



PREDICTING DETERMINANTS OF IoT ADOPTION IN BOTSWANA'S SMES USING HYBRID SEM-ANN APPROACH

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Abstract

Previous research on Internet of Things (IoT) adoption in Small and Medium Sized Enterprises (SMEs) has predominantly focused on contexts outside Botswana, consequently restricting the findings' direct applicability to the local setting. This study examines factors influencing IoT adoption in Botswana's SMEs. A cross-sectional survey of 440 SMEs in Gaborone city tested a multi-theoretical model using a hybrid Structural Equation Modelling - Artificial Neural Network (SEM-ANN) approach. Both the hidden and output layers of the Multilayer Perceptron Artificial Neural Network were activated using the sigmoid function. Model training utilized a Batch-based approach, and the optimization of the model parameters was achieved through the scaled conjugate gradient algorithm. Findings revealed significant factors including; relative advantage, complexity, compatibility, trust, security, technology readiness, competitive pressure, top management support, financial resources, government support, perceived usefulness, vendor support, and perceived ease of use. Additionally, sensitivity analysis underscored compatibility as the most significant factor, followed by security and privacy, technology readiness, top management support, and financial resources. Educational level and computer experience significantly moderated IoT adoption among Botswana's SMEs. Findings contribute to better understanding IoT adoption by Botswana's SMEs, providing valuable insights for policymakers and decision-makers. The proposed framework can guide IoT adoption policies in Botswana and other emerging economies. Future research could investigate additional factors and approaches to enhance understanding of IoT adoption in SMEs.

Keywords: Internet of Things, IoT, SMEs, Small and Medium-sized Enterprises, Structural Equation Modelling, Artificial Neural Network, Multi-layer Perceptron

Introduction

Over several decades, rapid technological progress, fueled by continuous research and innovation, has dramatically reshaped various aspects of modern life. Concurrently, this technological evolution has fostered the development of the Internet of Things (IoT), a paradigm that establishes pervasive and contextually intelligent networks (Harbi et al., 2022). This state-of-the-art technology has revolutionized the global production, work practices, business operations, trade, and consumption behaviors among both enterprises and consumers (Mphale et al., 2024b). The IoT operates by collecting data from "things" without requiring human intervention (Lim et al., 2024). It transmits this data to computers over the Internet, ultimately generating valuable insights (Lim et al., 2024). IoT can monitor and trace items,

issue alerts for necessary replacements, repairs, or recalls, and contribute to minimizing waste, loss, and costs (Poornima et al., 2024). These capabilities have prompted various sectors to adopt IoT technology, including urban areas, households, universities, industrial factories, organizations, agricultural settings, hospitals, and healthcare facilities (Nassereddine & Khang, 2024). Many businesses view IoT as essential to their success, with a belief that those who fail to adopt it will lag behind their competitors within five years (Arnold & Voigt, 2019). As a result, IoT technology is not merely advantageous but indispensable for all sectors undergoing a transition from conventional business models to intelligent, data-driven business environments (Lim et al., 2024).

Studies indicate that IoT offers substantial potential for SMEs, to decrease costs, boost profitability, streamline processes, and eventually improve their competitiveness in the market (Parab et al., 2023). However, the widespread IoT adoption among SMEs remains a challenge. Research suggests that SMEs across diverse sectors demonstrate either a lack of adoption or slow uptake of IoT concepts, consequently hindering their competitiveness (Wungcharoen, 2022). Furthermore, a recent United Kingdom survey by Analysys Mason, showed that more than half of SMEs (51%) were either uninformed or hesitant about IoT, and another 23 percent showed little interest in the technology (IoTNOW, 2018). This low adoption rate translates into missed opportunities for automation, personalized customer experiences, and overall operational improvements (Onu & Mbohwa, 2021). Given the pivotal role of SMEs in driving economic growth and mitigating poverty, governments worldwide prioritize fostering their development to maintain global competitiveness (Mubeen et al., 2023).

Prior research on IoT adoption in SMEs has largely overlooked the context of Botswana (Grandon et al., 2018; Mubeen et al., 2023; Shukor et al., 2022). Notably, within the African context, this scholarly investigation has been extremely limited. For instance, Peter et al. (2023) examined the impact of Industrial IoT (IIoT) on manufacturing in developing economies, by interviewing 49 SMEs experts across Morocco, Nigeria, and South Africa. Similarly, Okafor's 2023 study, cited in Gorejena et al. (2024), investigated the benefits and application of IoT technologies in Nigerian SMEs. Moreover, Barnes et al. (2024) conducted examined the drivers and underlying reasons for the adoption of digital technologies (DTs), such as IIoT, by South African manufacturing SMEs. According to Maisiri and van Dyk (2021), as cited in Barnes et al., there is a notable lack of dedicated research examining the adoption of DTs like IIoT within South African SME manufacturing firms. This limited body of empirical evidence, coupled with a significant gap in studies employing multi-theoretical models to analyse the factors influencing IoT adoption among SMEs in emerging economies (Mphale et al., 2024a), underscores the necessity for further scholarly inquiry for better understanding of this phenomenon. While Structural Equation Modelling (SEM) has demonstrated its utility in explaining IoT determinants in SMEs, the potential of integrating Artificial Neural Networks (ANN) within such frameworks remains largely unknown (Soomro et al., 2024).

This research extends the work of Mphale et al. (2024a), by employing and empirically testing a multi-theoretical model to explain factors influencing IoT adoption among Botswana's SMEs. This model integrates key technology adoption theories and frameworks, such as the Unified Theory of Acceptance and Use of Technology (UTAUT), Diffusion of Innovation (DOI) theory, Technology-Organization-Environment (TOE) framework and Technology Acceptance Model (TAM). A two-stage approach was employed to test this multi-theoretical model, integrating SEM with a Multilayer Perceptron Artificial Neural Network (MLP-ANN). SEM analysis was conducted on 440 valid survey responses from SMEs

in Gaborone city. Subsequently, MLP-ANN validated the SEM results and factor rankings. Additionally, the study evaluated the impact of moderator variables on IoT adoption. Findings are expected to provide valuable insights for stakeholders, including government agencies, SME organizations, and the private sector. These insights can inform policy development to encourage widespread IoT adoption among SMEs, aligning with Botswana's vision 2036 goals (NDP11, 2017). The proposed framework can guide IoT adoption policies in Botswana and other developing countries.

Research aim and Objectives

The primary goal of this research is to investigate the factors that influence the IoT adoption among Botswana's SMEs, employing a multi-theoretical model that integrates a hybrid SEM-ANN approach. Hence, the following specific objectives were pursued to:

- 1) Test the multi-theoretical model using data and a hybrid SEM-ANN approach.
- 2) Identify the factors influencing IoT adoption in Botswana's SMEs.
- 3) Confirm the factors influencing IoT adoption in Botswana's SMEs.
- 4) Rank the factors influencing IoT adoption in Botswana's SMEs.
- 5) Assess the influence of moderators (including; age, gender, computer experience, and education level) on actual IoT adoption in Botswana's SMEs.

Literature Review

Existing research has identified numerous factors influencing IoT adoption in SMEs. However, to narrow the scope and enhance the granularity of our literature review, this study examined only those studies employing SEM and ANN methodologies, alongside various technology adoption theories and models. For instance, Wasim et al. (2024) utilized SEM to scrutinise the connection amongst market orientation and the performance of SMEs. Findings demonstrated that IoT serves as a moderating factor, enhancing both creativity and overall firm performance. Similarly, Soomro et al. (2024) looked into how digital technology adoption, including IoT, affects economic and social value creation, as well as SME performance in Upper Sindh, Pakistan. Their study took a hybrid method, combining SEM and ANN approaches with the Smart-PLS 4.0 program. The findings demonstrated that diverse digital technologies, including IoT applications, help SMEs create significant economic and societal value.

Kwak et al. (2023) examined factors influencing Korea's SME leaders' intentions to implement smart factories, employing SEM on a sample of 175 executives. Their study, utilizing TAM, TOE, and resource dependence theory models, found that perceived importance strongly influences adoption intentions. Similarly, Mubeen et al. (2023) investigated TOE factors influencing IoT adoption and SME performance in Pakistan. Utilizing the TOE and resource based view frameworks and employing partial least squares SEM (PLS-SEM) on data from Pakistani SMEs, their results showed that the association between IoT adoption and SME performance is mediated by organizational resilience. In line with this perspective, Usman et al. (2021) explored IoT adoption by village-owned companies (BUMDes) in Indonesia. Their study, employing TAM and PLS-SEM on a sample of 237 managers and staff, found that perceived usefulness, credibility, and intention positively influence IoT adoption, with intention partially mediating the interplay between ease of use, perceived usefulness and IoT adoption.

