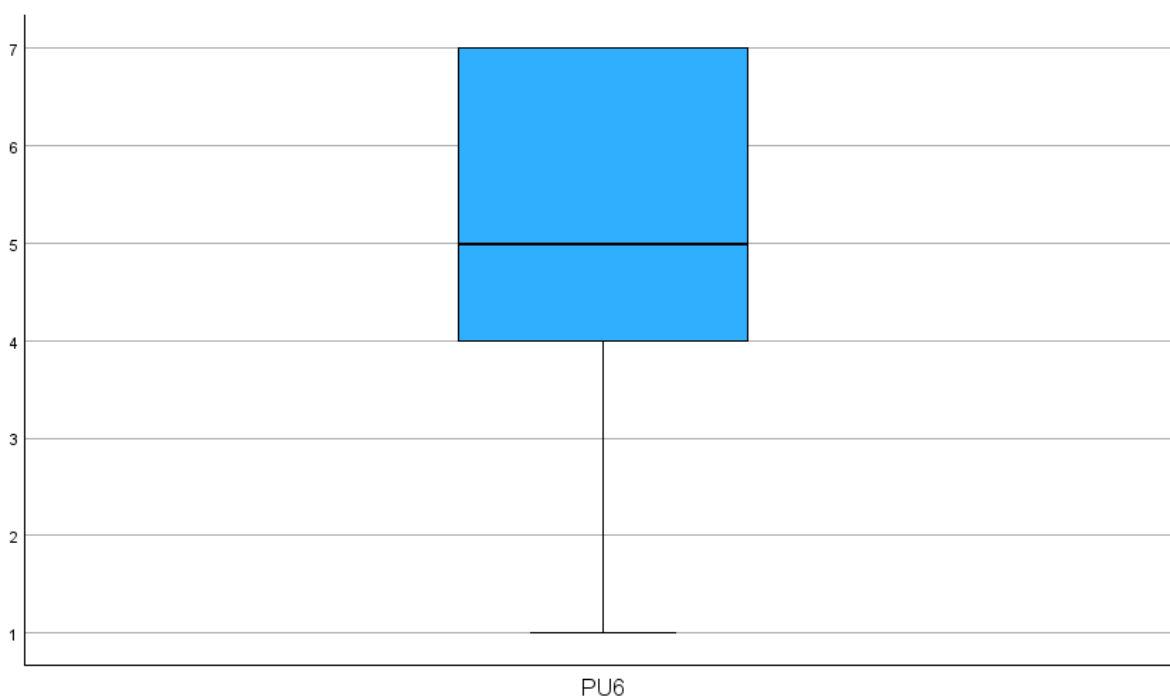
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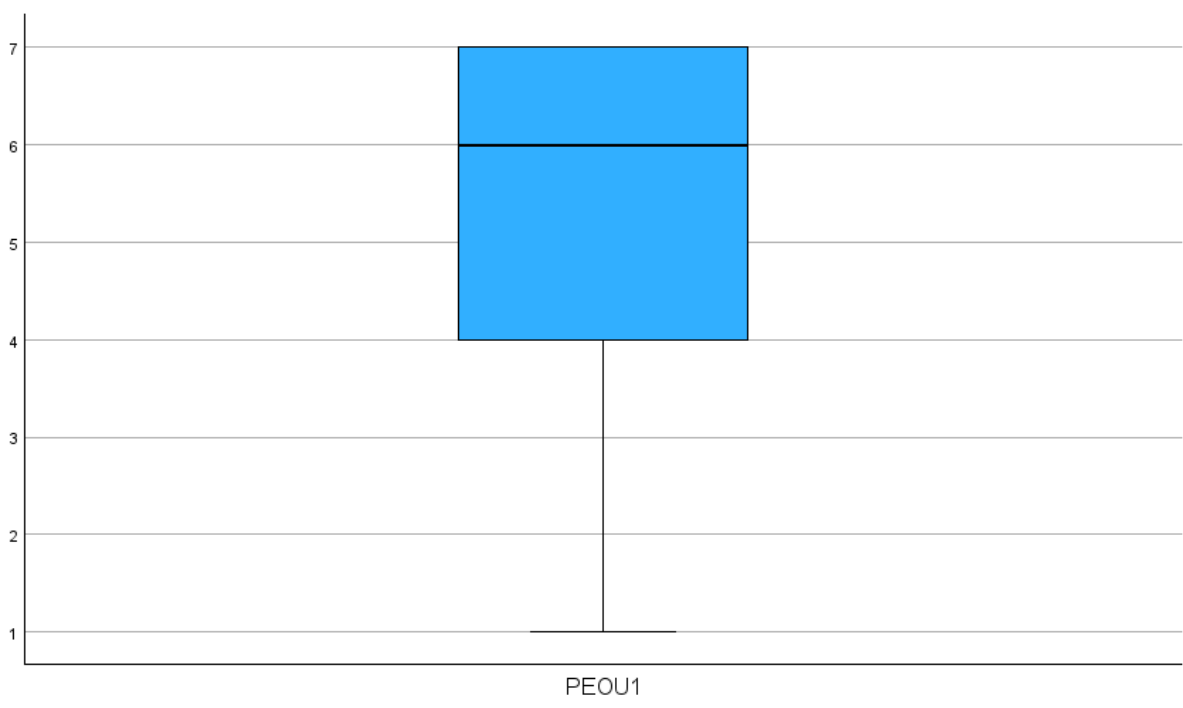
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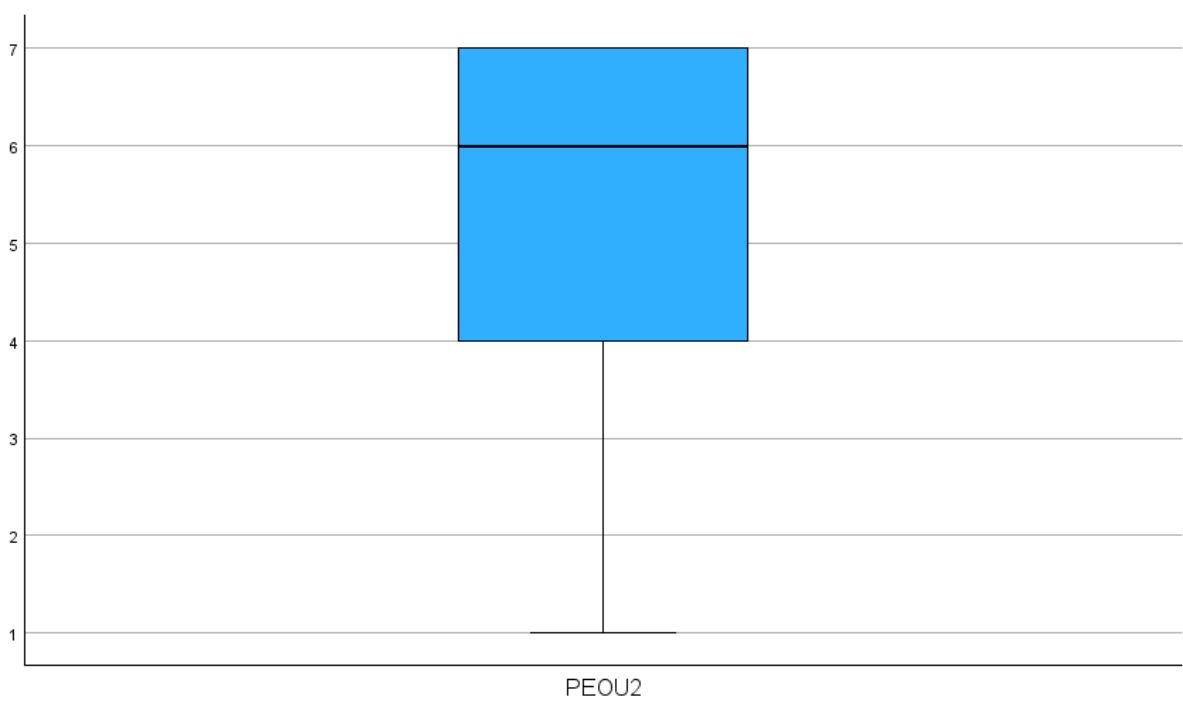