Sivathanu (2019) investigated the adoption of Industrial Internet of Things (IIoT) within Indian auto-component manufacturing SMEs, employing the TOE framework and PLS-SEM to analyse data collected from Information and Communication Technology (ICT) officers, managers, and owners. The study found that the main factors driving IIoT adoption were vendor support, competitive pressure, infrastructure, relative advantage, compatibility, cost, security, organizational readiness, top management support, and IIoT knowledge. Similarly, Grandon et al. (2018) examined factors influencing IoT adoption among Chilean SMEs, utilizing the UTAUT model and PLS-SEM to analyse data collected from ICT managers. Their results showed that while performance expectancy had a negative impact on the intention to adopt IoT, social influence and enabling conditions had a positive impact.

Literature summary and research gaps

While previous research offers insightful information about IoT adoption in SMEs, several research gaps exist that require attention to enhance adoption rates within this sector. Firstly, prior studies on the adoption of IoT in SMEs have primarily focused on contexts outside Botswana (e.g., Grandon et al., 2018; Kwak et al., 2023; Sivathanu, 2019; Soomro et al., 2024; Usman et al., 2021), restricting the findings' direct relevance to Botswana's unique context. Secondly, while advanced methodologies such as SEM-ANN have been employed in SME technology adoption research, their application within the specific context of IoT adoption remains limited (Soomro et al., 2024). Finally, there is a substantial gap in the research on the application of multi-theoretical models to explain adoption of IoT by SMEs within emerging economies (Mphale et al., 2024a). This study aims to fill these gaps in research by applying and testing a multi-theoretical model to investigate the factors influencing IoT adoption among Botswana's SMEs. Empirical data is analyzed using a hybrid SEM-ANN technique.

Conceptual Framework

The primary aim of this research is to investigate the factors influencing IoT adoption among Botswana's SMEs. To achieve this, the study adopts a multi-theoretical model proposed in prior research (Mphale et al., 2024a). There are 20 constructs in this model: 5 extra constructs found through literature analysis (technology readiness, security and privacy concerns, financial resources, perceived usefulness, and trust) and 11 core constructs drawn from well-known technology adoption theories (TOE, UTAUT, DOI and TAM). Age, gender, computer experience, and educational level are included as moderating factors. This multi-theoretical approach, consistent with previous research (Sinha & Mukherjee, 2016), provides a comprehensive understanding of IoT adoption within SMEs. Figure 1 illustrates the research conceptual model and its moderating variables.

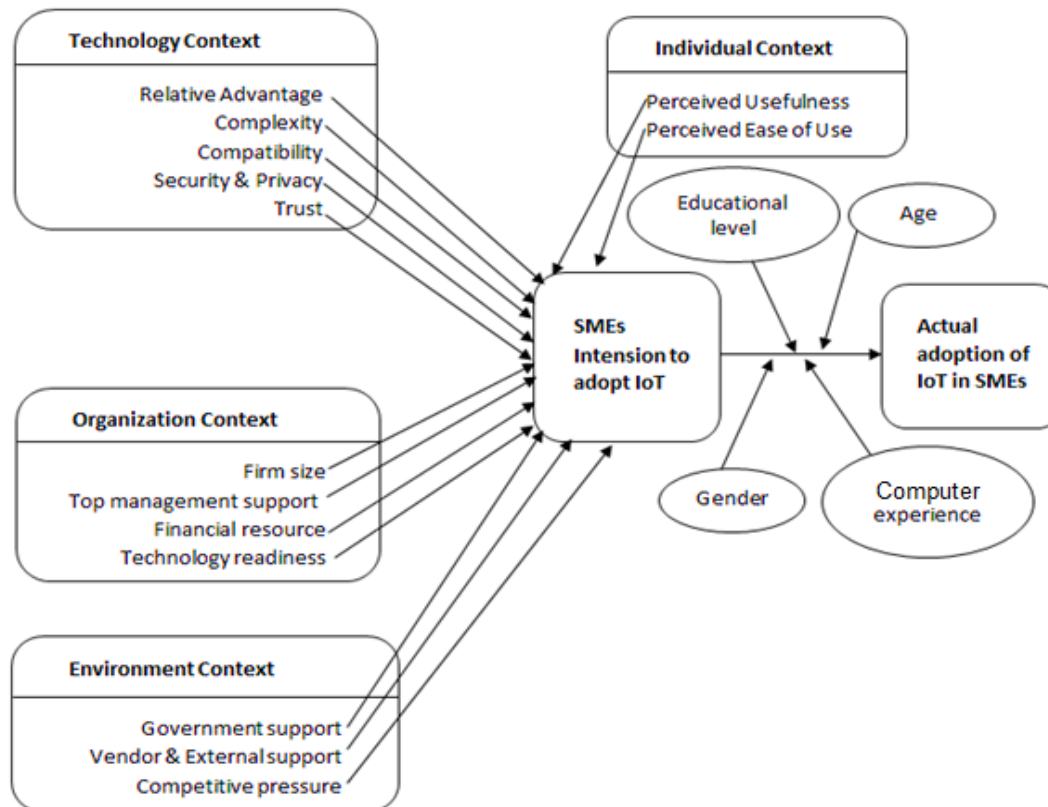


Figure 1: Research Conceptual Model - Adopted from (Mphale et al., 2024a)

A synopsis of Research model constructs

This subsection offers a brief summary of the research model constructs, drawing upon the previous work of (Mphale et al., 2024a). These constructs are categorized into technology, organization, environment, and individual-related context factors. These categories are described in the discussion that follows:

Technology context factors

Relative advantage: IoT can provide SMEs a competitive edge by streamlining procedures and increasing efficiency (Sriram & Vinodh, 2021). These potential benefits contribute to the perceived relative advantage of IoT solutions for SMEs.

Complexity: The perceived complexity of integrating and managing IoT devices is considered as a substantial factor influencing SMEs' intentions to adopt IoT (Blanchier et al., 2019).

Compatibility: A significant challenge for IoT adoption is the lack of universally recognised standards, making it difficult to ensure seamless interoperability between devices (Jones & Graham, 2018). Therefore, perceived compatibility of IoT with existing operations is crucial for SME IoT adoption.

Security and privacy concerns: The unique characteristics of IoT gadgets—such as their diversity, extensive use, inconsistent protocols, and resource constraints—a complex web of security and privacy issues arises. (Parker, 2020). This can lead to reluctance of the SMEs to adopt IoT solutions (Haddud et al., 2017).

Trust: This describes a multitude of trust-related challenges for SMEs that hinder IoT adoption, including data security, vendor trustworthiness, unclear algorithms, interoperability issues, uncertain value propositions, and a lack of awareness and skills needed to manage IoT systems (Parker, 2020).

Organisational Context Factors

Top management support: Ensuring proper resource allocation and promoting successful technology deployment require the support and active participation of top management (Dai et al., 2013). Therefore, top management buy-in is a crucial factor for SME IoT adoption.

Firm size: Larger firms, with their stronger financial muscle and higher risk tolerance, appear better positioned for development in technology. In contrast, SMEs, due to their smaller scale and resource constraints can introduce bureaucratic hurdles, that can slow down technology adaptation processes (Ngidi, 2019).

Financial resources: Compared to larger companies, SMEs typically have tighter financial constraints (Parra et al., 2021).

Technology readiness: This denotes to the infrastructure, personnel competencies, and overall information technology (IT) capabilities of an organization. It is a critical factor for successful IoT adoption in organisations (Olushola, 2019).

Environment context factors

Government support: Government initiatives providing infrastructure, IT support, direct financial assistance through grants and subsidies can lessen the financial burden of IoT implementation, making it more accessible to resource-constrained SMEs (Fauzan & Dhewanto, 2021).

Vendor/External support: Without comprehensive and quality vendor assistance, SMEs often struggle to integrate new technologies like IoT systems with existing infrastructure, hindering the realization of potential benefits (Sivathanu, 2019).

Competitive pressure: Competitive pressure can be a significant driver for SME adoption of IoT, as firms seek to keep pace with rivals and avoid falling behind (Arnold & Voigt, 2019).

Individual level factors

Perceived Ease of Use: Individuals are more inclined to embrace solutions that are simple to use and require little training. Thus, for SMEs with little funding and technological know-how, this is particularly important (Jamalut et al., 2022).

Perceived Usefulness: SMEs are more likely to adopt IoT solutions that offer tangible benefits such as enhanced customer satisfaction, lower expenses, and greater efficiency (Okafor, 2023).

Moderator variables

Age: Literature suggests that younger users are more likely to embrace innovation (Yi et al., 2006) and are often more task-oriented, leading to a greater willingness to adopt technologies that facilitate task completion (Venkatesh et al., 2003). Age is therefore regarded as a significant variable for IoT adoption in SMEs.

Gender: Literature suggests that men are generally considered to be more receptive than women to technological advancements (Hasan, 2010). In this regards, gender is considered an important moderator for adoption of IoT in SMEs.