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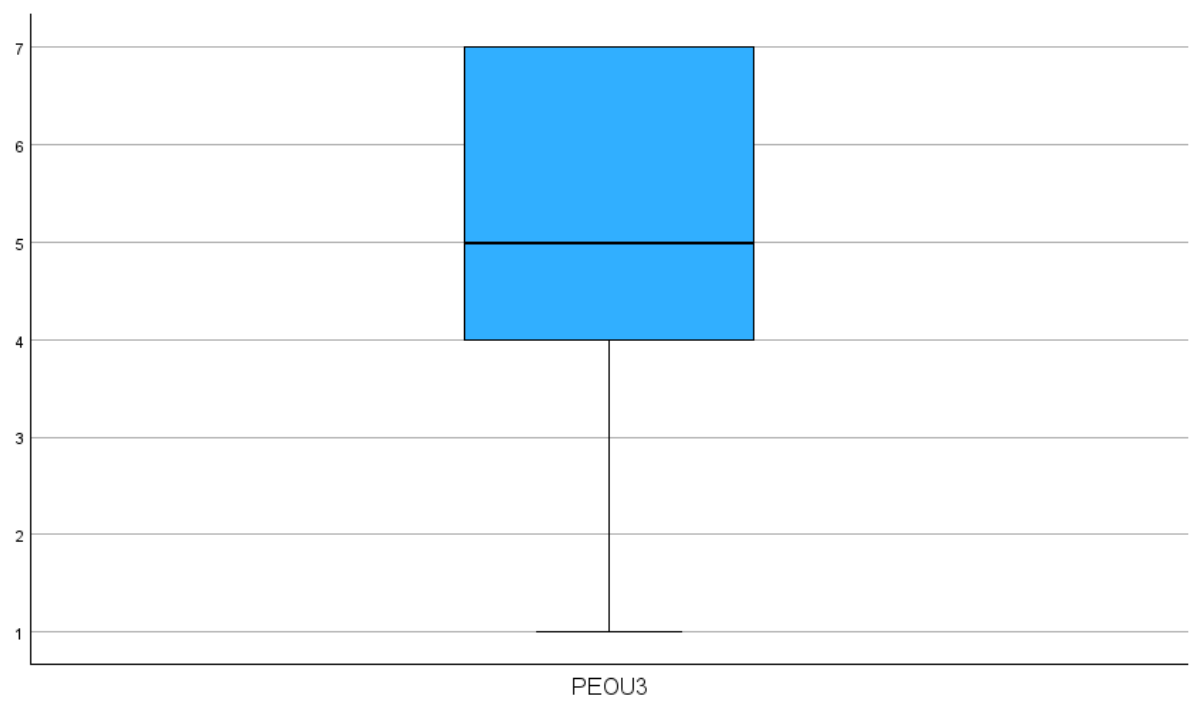
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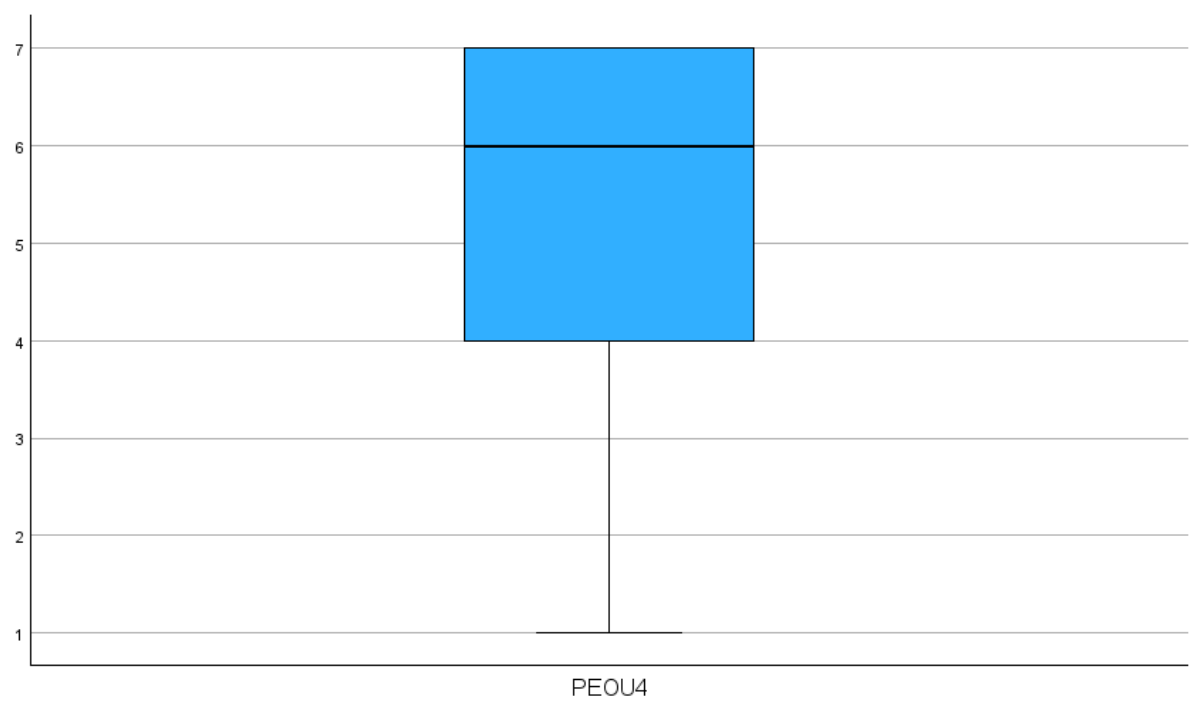
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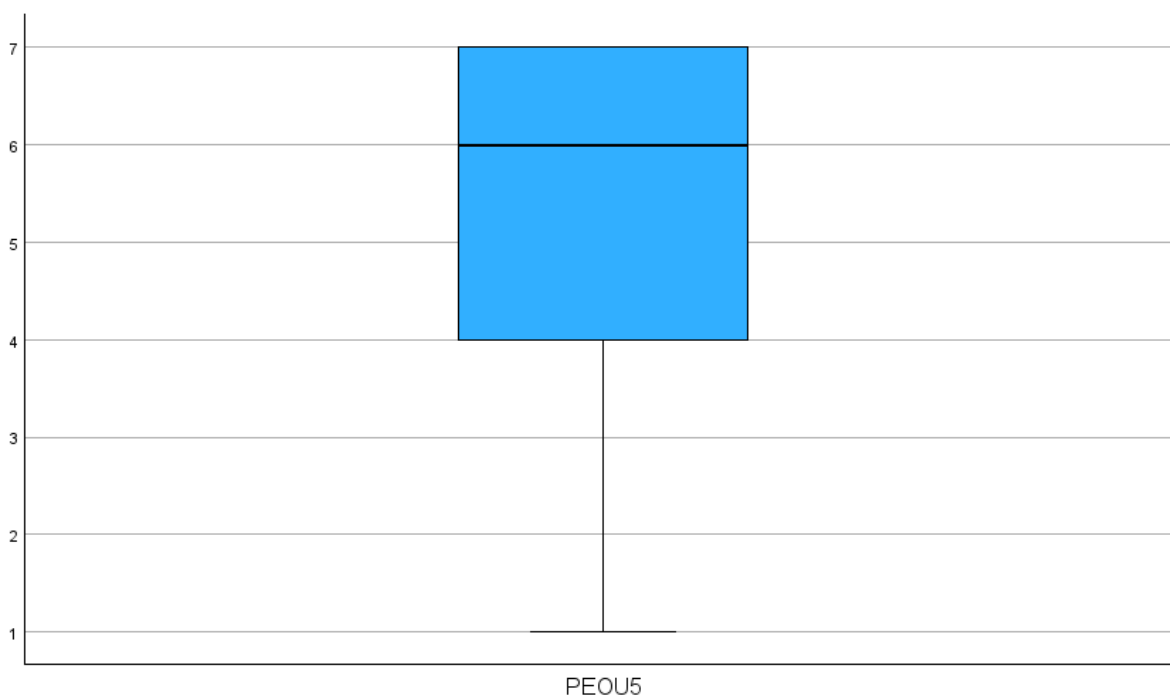