Educational level: Higher education can help people overcome fear of computers and embrace technology (Burton-Jones & Hubona, 2006). This suggests that education level influences how readily SMEs adopt IoT.

Computer experience: Computer skills can ease the adoption of IoT in small businesses. This is because these skills help people understand and use new technologies more quickly (Coffman, 2014).

Methodology

This study adopted a quantitative research approach and positivist research philosophy. SME respondents' information was gathered via self-administered survey questionnaires. A deductive reasoning process was adopted, and a cross-sectional horizon was chosen to capture a snapshot of IoT adoption in SMEs at a certain point in time. The respondents' opinions were gauged using a 5-point Likert scale, which ranged from strongly disagree (1) to strongly agree (5). This scale is widely recognized for its reliability and ease of use in research studies (Farhan, 2023).

Data collection method and Sample size

Data was acquired from participating SME respondents in Gaborone city, Botswana. The study targeted key decision-makers in SMEs, specifically executives, supervisors, managers, and business owners, given their significant influence on IoT adoption and technology budget allocation (Zaidi & Belal, 2019). Both hard copy and online questionnaires were provided to consenting SME participants employing a random sampling technique. Utilizing Slovin's formula (1960), a required sample size of 382 participants was determined. Out of 550 issued surveys, 440 valid responses were obtained, yielding a 77.2% response rate. This response rate was considered adequate for SEM analysis (Hair Jr et al., 2021).

Reliability and Validity measurement

Internal Consistency

To evaluate the Likert-scale items' internal consistency, Cronbach's alpha coefficients were computed. Cronbach's alpha values above 0.9 indicate excellent reliability, 0.8-0.9 very good reliability, 0.7-0.8 good reliability, 0.6-0.7 moderate reliability, and below 0.6 poor reliability (Tavakol & Dennick, 2011). In this study, some items exhibited negative alpha coefficients, necessitating reverse coding to ensure consistent measurement direction (Chand, 2015). Furthermore, items significantly reducing Cronbach's alpha were removed. The final alpha values for most constructs exceeded 0.8, indicating very good reliability.

Validity Measurement

The validity of the research instrument was assessed through a comprehensive approach, encompassing content, face, and construct validity. Face validity was established through expert evaluation of the instrument's accuracy in measuring the intended constructs. Content validity was assessed through a two-step process: pre-testing and a pilot study. During pre-testing, a panel of academic experts and study supervisors evaluated the questionnaire for clarity, precision, and relevance to the study objectives. A pilot study was employed using a random sample of thirty SME owners, managers, and executives who were not included in the primary study. This pilot study assessed the questionnaire's suitability for the target population and its clarity. Feedback from experts, participants, and supervisors regarding the questionnaire's clarity and interpretability was used to refine the research instrument.

Data analysis Methods

Paper-based responses were digitized using Google Forms and merged with existing online responses. The consolidated dataset was cleaned and preliminarily coded in Microsoft Excel using a pre-designed codebook. After being cleaned, the data was imported into the Statistical Package for Social Sciences (SPSS) version 28 software for additional analysis. The raw SPSS data was subjected to stringent data screening methods, which included checks for validity, normality, and reliability as well as outlier detection. The data was summarized using descriptive statistics like percentages and frequencies.

Assessing for Data normality

Data normality was evaluated using the Shapiro-Wilk test, considered more robust than the Kolmogorov-Smirnov test for various distribution types (Tomšik, 2019). Consequently, the following null and alternative hypotheses were formulated:

- H_0 : The data is normally distributed.
- H_1 : The data is not normally distributed.

Shapiro-Wilk test with a p-value < 0.05 indicates a significant departure from normality (Ahad et al., 2011).

Assessing for Sampling Adequacy and Accuracy

Bartlett's Test of Sphericity and the Kaiser-Meyer-Olkin (KMO) measure were calculated to determine whether the data was suitable for factor analysis. A KMO value between 0.60 and 0.90 is generally considered acceptable, with values above 0.90 indicating excellent sampling adequacy (Shrestha, 2021). Furthermore, a significant Bartlett's Test ($p < 0.05$) is recommended for robust factor analysis.

SEM-ANN analysis approach

A hybrid SEM-ANN approach was employed for data analysis. SEM was implemented to examine the validity of the study model as a whole and the interactions among its constructs (Hair Jr et al., 2021).

SEM is particularly well-suited for testing complex theories in exploratory research and enables the simultaneous analysis of multiple regression relationships (Hair Jr et al., 2021). Furthermore, ANN was employed to validate the findings of the SEM analysis, aligning with established practices within the Information Systems (IS) field (Farhan, 2023). ANNs are valuable tools for predictive modelling, as they possess the capability to capture both linear and non-linear interactions, thus revealing intricate patterns within the data (Al Shamsi, 2023). Hyper parameter tuning, a critical aspect of ANN model development, involves an empirical process of iteratively evaluating various hyper parameter configurations to identify the optimal set (Abuhaija et al., 2023). In IBM SPSS, the ANN procedure offers functionalities to tune key hyper parameters during model development. The adaptable hyper parameters include; the quantity of training iterations, the learning rate, setting initial parameter values, identifying the activation function utilized, the number of training epochs, and the data distribution (Abuhaija et al., 2023).

To identify the optimal hyper parameters for the ANN model, the sigmoid activation function was implemented in both the hidden and output layers (Zabukovšek et al., 2022). Model training utilized a Batch-based approach, and the scaled conjugate gradient algorithm was employed for optimization. However, to mitigate the risk of over fitting and ensure strong generalization capabilities, a 10-fold cross-validation technique was implemented. Consequently, 90% of the dataset was allocated for training purposes, while the remaining 10% was reserved for evaluating the ANN model's performance. The Sum of Squared Errors (SSE) metric was used to assess the performance and measurement accuracy of each ANN model during the cross-validation procedure. The model exhibiting the lowest SSE on its respective validation fold was subsequently selected as the optimal model and used for final performance assessment on the dedicated 10% testing dataset. To assess the relative relevance of the exogenous constructs (ANN input nodes), a sensitivity analysis was conducted. This ranked the constructs according to their normalized importance (Leong et al., 2019). Moreover, for each multi-class IoT adoption category, the Area under the Curve (AUC) metric was computed to assess the ANN model's classification accuracy across all adoption groups. This strategic integration of SEM and ANN provided a comprehensive and rigorous analytical framework for expounding the determinants of IoT adoption within Botswana's SMEs.

Evaluating the Goodness-of-fit indices

Standard fit indices were employed to measure the model's goodness-of-fit, including the; Standardized Root Mean Residual (SRMR), Chi-square/Degrees of Freedom ratio (CMIN/DF), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA). These indices were selected based on common practices in technology adoption research (K. Gorejena, 2017; Kademeteme, 2020; Ngidi, 2019). Table 1 shows the cut-off criteria for goodness of fit indices.

Table 1: Goodness-of-fit evaluation criteria

Measurement Fit Indices	Unacceptable	Acceptable	Excellent
CMIN/DF	>5	>3	>1
CFI	<0.95	0.95	>0.95
SRMR	>0.10	>0.08	<0.08
RMSEA	>0.08	>0.06	<0.06

Source: adapted from (K. Gorejena, 2017; Kademeteme, 2020; Ngidi, 2019).

Ethical Consideration

The study obtained ethical clearance from North-West University in South Africa and necessary permissions from the Ministry of Trade and Industry and Gaborone City Council in Botswana. All participants provided informed consent and were assured of confidentiality through the use of pseudonyms.

Results

Demographic Analysis

Table 2 provides an overview of the respondents' demographic information as shown.

Table 2. Respondents' demographic information (n= 440)

Sr. No	Variable	Dimension	Frequency	Valid Percentage
1	Gender	Male	238	54.1
		Female	202	45.9
2	Age	18-25	73	16.6
		26-35	146	33.2
		36-55	189	43.0
		56 and above	32	7.3
3	Education level	High school and Below	206	46.8
		Certificate	77	17.5
		Diploma	105	23.9
		Bachelor degree	46	10.5
		Post graduate degree	6	1.4
4	ICT qualification	Yes	12	2.7
		No	403	91.6
		I don't know	25	5.7
5	Computer experience	Novice	308	70.0
		Intermediate	114	25.9
		Expert	18	4.1

Table 2 shows that 54.1% of respondents were male and 45.9% were female. The majority of respondents were aged between 36 and 55 (43.0%), followed by the 26-35 age group (33.2%). A smaller proportion were aged 18-25 (16.6%) and 56+ (7.3%). Most respondents had a high school or lower level of education (46.8%), followed by diploma holders (23.9%) and certificate holders (17.5%). A smaller proportion held bachelor's degrees (10.5%) or postgraduate degrees (1.4%). Most respondents (91.6%) did not possess an ICT qualification, while 5.7% were unsure and only 2.7% held an ICT qualification. Regarding computer experience, most respondents were novice users (70%), with smaller proportions having intermediate (25.9%) or expert (4.1%) levels of experience.