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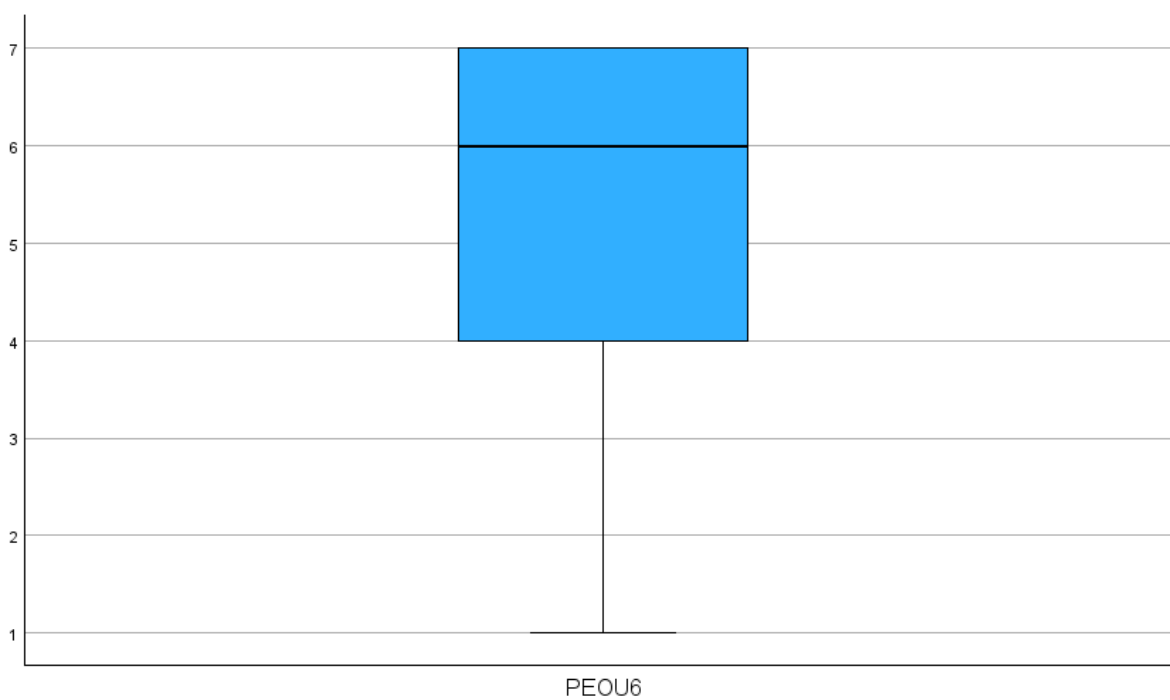
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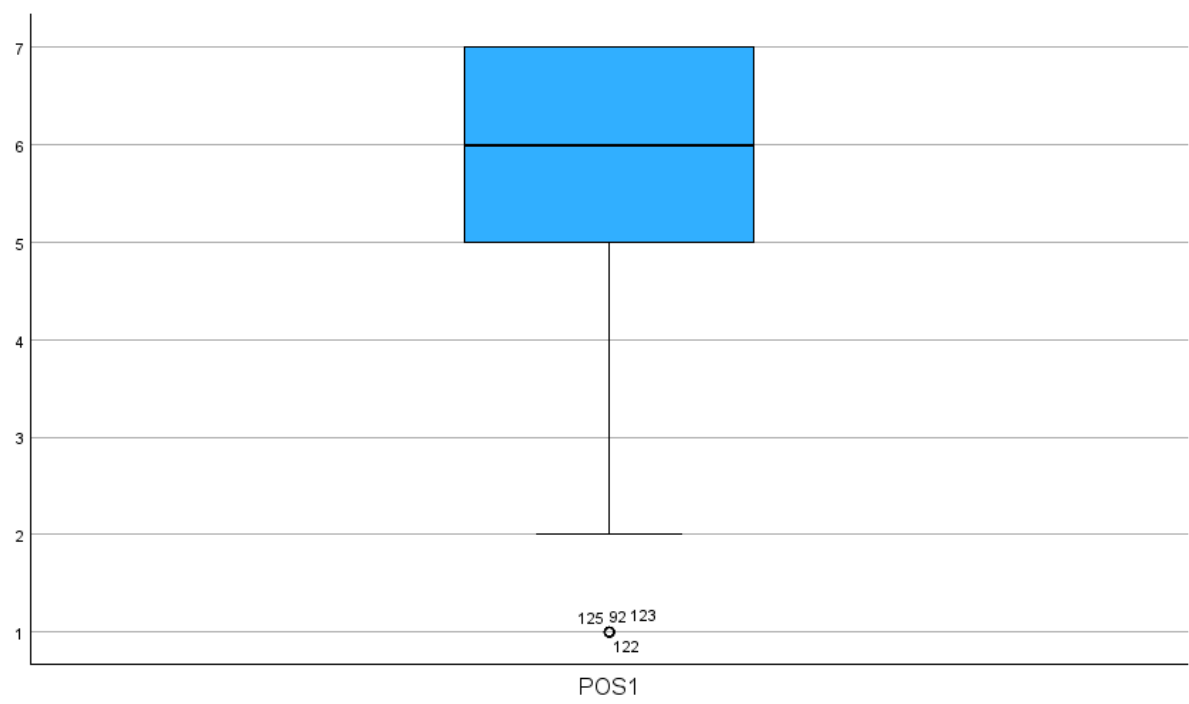
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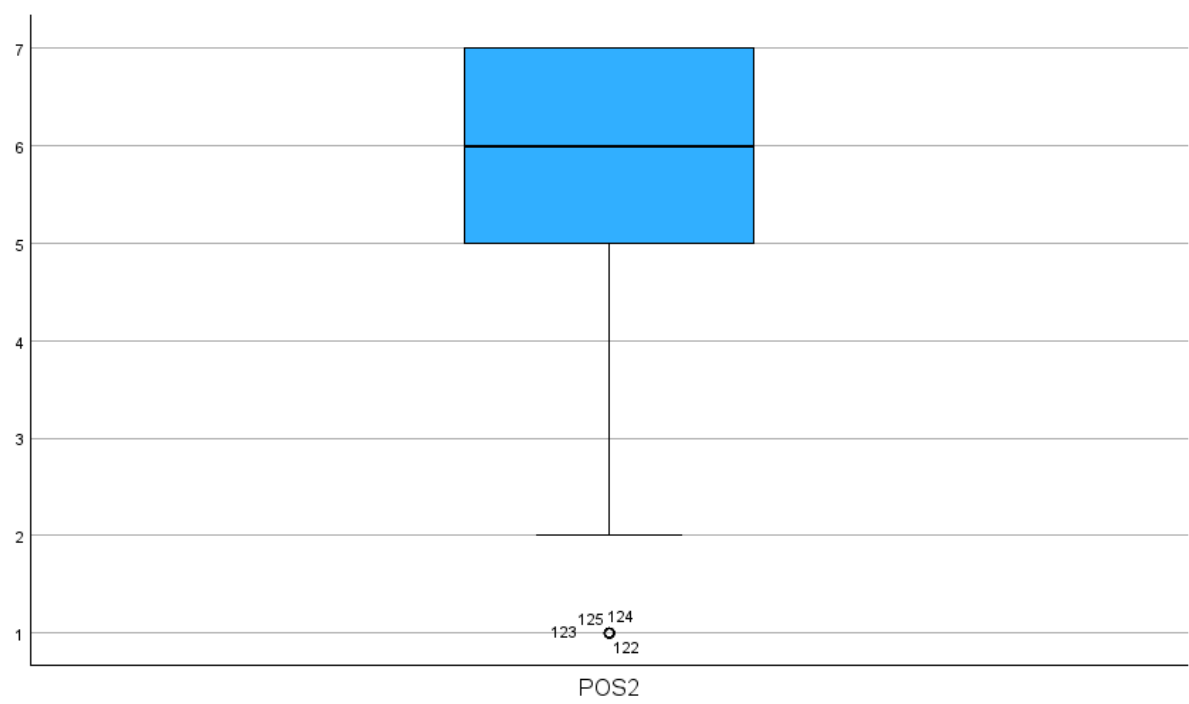
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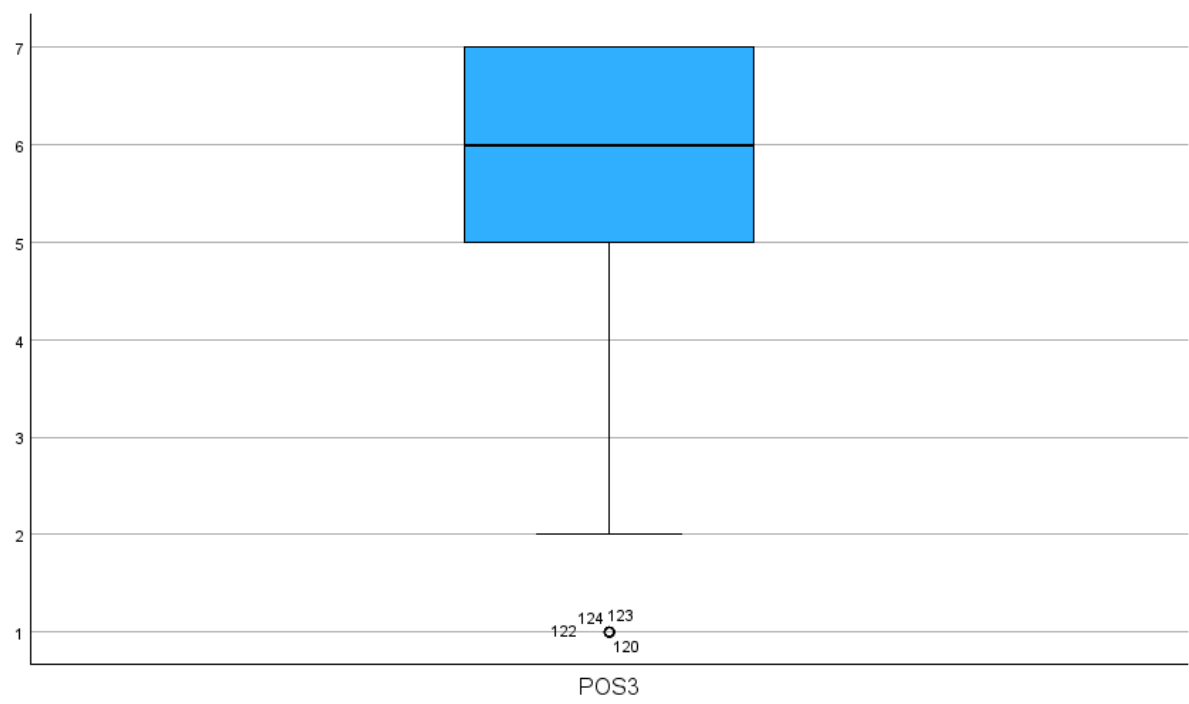
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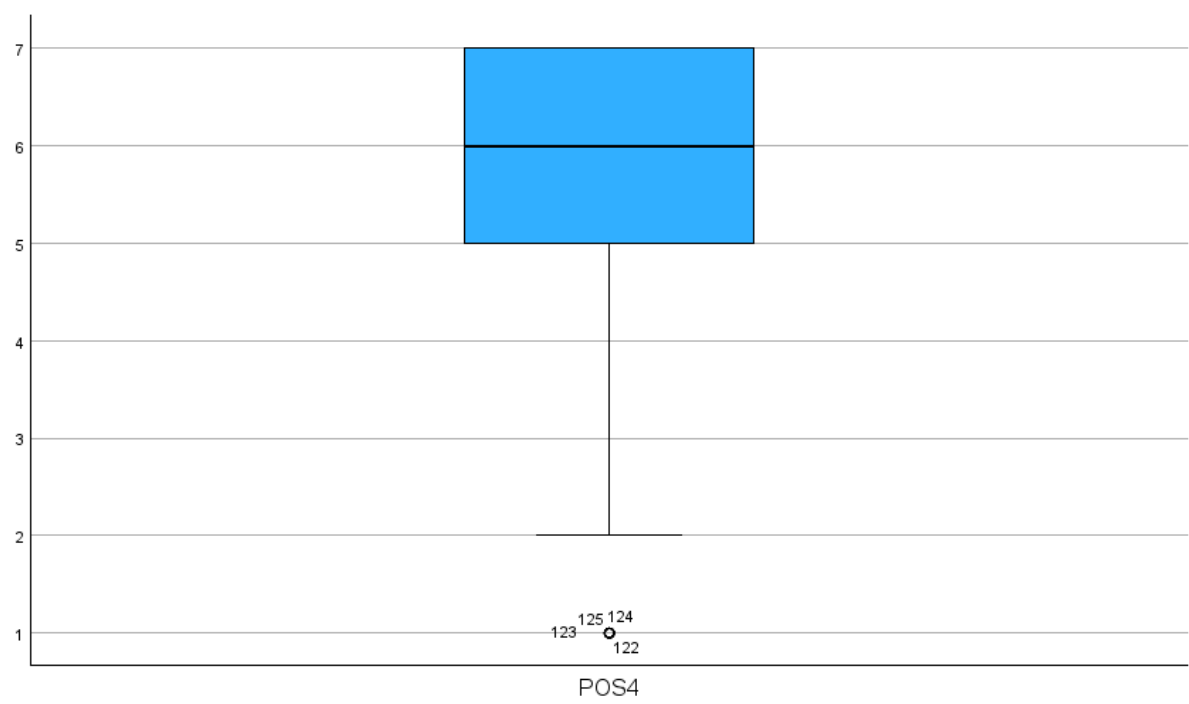
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