Table 3. SMEs demographic profile (n= 440)

Sr. No	Variable	Dimension	Frequency	Valid Percentage
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1	Firm's industry type	Retail	165	37.5
		Communication	33	7.5
		Education	30	6.8
		Health care	20	4.6
		Manufacturing	76	17.3
		Agriculture	6	1.4
		Transport	62	14.1
		Hospitality	14	3.2
		Finance	10	2.3
		Other	24	5.5
2	Years of operation of the firm	<=2	86	19.6
		3-5	169	38.4
		6-10	120	27.3
		11 – 20	44	10.0
		>= 21	21	4.8
3	Firm's employee size	5 or less	294	66.8
		6 - 10	84	19.1
		11 - 50	46	10.5
		51 - 100	16	3.6
4	Firm's annual revenue	Up to P100,000	279	63.4
		P100,001- P1,500, 000	137	31.1
		P1,500,001 – P5,000,000	24	5.5
5	Computer experience	Novice	308	70.0
		Intermediate	114	25.9
		Expert	18	4.1

Table 3 shows that the retail sector was the most prevalent industry, accounting for 37.5% of the sample, followed by manufacturing (17.3%) and transport (14.1%). Furthermore, most firms were small enterprises with five or fewer employees (66.8%) and annual revenues of up to P100, 000 (63.4%). Results further showed that the majority of firms were relatively young, with 77.8% operating for five years or less. Additionally, 70% of the firms had novice computer experience.

Assessing data for Normality

The Shapiro-Wilk test results showed that the data was not normally distributed ($p < .001$). This finding was also visually confirmed by histograms (see Figure 2), which deviated significantly from a normal distribution. These results suggest that non-parametric tests were appropriate for further analysis (Ngidi, 2019).

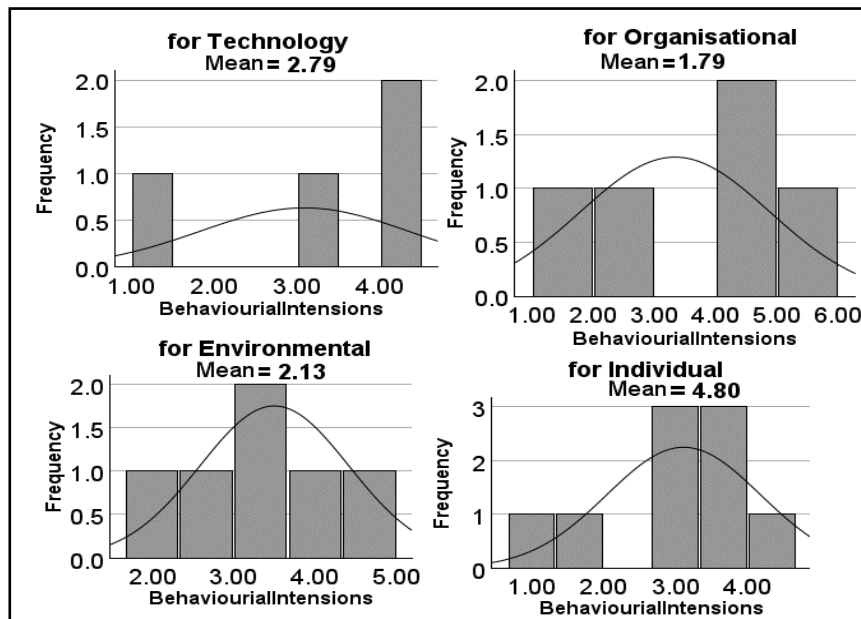


Figure 2: Histogram of the data distribution

Assessing for sampling Adequacy and Accuracy

In assessing for sampling adequacy and accuracy, the data was found to be suitable for factor analysis. This was supported by a KMO value of 0.982 and a highly significant Bartlett's Test of Sphericity ($\chi^2 = 30686.652$, $p < 0.001$). The results are summarized in Table 4.

Table 4: Sampling adequacy and accuracy

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.982
Bartlett's Test of Sphericity	Approx. Chi-Square	30686.652
	df	2080
	Sig.	<.001

Structural Equation Modelling

The SEM approach, specifically employing Confirmatory Factor Analysis (CFA), was employed to test a multi-theoretical model using empirical data from 440 SME participants in Gaborone City. AMOS software version 24 was used for data analysis since it was thought to be suitable for the study's objectives (Byrne, 2013).

Analysis of unmodified model fit indices

(Hair et al., 2009), suggest a minimum factor loading of 0.5 to ensure construct validity. Table 5 presents the results of the unmodified model fit indices. This table reveals that some items within the Complexity (CO), Technology Readiness (TECH), Perceived Ease of Use (PEO), and Actual IoT adoption (ATU) constructs exhibited factor loadings below this threshold. This indicates that these items may not

adequately represent the underlying constructs, potentially compromising the overall validity of the model. Table 5 presents the results of the factor loadings.

Table 5: Standardised factor loadings less than 0.50 threshold

			Estimate				Estimate
C2	<---	CO	-0.855	PE2	<---	PEO	0.848
C4	<---	CO	-0.849	S3	<---	SEC	0.851
TR6	<---	TECH	-0.798	CP4	<---	CMP	0.853
C3	<---	CO	-0.771	FR1	<---	FIN	0.863
PE5	<---	PEO	-0.21	PE1	<---	PEO	0.863
PE3	<---	PEO	0.17	TOP1	<---	TMS	0.864
ACT3	<---	ATU	0.41	PU3	<---	PUS	0.864
FS2	<---	FMS	0.514	R6	<---	RA	0.866

The unmodified model was evaluated using fit indices criteria (K. Gorejena, 2017; Kademeteme, 2020; Ngidi, 2019). While most fit indices were satisfactory, the CFI fell below acceptable thresholds. In addition, several factor loadings were below 0.50 (refer to Table 5), necessitating model refinement (Kademeteme, 2020; Kline, 2023). Table 6 illustrate results of the fit evaluation for the unmodified model, along with corresponding recommendations.

Table 6: Unmodified model fit assessment and recommendations

Measurement Fit Indices	Obtained Measurement Model Value	Interpretation	Recommendations
CMIN/DF	2.170	Acceptable	Below 3 shows a good fit
CFI	0.923	Least acceptable	Less than 0.095 suggesting model modification
GFI	0.753	Unacceptable	Less than 0.090 suggesting model modification
SRMR	0.0572	Excellent	Below 0.08 suggesting the best fit
RMSEA	0.052	Excellent	Below 0.06 suggesting the best fit

Modification of the Measurement model

To refine the measurement model, a series of modifications were made without compromising model integrity (Kademeteme, 2020). Firstly, the factor loadings which were less than 0.50 were discarded. Subsequently, the measurement model was iteratively refined and evaluated, ensuring all factor loadings met the specified criteria (K. Gorejena, 2017). Moreover, modification indices were examined to identify potential improvements, such as deleting covariance or regression weights (Kademeteme, 2020). This iterative process continued until the optimal model fit was achieved at the tenth iteration, as indicated by AMOS software. Figure 3 illustrates the iterative process of model refinement, culminating in the identification of the best-fitting model.

Iteration no.	Activity	CMIN/DF	CFI	SRMR	RMSEA
0		2.170	0.923	0.0572	0.052
	Delete path: C2 <--- CO				
1		2.159	0.925	0.0572	0.051
	Delete path: C4 <--- CO				
2		2.177	0.925	0.0576	0.052
	Delete path: TR6<--- TECH				
3		2.159	0.927	0.0579	0.051
	Delete path:C3 <--- CO				
4		2.156	0.929	0.0581	0.051
	Delete path: PE5<--- PEO				
5		2.145	0.931	.0576	0.051
	Delete path: PE3<--- PEO				
6		2.161	0.933	0.0573	0.051
	Delete path: ACT3<--- ATU				
7		1.963	0.945	0.0442	0.047
	Covariate e23 <--> e26				
8		1.942	0.947	0.0443	0.046
	Covariate e7<--> e8				
9		1.919	0.948	.0443	0.046
	Covariate e34 <--> e35				
10		1.856	0.951	0.0397	0.044

The best fitting model

Figure 3: Iterative process of model refinement to achieve the best model fit.

Structural model assessment

Once the best-fit model has been determined, its goodness-of-fit was assessed using standard fit indices. Results showed that CMIN/DF, CFI, SRMR, and RMSEA values all fell within acceptable ranges, indicating the empirical data and the measurement model fit each other adequately. These results are presented in Table 7.

Table 7: Assessment of optimal model fit and recommendations

Measurement fit indices	Obtained measurement model value	Interpretation	Recommendations
CMIN/DF	1,856	Excellent	Below 3 shows the best fit
CFI	0.951	Excellent	Greater than 0.95 shows a good fit
SRMR	0.0397	Excellent	Below 0.08 shows the best fit
RMSEA	0.044	Excellent	Below 0.06 shows the best fit

Reliability and Validity assessment

To assess the model's reliability and validity, Composite Reliability (CR) and Average Variance Extracted (AVE) were computed for all latent factors. Results showed that all latent factors, except for

Firm Size (FMS), met the acceptable thresholds. Therefore, FMS was excluded from the final model. However, Behavioral Intention (INTE) and Actual IoT adoption (ATU) were not assessed as they were model-predicted variables. Table 8 presents the results

Table 8: Assessment of latent variables CR, AVE, and interpretation

Latent variable/ Factor	CR	AVE	Interpretation
Relative advantage (RA)	0.953	0.77	Supported
Complexity (COM)	0.909	0.67	Supported
Compatibility (CO)	0.789	0.652	Supported
Trust (TRST)	0.873	0.696	Supported
Security and privacy (SEC)	0.868	0.687	Supported
Technology readiness (TECH)	0.894	0.629	Supported
Top management support (TMS)	0.91	0.716	Supported
Firm size (FMS)	0.631	0.379	Not supported
Financial resources (FIN)	0.912	0.776	Supported
Government support (GOV)	0.891	0.672	Supported
Competitive pressure (CMP)	0.928	0.722	Supported
Vendor/External support (VEN)	0.931	0.729	Supported
Perceived Usefulness (PUS)	0.943	0.767	Supported
Perceived Ease of Use (PEO)	0.883	0.716	Supported
Behaviour Intentions (INTE)	-----	-----	Not tested
Actual IoT adoption (ATU)	-----	-----	Not tested

The final measurement model

The refined SEM model in Figure 4 displays the standardized factor loadings for each construct item. This final model indicates that no further adjustments were necessary for optimization based on AMOS software

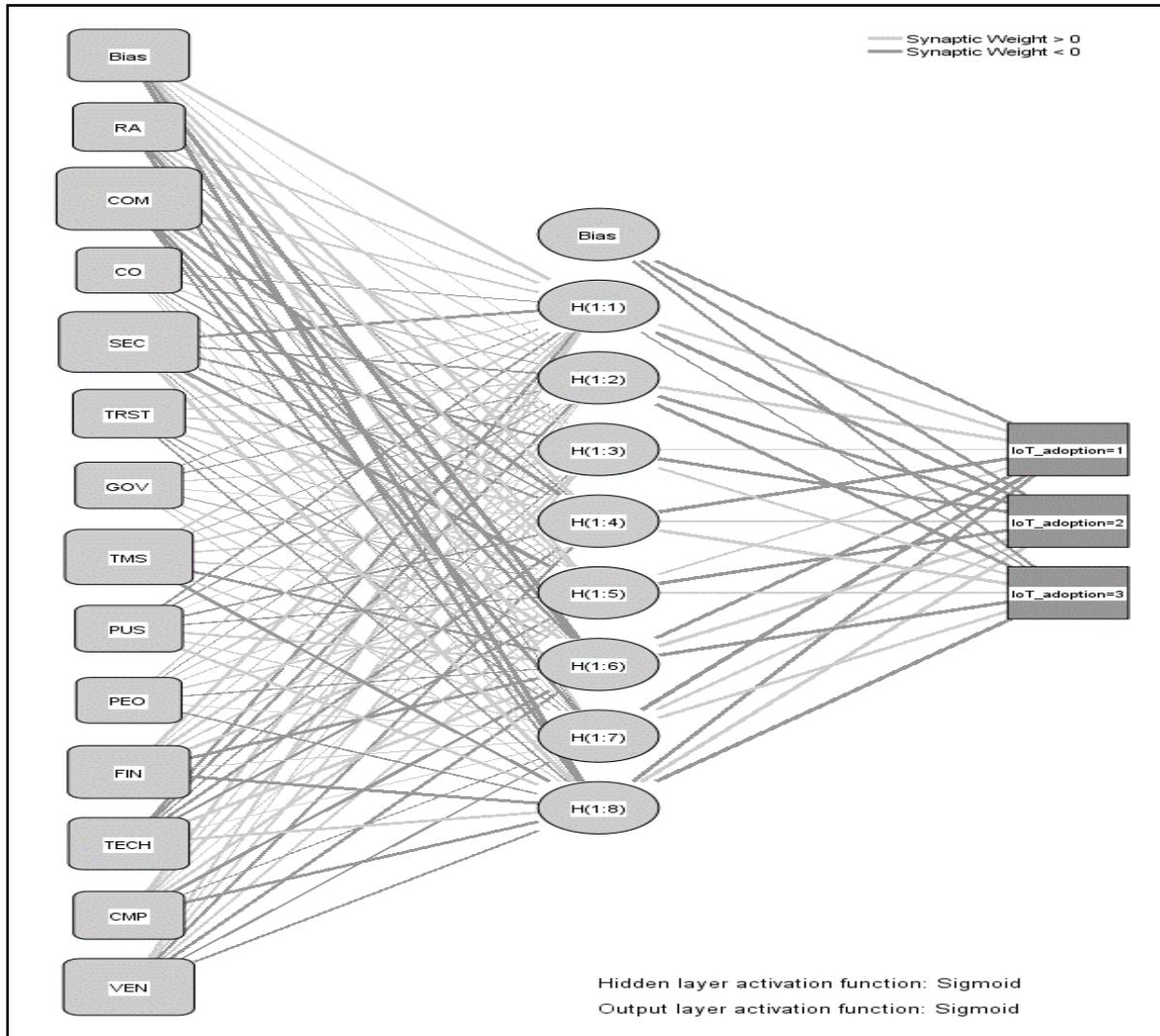


Figure 5: The MLP-ANN model architecture

Assessing prediction performance of the MLP-ANN

To compute the MLP-ANN prediction performance, the SSE was used to quantify the discrepancy between predicted and actual values of the ANN model. Additionally, the Percentage of Incorrect Predictions (PIP) was calculated to provide a more intuitive measure of the model's accuracy. Table 9 summarizes the evaluation results of the optimal MLP-ANN model.

Table 9: MLP-ANN model summary

Training	Sum of Squares Error	13.953
	Percent Incorrect Predictions	4.3%
	Stopping Rule Used	1 consecutive step(s) with no decrease in error ^a
	Training Time	0:00:00.17
Testing	Sum of Squares Error	.740
	Percent Incorrect Predictions	2.0%

Dependent Variable: IoT_adoption
a. Error computations are based on the testing sample.

Table 9 demonstrates the strong predictive performance of the MLP-ANN model during both training and testing phases. For the training data, SSE was 13.953, corresponding to a Prediction Improvement Percentage (PIP) of 4.3%, resulting in a prediction accuracy of 95.7%. During the testing phase, SSE decreased to 0.740, and PIP increased to 2.0%, indicating strong generalization capabilities and a prediction accuracy of 98%. The AUC was calculated for each IoT adoption category. The model exhibited exceptional classification accuracy for "Already Adopted IoT" and "Not Adopting IoT" categories, with AUC values of 0.992 and 1.000, respectively. The "Plan to Adopt IoT" category also demonstrated strong performance, with an AUC of 0.994. These results, consistent with (Trifonova et al., 2013), confirm the MLP-ANN model's ability to accurately predict and validate the identified influential factors.

Ranking of the Influential factors

A sensitivity analysis was performed to establish the relative importance of each element by comparing their mean values to the highest mean value. Results indicated that Compatibility (COM) was the most significant factor (100%). Security concerns (SEC) followed with a score of 82.10%. Technology readiness (TECH), top management support (TMS), and financial resources (FIN) were also significant, with scores of 72.20%, 65.10%, and 60.30%, respectively. Table 10 presents the results.

Table 10: Independent variable importance ratings

Factor	Importance	Normalised Importance
COM	0.177	100.00%
SEC	0.146	82.10%
TECH	0.128	72.20%
TMS	0.115	65.10%
FIN	0.107	60.30%
VEN	0.106	59.90%
PUS	0.046	26.00%
TRST	0.046	25.90%
RA	0.034	19.10%
CMP	0.027	15.30%
CO	0.026	14.70%
GOV	0.024	13.60%
PEO	0.017	9.80%

Figure 6 presents a hierarchical ranking of the most critical determinants IoT adoption. This shows that factors of COM, SEC, TECH, TMS, and FIN are the most influential in Botswana's SMEs.