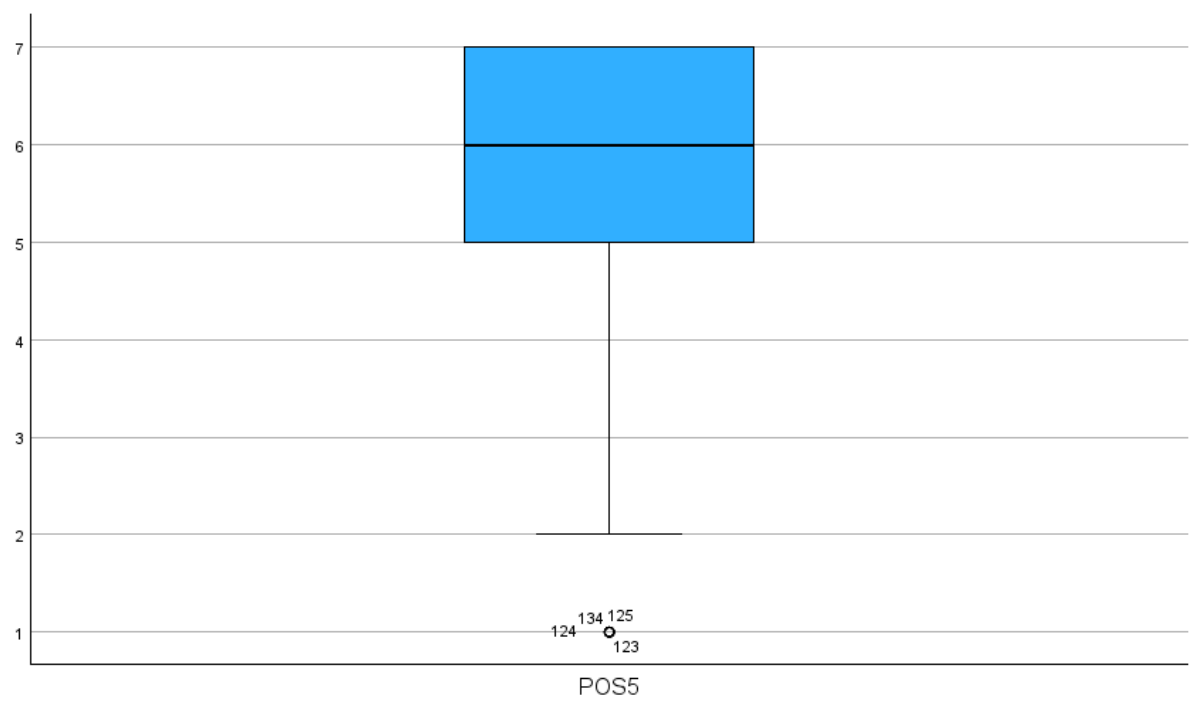
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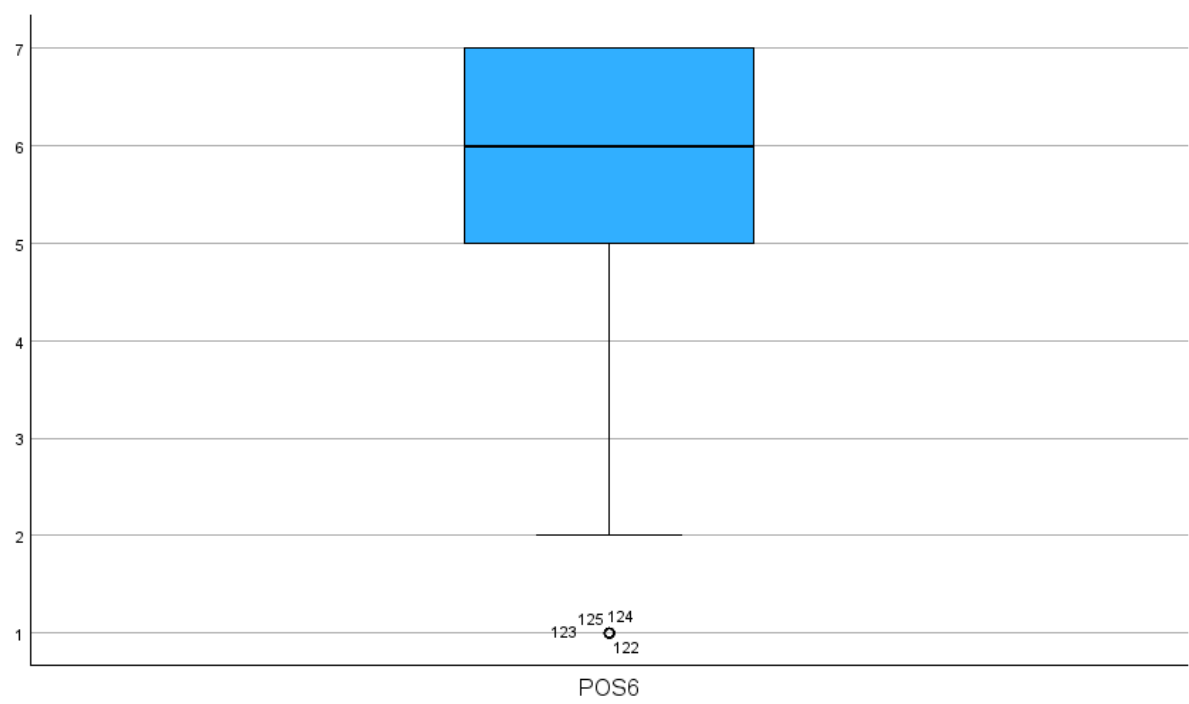
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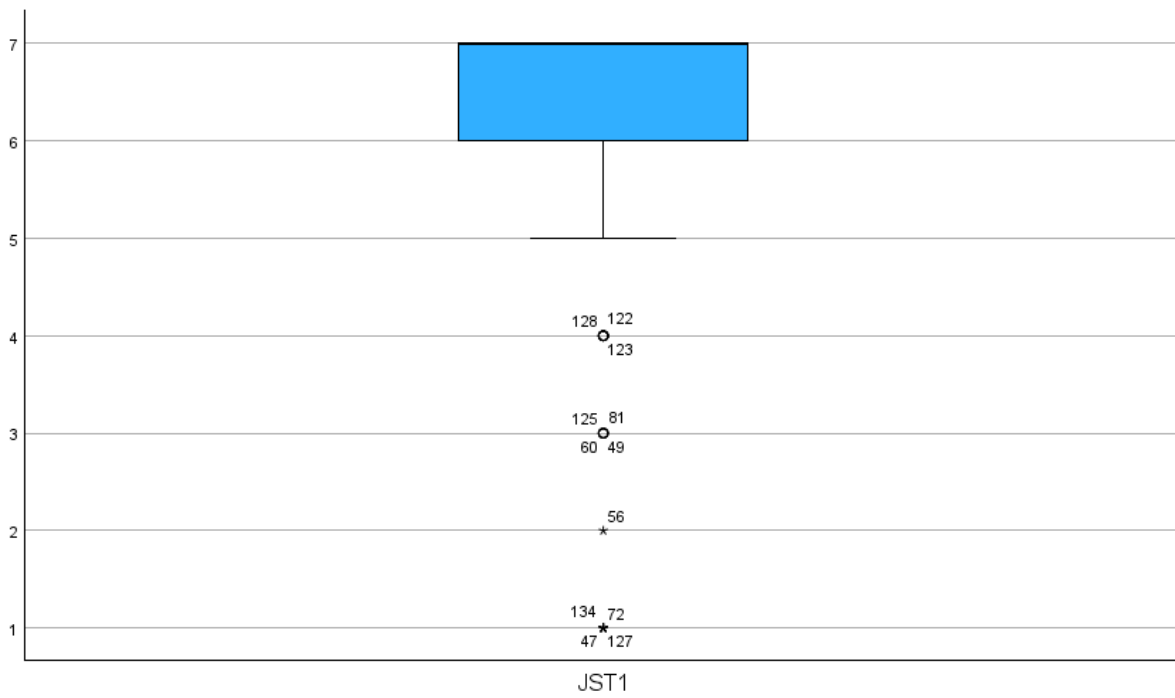