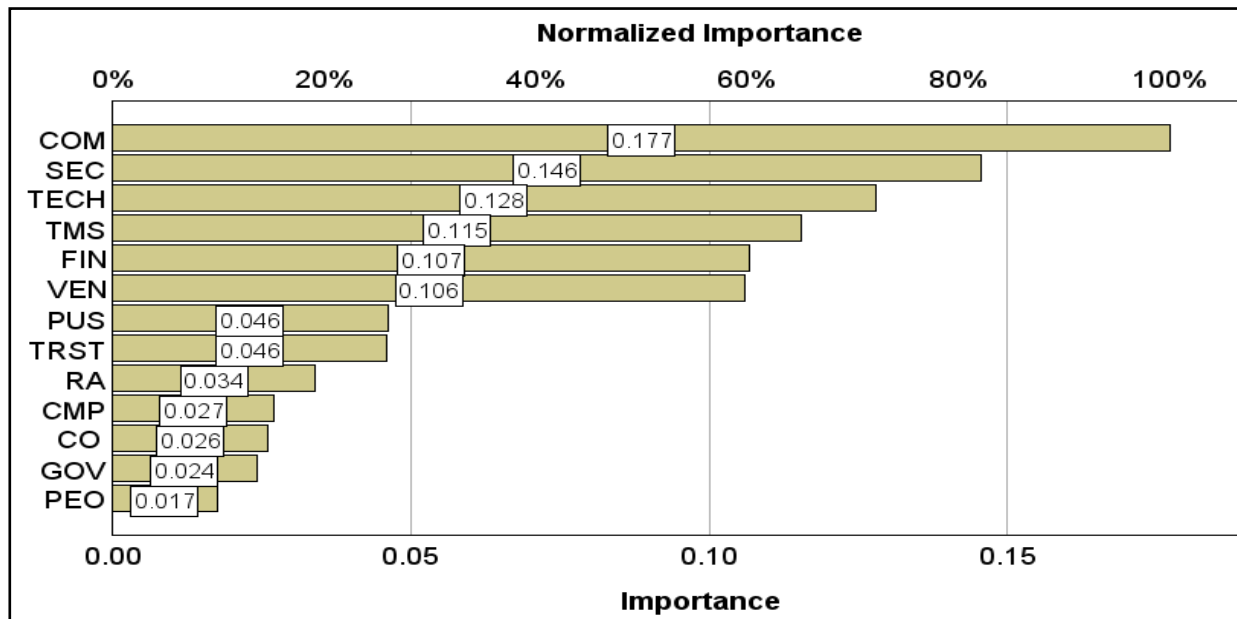


Figure 6: Ranking of the influencing factors

Moderator variable Analysis

To evaluate the moderating effects of demographic variables on actual IoT adoption (ATU), a non-parametric Mann-Whitney U test was employed using SPSS software. The study adopted a categorization scheme proposed by (Moriényane & Marnewick, 2019) to examine factors affecting IoT adoption in organizations. This categorization scheme is presented in Table 10 below.

Table 10: Grouping of the moderators influencing IoT adoption

Moderator Variable	Group 1	Group 2
Gender	Male	Female
Age	Younger adopters (18-25, 26-35, 36-55 years)	Older adopters (56 years and above)
Educational level	Non-tertiary (higher education, below)	Tertiary (certificate, diploma, degree, postgraduate qualification)
computer experience	Less experienced (novice)	More experienced (intermediate and expert)

Figure 7 presents the findings of the Mann-Whitney U test when evaluating the moderating effects of demographic variables on ATU in Botswana's SMEs.

Gender		Education level	
Test Statistics ^a		Test Statistics ^a	
	ATU		ATU
Mann-Whitney U	21742.500	Mann-Whitney U	18767.500
Wilcoxon W	50183.500	Wilcoxon W	40088.500
Z	-1.798	Z	-4.173
Asymp. Sig. (2-tailed)	.072	Asymp. Sig. (2-tailed)	<.001
a. Grouping Variable: Gender		a. Grouping Variable: Education_level	

Age		Computer experience	
Test Statistics ^a		Test Statistics ^a	
	ATU		ATU
Mann-Whitney U	5784.000	Mann-Whitney U	15021.500
Wilcoxon W	89200.000	Wilcoxon W	62607.500
Z	-1.148	Z	-4.520
Asymp. Sig. (2-tailed)	.251	Asymp. Sig. (2-tailed)	<.001
a. Grouping Variable: Age		a. Grouping Variable: Computer_experience	

Figure 7: results of the moderator variables on ATU in Botswana's SMEs

Figure 7 reveals no significant gender difference in ATU among Botswana SMEs, as highlighted by a p-value of 0.072, which is greater than p-value of 0.05. Similarly, no significant age-related differences were observed in ATU, with a p-value of 0.251. However, significant differences in ATU were observed based on both education level and computer experience. The Mann-Whitney U test yielded p-values less than 0.001 for both education level and computer experience of SME participants.

Discussions

Prior research identified diverse determinants of IoT adoption in SMEs, including technological, organizational, and environmental factors (Grandon et al., 2018; Kwak et al., 2023; Sivathanu, 2019; Soomro et al., 2024; Usman et al., 2021). Findings of the study demonstrated a strong fit of the proposed model to the empirical data (CMIN/DF = 1.856, CFI = 0.951, SRMR = 0.0397, RMSEA = 0.044). Hence, key factors influencing IoT adoption in Botswana's SMEs were identified as: relative advantage, complexity, compatibility, trust, security and privacy, technology readiness, top management support, financial resources, government support, competitive pressure, vendor support, perceived usefulness, and perceived ease of use. These findings imply that giving these aspects top priority is essential to maximizing IoT adoption rates among SMEs in Botswana. Furthermore, sensitivity analysis using the MLP-ANN model ranked compatibility as the most significant factor, followed by security concerns, technology readiness, top management support, and financial resources. These findings align with those of Wungcharoen (2022) but differs from others Mukherjee et al. (2023) regarding the impact of factors like relative advantage and competitive pressure. This suggests that the influence of these factors may vary across different regions and industries. Figure 8 shows a hierarchical ranking of the elements that influence IoT adoption among Botswana's SMEs.

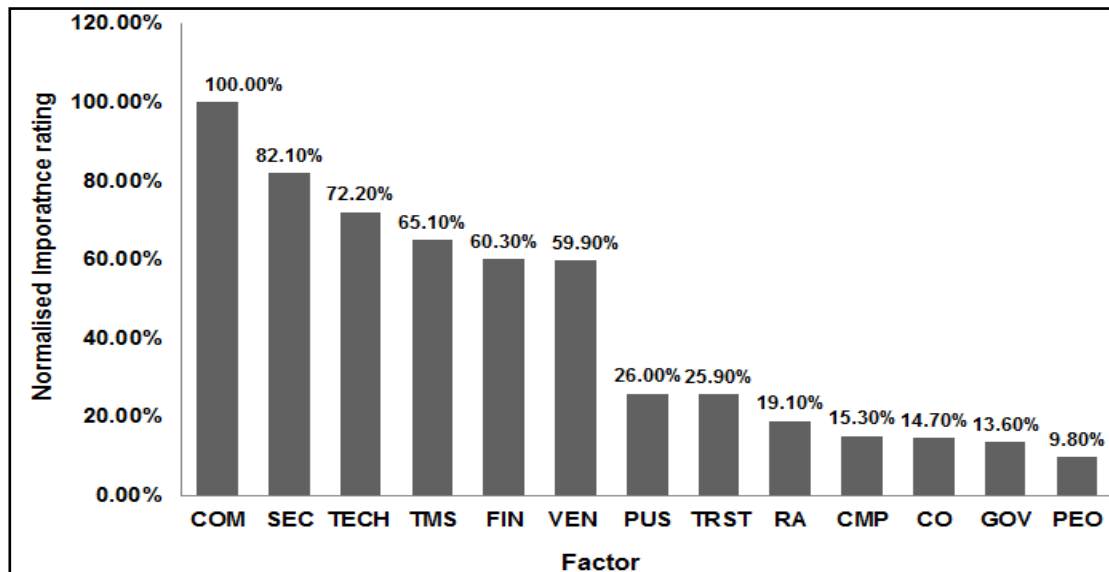


Figure 8: Rankings of factors affecting the adoption of IoT in Botswana's SMEs

To further examine IoT adoption in Botswana's SMEs, the study examined the moderating effects of demographic variables (age, gender, education level, and computer experience) on ATU. Mann-Whitney U test results showed no significant difference in IoT adoption between younger and older SME owners/managers. Thus, this suggested that age is not a critical determinant of IoT adoption. This aligns with Morienyane and Marnewick (2019) findings on the non-significant impact of age on IoT technology adoption. The study also compared the adoption rates between male and female SME owners/managers. Results revealed no statistically significant difference, suggesting that gender is not a primary determinant of IoT adoption among Botswana's SMEs. While consistent Morienyane and Marnewick (2019), this contradicts findings suggesting a gender-related gap in technology adoption, particularly in developing countries (Acilar & Sæbø, 2023). Moreover, a comparative analysis of firms led by tertiary-qualified and non-tertiary-qualified individuals confirmed a strong positive correlation between educational level and ATU in Botswana's SMEs. This finding aligns with previous research linking higher education levels to increased technology adoption in organizations (Jones & Graham, 2018)..

When examining the moderating effect of computer experience on IoT adoption rates, a significant difference in ATU was found between SMEs led by owners/managers with high and low levels of computer experience. This suggests that extensive computer experience is a crucial factor influencing IoT adoption within Botswana SMEs. Coffman (2014) argues that individuals with prior experience with computers or similar technologies are more open to trying new technology. Their familiarity with technology trends and best practices can streamline the adoption process (Venkatesh et al., 2003).

Contributions of the Study

The present research significantly adds to comprehension of the variables affecting IoT adoption among Botswana's SMEs. Previous research has primarily focused on contexts outside Botswana (Grandon et al., 2018; Kwak et al., 2023; Sivathanu, 2019; Soomro et al., 2024; Usman et al., 2021), restricting the findings' direct relevance to the local setting. Additionally, this research addresses the limited comparative analyses on factors influencing IoT adoption within SMEs in emerging economies

(Wungcharoen, 2022). Methodologically, this study pioneers the combination of a multi-theoretical perspective model with the SEM-ANN approach to examine factors influencing IoT adoption in Botswana's SMEs. Additionally, this research offers valuable insights for a broad spectrum of stakeholders, such as government entities, SMEs, private sector and the academia. Findings provide a practical framework for policymakers to develop strategies that facilitate IoT integration within the SME sector. Furthermore, this research carries significant implications for SME managers and owners, serving as a fundamental resource for considering the practicality and feasibility of IoT adoption. For academia, the findings highlight the significance of incorporating practical IoT skills into curricula. Finally, for the research community specializing in IS, IT, and SME technology adoption, the study lays the groundwork for further research while making a substantial addition to the body of existing knowledge.

Limitations and Direction for Future research

The study's focus was limited to IoT adoption in Gaborone SMEs. Hence, future research should broaden its scope to include SMEs in various regions of Botswana, particularly rural areas, and adopt a longitudinal approach to examine the evolution of IoT adoption factors. Additionally, incorporating the perspectives of general SME employees, beyond owners and managers, could provide further insights into organizational and individual-level impacts of IoT adoption. Moreover, given the early stage of IoT adoption research in Botswana, future studies should prioritize methodological rigor. A mixed-methods approach could complement quantitative findings and provide a thorough comprehension of the subject of the study.

Conclusion

Even with IoT's potential advantages, SMEs in emerging economies including Botswana are not adopting it. Previous research on IoT adoption in SMEs has primarily focused on contexts outside Botswana, leaving the Botswana context understudied. Additionally, while SEM has contributed to understanding IoT adoption determinants in SMEs, the potential of integrating ANN in this context has been largely overlooked. This study validated a multi-theoretical model through a hybrid SEM-ANN approach. Findings revealed that significant factors influencing IoT adoption include relative advantage, complexity, compatibility, trust, security and privacy, technology readiness, top management support, financial resources, government support, competitive pressure, vendor support, perceived usefulness, and perceived ease of use. A sensitivity analysis highlighted compatibility as the most significant factor, followed by security, technology readiness, top management support, and financial resources. Furthermore, the study identified educational level and computer experience as key moderators of actual IoT adoption among Botswana's SMEs. This study contributes to a deeper understanding of IoT adoption in Botswana's SMEs and provides valuable insights for policymakers and decision-makers. The proposed framework can guide the adoption of IoT policy in Botswana, along with other emerging economies. Future research could investigate additional factors and approaches to deepen our understanding of IoT adoption among SMEs in Botswana.

References

Abuhaija, B., Alloubani, A., Almatari, M., Jaradat, G. M., Hemn, B. A., Abualkishik, A. M., & Alsmadi, M. K. (2023). A comprehensive study of machine learning for predicting

- cardiovascular disease using Weka and SPSS tools. *International Journal of Electrical and Computer Engineering*, 3(2), 1891.
- Acilar, A., & Sæbø, Ø. (2023). Towards understanding the gender digital divide: A systematic literature review. *Global Knowledge, Memory and Communication*, 72(3), 233–249.
- Ahad, N. A., Yin, T. S., Othman, A. R., & Yaacob, C. R. (2011). Sensitivity of normality tests to non-normal data. *Sains Malaysiana*, 40(6), 637–641.
- Al Shamsi, M. S. M. (2023). *Examining the Factors affecting the sustainability of blockchain technology in higher education using a hybrid SEM-ANN approach*. The British University in Dubai.
- Arnold, C., & Voigt, K. I. (2019). Determinants of Industrial Internet of Things Adoption in German Manufacturing Companies. *Int. J. Innov. Technol. Manag*, 16, 1950038.
- Barnes, J., Sachs, W., & Pelsier, T. (2024). The Challenges of Digital Technology Adoption within a Group of South African Manufacturing SMEs. *International Business Conference*.
- Blanchier, C., Down, E., Manghi, A. I., & O'Brien, J. K. (2019). *Burden or Benefit: Do Standards Work for IoT SMEs?* Available at SSRN 3454591.
- Burton-Jones, A., & Hubona, G. S. (2006). The mediation of external variables in the technology acceptance model. *Information & Management*, 43(6), 706–717.
<https://doi.org/http://dx.doi.org/10.1016/j.im.2006.03.007>
- Byrne, B. M. (2013). *Structural equation modeling with AMOS : basic concepts, applications, and programming*.
- Chand, M. (2015). *Exploring the role of emotions during the Fair Trade shopping experience* [Auckland University of Technology]. <https://openrepository.aut.ac.nz/items/7c41f910-735c-4daf-bbcc-f19e64b08dbe>
- Coffman, K. B. (2014). Evidence on self-stereotyping and the contribution of ideas. *The Quarterly Journal of Economics*, 129(4), 1625–1660.
- Dai, X., Peng, J., & Zhiyuan, F. (2013). Senior executive and staff: What effect do they exert on success of information system? In *Proceedings of the 10th IEEE International Conference on E-Business Engineering (ICEBE 2013)*.
- Farhan, B. (2023). *Theoretically assessed framework for cyberbullying prediction: a study on undergraduate students from universities in Malaysia using pls-sem and neural network approach*. UTAR.
- Fauzan, T. R., & Dhewanto, W. (2021). Fostering innovation through Industry 4.0 technologies in emerging countries: An explorative multiple case study of Indonesian Internet-of-Things (IoT)-based start-ups. *Journal of Research in Emerging Markets*, 3(2), 71–85.
- Gorejena, K. (2017). *Towards an adaptive socio-technical Broadband Growth and Penetration (BGP) framework: a case of SADC* [North-West University, South Africa].
<https://repository.nwu.ac.za/handle/10394/36743>
- Gorejena, K. N., Mphale, O., & Nojila, O. (2024). Harnessing the Internet of Things: A Review of Opportunities and Barriers for SMEs within Emerging Economies. *Ponte Academic Journal*, 80(9). <https://doi.org/doi: 10.21506/j.ponte.2024.9.4>
- Grandon, E. E., Ibarra, A. A., Guzman, S. A., Ramirez-Correa, P., & Alfaro-Perez, J. (2018). Internet of Things: Factors that influence its adoption among Chilean SMEs. In *2018 13th Iberian Conference on Information Systems and Technologies (CISTI)*, 1–6.
- Haddud, A., DeSouza, A., Khare, A., & Lee, H. (2017). Examining potential benefits and challenges associated with the internet of things integration in supply chains. *Journal of Manufacturing Technology Management*, 28(8). <https://doi.org/1055-1085>. <https://doi.org/10.1108/JMTM-05->