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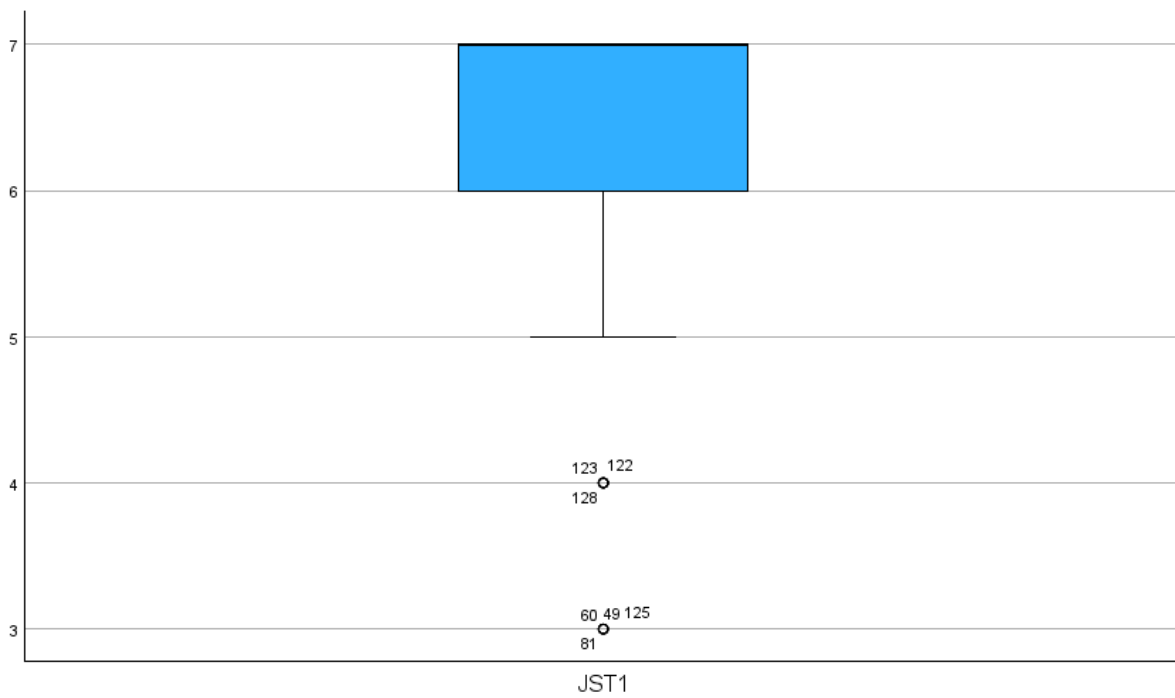
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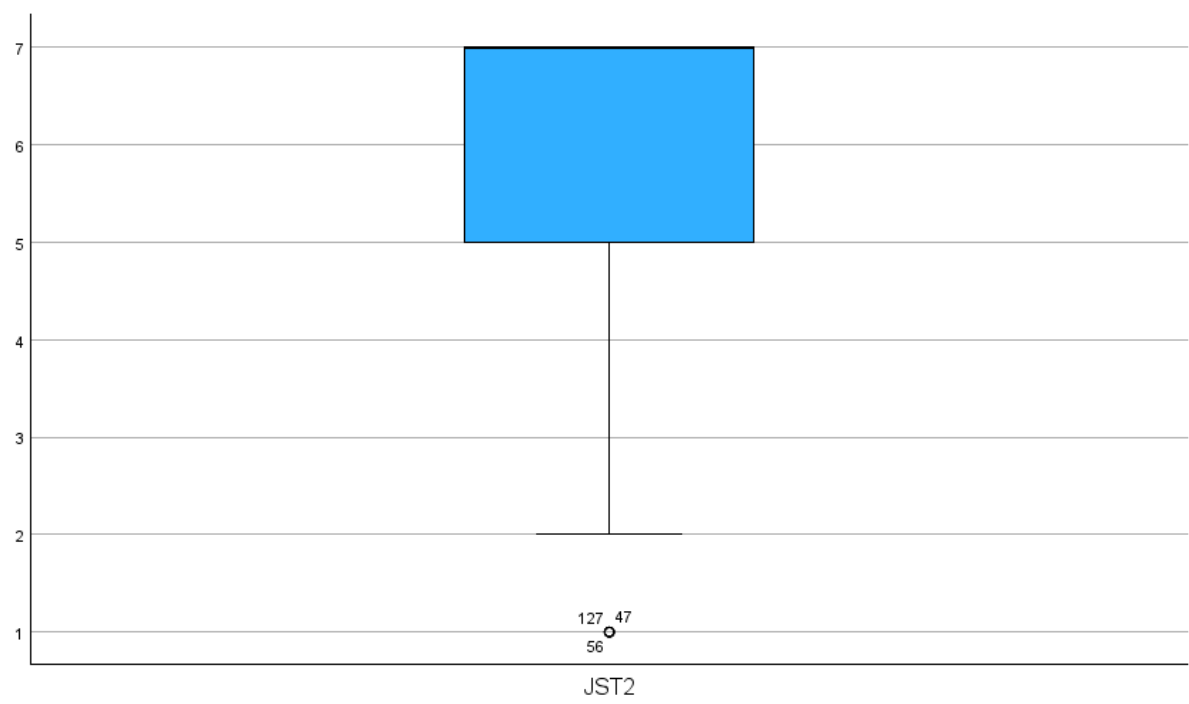
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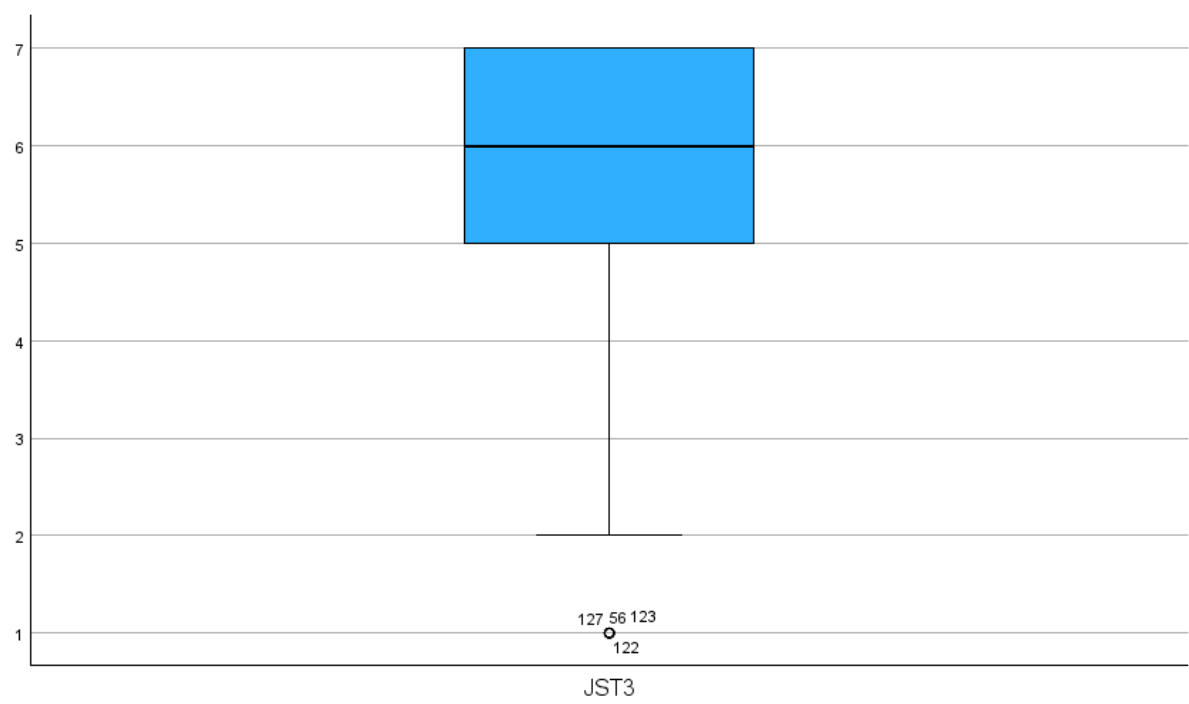
JST1 (Without outliers)



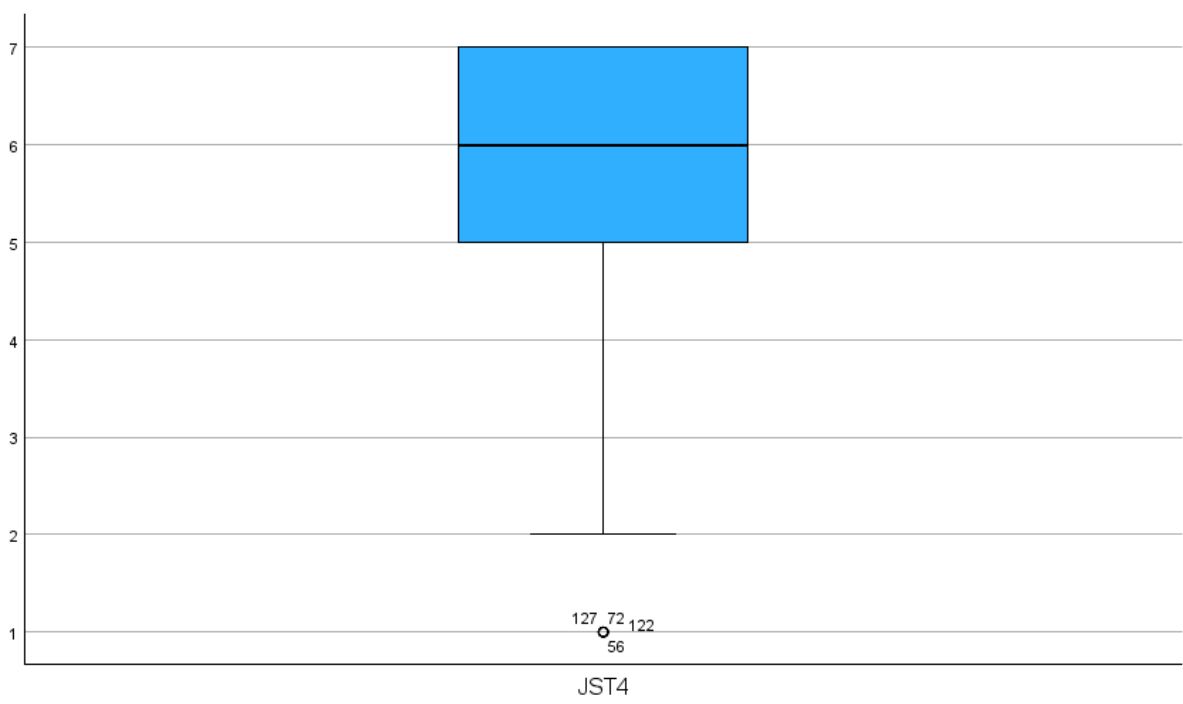
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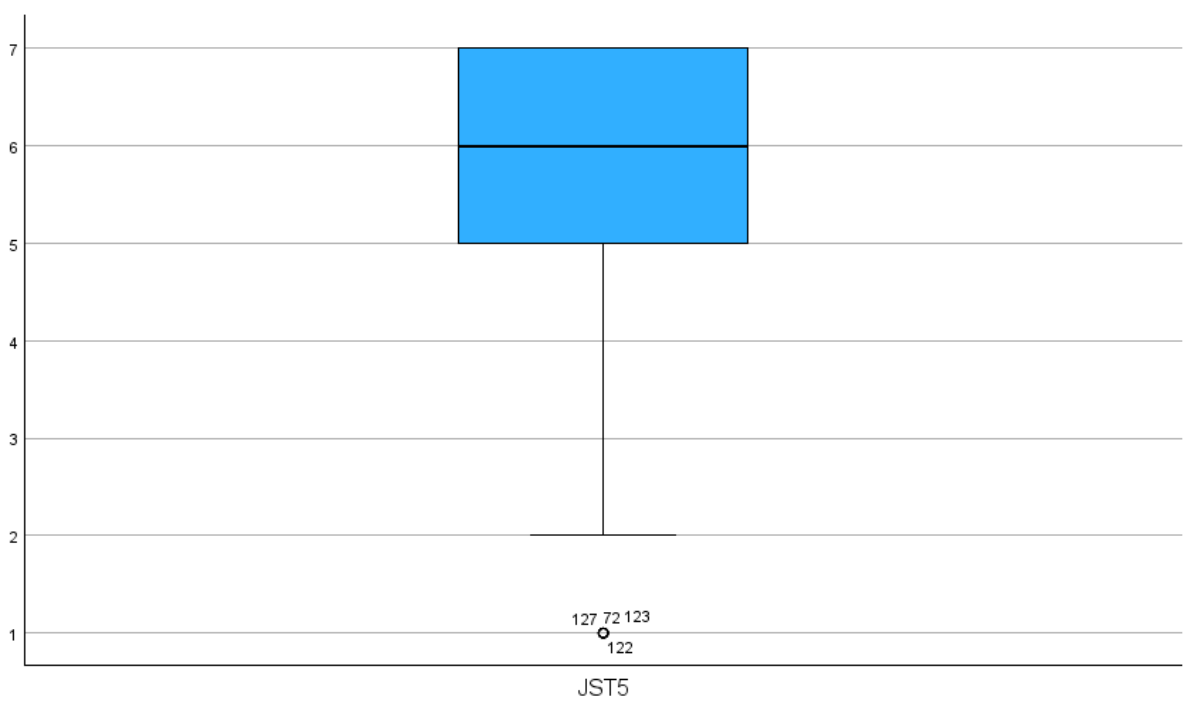
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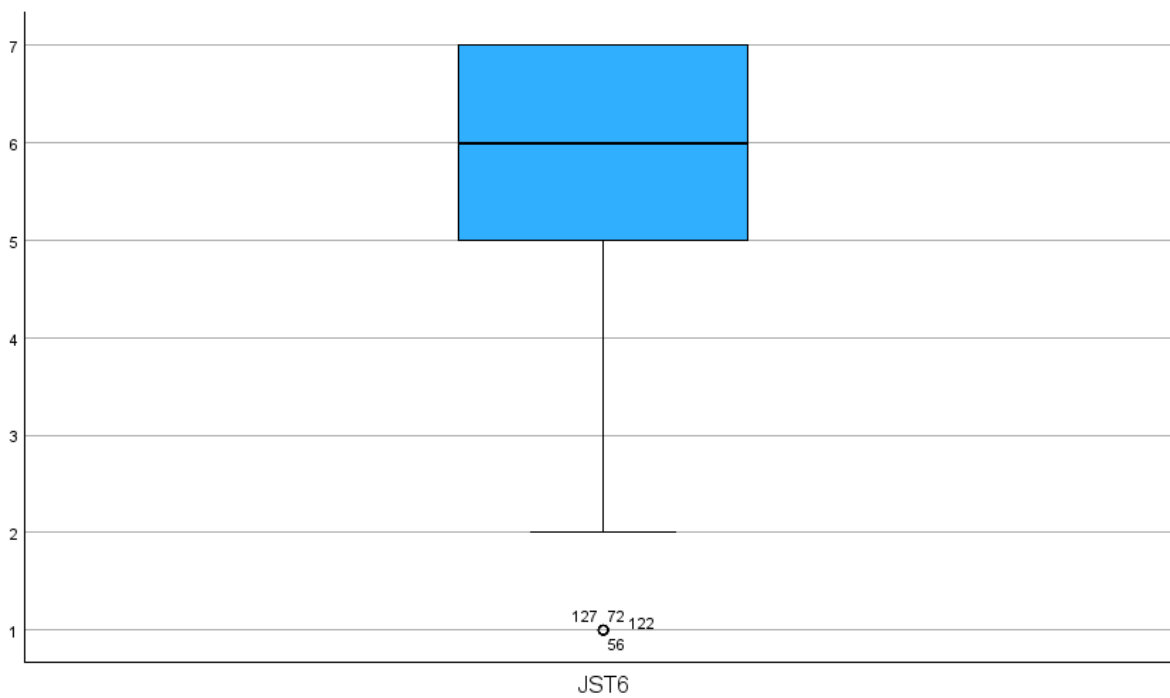