2017-0094

- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2009). *Multivariate data analysis* (7th ed.). Prentice-Hall.
- Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., Ray, S., & Ray, S. (2021). *An introduction to structural equation modeling*. Partial least squares structural equation modeling (PLS-SEM) using R: a workbook.
- Harbi, Y., Aliouat, Z., & Harous, S. (2022). Fog computing security and privacy for internet of things (iot) and industrial internet of things (iiot) applications: State of the art. *Security Issues in Fog Computing from 5G to 6G: Architectures, Applications and Solutions*, 145–157.
- Hasan, B. (2010). Exploring gender differences in online shopping attitude. *Computers in Human Behavior*, 26(4), 597–601. <https://doi.org/10.1016/j.chb.2009.12.012>
- IoTNOW. (2018). *How SMEs can use IoT for business growth*. IoTNOW. <https://www.iot-now.com/2018/04/17/80739-smes-can-use-iot-business-growth/>
- Jamalut, Y., Abd Rahim, M. F., & Ong, J. W. (2022). A Framework on Intention to Adopt Internet of Things Among MSMEs in Farming. In *International Conference on Technology and Innovation Management (ICTIM 2022)*, 321–332.
- Jones, N. B., & Graham, C. M. (2018). Can the IoT help small businesses? *Bulletin of Science, Technology & Society*, 38(1–2), 3–12.
- Kademete, E. (2020). *A 4IR Framework for ICT Evaluation: a Case from South African SMEs* [University of South Africa]. https://scholar.google.com/scholar?hl=en&as_sdt=0%2C5&q=A+4IR+framework+for+ICT+evaluation+%3A+a+case+from+South+Africa+SMEs&btnG=
- Kline, R. B. (2023). Principles and practice of structural equation modeling. In *Guilford publications*.
- Kwak, C., Yoon, C., & Martí-Parreño, J. (2023). Factors affecting SME executives' intentions to adopt smart factories: The case of Korea. *Information Development*, 02666669231205525.
- Leong, L. Y., Hew, T. S., Ooi, K. B., Lee, V. H., & Hew, J. J. (2019). A hybrid SEM-neural network analysis of social media addiction. *Expert Systems with Applications*, 133, 296–316. <https://doi.org/doi:10.1016/j.eswa.2019.05.024>
- Lim, C., Osman, B. B., Yusof, Y., & Rahmat, A. R. (2024). Integrating IoT and Mobile Applications for efficient Plant Watering: The Io T Smart Watering System (SWS). *Journal of Digital System Development*, 124–139.
- Maisiri, W., & van Dyk, L. (2021). Industry 4.0 skills: A perspective of the South African manufacturing industry. *SA Journal of Human Resource Management*, 19, 1416. <https://doi.org/https://doi.org/10.4102/sajhrm.v19i0.1416>
- Morinyane, L. D., & Marnewick, A. (2019). Technology Acceptance Model of Internet of Things for Water Management at a local municipality. In *2019 IEEE Technology & Engineering Management Conference (TEMSCON)*, 1–6.
- Mphale, O., Gorejena, K. N., & Nojila, O. (2024a). A Multi-Theory Framework for Assessing IoT Adoption in Botswana SMEs. *Journal of Information Systems and Informatics*, 6(2), 1237–1262.
- Mphale, O., Gorejena, K. N., & Nojila, O. (2024b). The Future of Things: A Comprehensive Overview of Internet of Things History, Definitions, Technologies, Architectures, Communication and beyond. *Journal of Information Systems and Informatics*, 6(2), 1263–1286.
- Mubeen, S. K., Nie, C. P., & Amran, A. (2023). Investigating the toe factors influencing IOT adoption and SMEs performance in Pakistan: The mediating role of organization resilience. *International Journal of Business and Technology Management*, 5(3), 175–192.
- Mukherjee, S., Baral, M. M., Chittipaka, V., Nagariya, R., & Patel, B. S. (2023). Achieving

- organizational performance by integrating industrial Internet of things in the SMEs: a developing country perspective. *The TQM Journal*.
- Mustafa, S., Zhang, W., Anwar, S., Jamil, K., & Rana, S. (2022). An integrated model of UTAUT2 to understand consumers' 5G technology acceptance using SEM-ANN approach. *Scientific Reports*, 12(1), 20056.
- Nassereddine, M., & Khang, A. (2024). Applications of Internet of Things (IoT) in smart cities. In *Advanced IoT Technologies and Applications in the Industry 4.0 Digital Economy*, 109–136.
- NDP11. (2017). Botswana National Development Plan (NDP) 11. *National Development Plan 11*, 1.
- Ngidi, N. V. (2019). *Determinants of ICT adoption by small and medium enterprises in Pietermaritzburg*. University of Kwazulu Natal.
- Okafor, P. (2023). *Benefits and Adoption of Internet of Things (IoT) to Nigeria's Small and Medium-Sized Enterprises (SMEs)*. <https://doi.org/10.13140/RG.2.2.22320.12806>
- Olushola, O. B. (2019). Factors affecting IoT adoption. *IOSR J. Comput. Eng.(IOSR-JCE)*, 21, 19–24.
- Onu, P., & Mbohwa, C. (2021). Industry 4.0 opportunities in manufacturing SMEs: Sustainability outlook. *Materials Today: Proceedings*, 44, 1925–1930. <https://doi.org/10.1016/J.MATPR.2020.12.095>
- Parab, S. D., Deshmukh, A., & Vasudevan, H. (2023). *Understanding the Drivers and Barriers in the Implementation of IoT in SMEs*. 267–279. https://doi.org/10.1007/978-981-19-7971-2_26
- Parker, D. S. (2020). *The implementation of the Internet of Things (IoT): A case study of the barriers that prevent implementation of IoT within small and medium enterprises (SME)*. Northcentral University.
- Parra, D. T., Talero-Sarmiento, L. H., Ortiz, J. D., & Guerrero, C. D. (2021). Technology readiness for IoT adoption in Colombian SMEs. In *2021 16th Iberian Conference on Information Systems and Technologies (CISTI)*, 1–6.
- Peter, O., Pradhan, A., & Mbohwa, C. (2023). Industrial internet of things (IIoT): opportunities, challenges, and requirements in manufacturing businesses in emerging economies. *Procedia Computer Science*, 856–865.
- Poornima, G., Vinay, J., Karthikeyan, P., & Jinesh, V. N. (2024). Inventory tracking via IoT in the pharmaceutical industry. In *Intelligent Wireless Sensor Networks and the Internet of Things*, 147–204.
- Shrestha, N. (2021). Factor analysis as a tool for survey analysis. *American Journal of Applied Mathematics and Statistics*, 9(1), 4–11.
- Shukor, R. A., Mooi, W. K., & Ahmad, M. N. (2022). Small and medium enterprises' business sustainability based on the Industry 4.0 internet of things adoption: a Malaysian Bumiputera case study. *Serbian Journal of Management*, 17(1), 99–110.
- Sinha, I., & Mukherjee, S. (2016). Acceptance of technology, related factors in the use of off branch ebanking: An Indian case study. *The Journal of High Technology Management Research*, 27, 88–100. <https://doi.org/doi:10.1016/j.hitech.2016.04.008>
- Sivathanu, B. (2019). Adoption of industrial IoT (IIoT) in auto-component manufacturing SMEs in India. *Information Resources Management Journal (IRMJ)*, 32(2), 52–75.
- Soomro, R. B., Memon, S. G., Dahri, N. A., Al-Rahmi, W. M., Aldriwish, K., A., Salameh, A., & Saleem, A. (2024). The Adoption of Digital Technologies by Small and Medium-Sized Enterprises for Sustainability and Value Creation in Pakistan: The Application of a Two-Staged Hybrid SEM-ANN Approach. *Sustainability*, 16(17), 7351.
- Sriram, R. M., & Vinodh, S. . (2021). Analysis of readiness factors for Industry 4.0 implementation in SMEs using COPRAS. *Int J Qual Reliab Manag* 38(5), 38(5), 1178–1192.

- <https://doi.org/https://doi.org/10.1108/IJQRM-04-2020-0121>
- Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International Journal of Medical Education*, 2(53).
- Tomšik, R. (2019). Power comparisons of shapiro-wilk, Kolmogorov-smirnov and jarque-bera tests. *Scholars Journal of Research in Mathematics and Computer Science*, 3(3), 238–243.
- Trifonova, O. P., Lokhov, P. G., & Archakov, A. I. (2013). Metabolic profiling of human blood. *Biochemistry (Moscow) Supplement Series B: Biomedical Chemistry*, 7, 179–186.
- Usman, B., Sentosa, I., & Nurrahmi, F. (2021). Structural equation modeling of internet of things (IoT) adoption for Indonesian Village-Owned Enterprises (BUMDes). *Informasi*, 51(1), 169–194.
- Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478.
- Wasim, M., Ahmed, S., Kalsoom, T., Khan, M. S., & Rafi-Ul-Shan, P. M. (2024). Market orientation and SME performance: Moderating role of IoT and mediating role of creativity. *Journal of Small Business Management*, 62(2), 938–965.
- Wungcharoen, Y. (2022). IoT adoption in SME manufacturers in Thailand. In *Swansea*. <https://cronfa.swan.ac.uk/Record/cronfa60536>
- Yi, M. Y., Jackson, J. D., Park, J. S., & Probst, J. C. (2006). Understanding information technology acceptance by individual professionals: Toward an integrative view. *Information & Management*, 43(3), 350–363. <https://doi.org/10.1016/j.im.2005.08.006>
- Zabukovšek, S. S., Bobek, S., Zabukovšek, U., Kalinić, Z., & Tominc, P. (2022). Enhancing PLS-SEM-enabled research with ANN and IPMA: Research study of enterprise resource planning (ERP) systems' acceptance based on the technology acceptance model (TAM). *Mathematics*, 10(9), 1379.
- Zaidi, M. F. A., & Belal, H. M. (2019). A Preliminary Study to Understand the SMEs' Readiness on IoT in Malaysia. *International Journal of Accounting, Finance and Business (IJAFB)*, 4(19).