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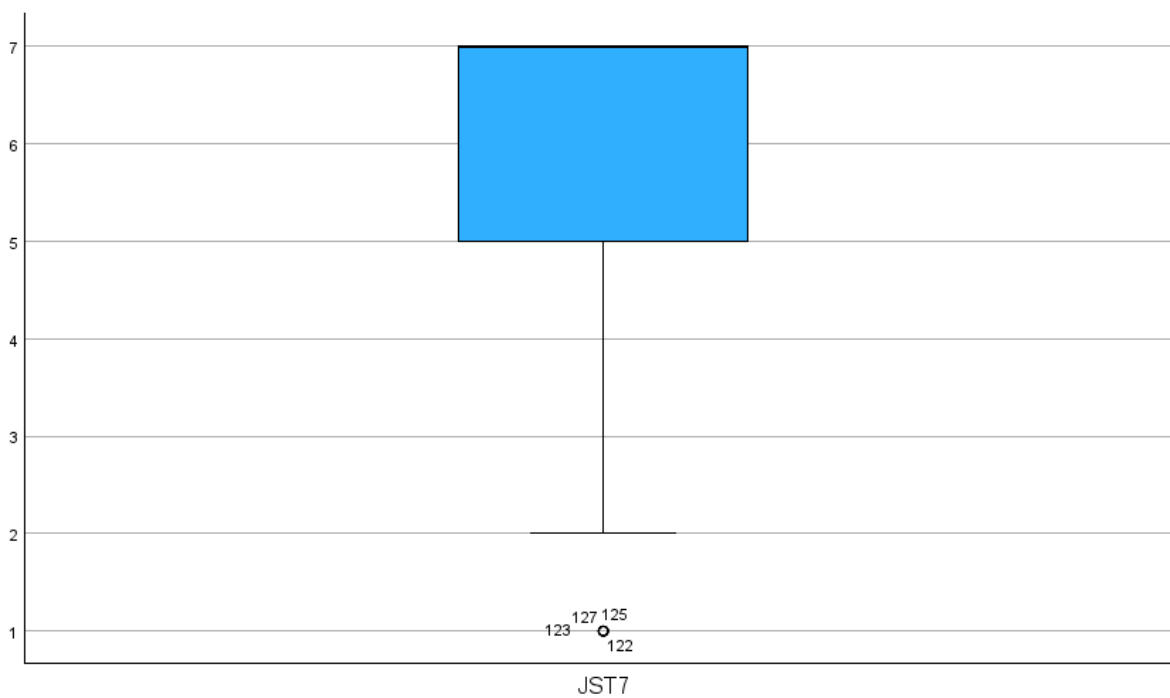
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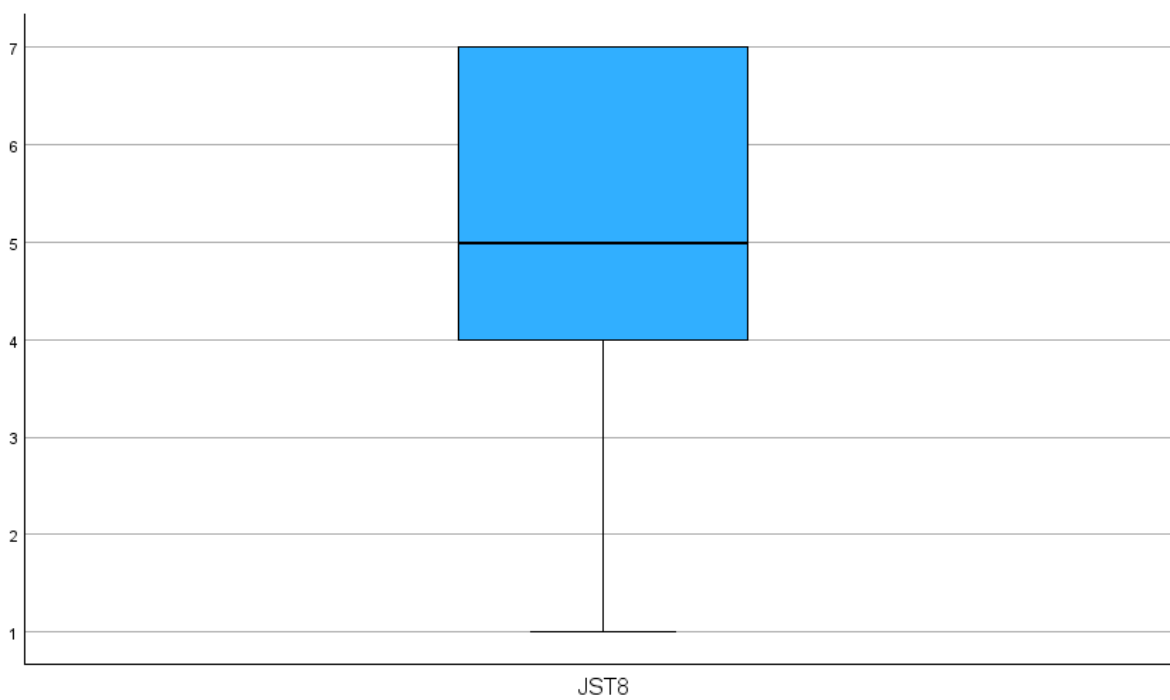
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JST7



JST8



JST9

