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EXAMINING THE INFLUENCE OF ARTIFICIAL INTELLIGENCE-ENABLED DIGITALISATION ON CUSTOMER SATISFACTION: EVIDENCE FROM THE TELECOMMUNICATIONS SECTOR IN ZAMBIA

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Abstract

This study investigates the influence of artificial intelligence (AI)-enabled digitalisation on customer satisfaction within the telecommunications sector in Kitwe, Zambia. Adopting a positivist paradigm with a cross-sectional survey design, data were collected from 401 respondents using a structured Likert-scale questionnaire. The study employed partial least squares structural equation modelling (PLS-SEM) to test the hypothesised relationships. The measurement model demonstrated acceptable reliability and validity, while the structural model exhibited adequate explanatory and predictive power. The findings reveal that AI-enabled consumer experience and trust significantly and positively influence customer satisfaction, whereas service quality does not have a significant impact. Furthermore, customer satisfaction significantly influences behavioural intention.

The study demonstrates that customer satisfaction partially mediates the relationship between AI-enabled digitalisation factors and behavioural intention, highlighting its central role in shaping customer responses. From a practical perspective, telecommunications firms should prioritise enhancing AI-driven customer experience and trust-building mechanisms without neglecting service quality improvements. The contribution of this study lies in integrating AI-enabled digitalisation constructs within the telecommunications industry of a developing economy and empirically validating their effects on customer outcomes using PLS-SEM.

Keywords: Artificial Intelligence, Digitalisation, Customer Satisfaction, Behavioural Intention, Telecommunications.

1.0 Introduction

Artificial intelligence (AI) has emerged as a transformative technology influencing business operations, customer engagement, and global economic development (Brandao, 2025). Although early evidence suggested limited awareness of AI among business leaders—with only 17% of senior executives in the United States reporting familiarity with AI technologies (Mhlanga, 2022)—organisations have increasingly embraced AI as a strategic tool for enhancing efficiency, innovation, and competitiveness. Recent studies indicate that 41% of marketers have experienced improved organisational performance and revenue growth through AI adoption, while 38% associate AI with enhanced customer experiences and personalised service delivery (Mohd et al., 2025; Potwora et al., 2024). Furthermore, AI is projected to contribute approximately US$13 trillion to the global economy by 2030, increasing global GDP by about 14%, which underscores its growing importance in digital transformation and economic development (Banerjee et al., 2023; PCW, 2025).

Over the past two decades, AI technologies have transformed numerous sectors, including finance, healthcare, education, marketing, and telecommunications (Huang & Rust, 2018). Through technologies such as predictive analytics, chatbots, recommendation systems, and automated customer service platforms, organisations are increasingly able to analyse large volumes of customer data, automate decision-making processes, and deliver personalised services more efficiently (Hibban, 2025). The integration of AI into digital marketing and customer relationship management has enabled firms to better understand customer preferences, improve service responsiveness, and strengthen customer engagement, making AI a critical enabler of modern business innovation (Stone et al., 2020; Wan, 2023).

The telecommunications industry has been among the sectors most affected by digital transformation. Telecommunications companies increasingly utilise AI-enabled technologies, including automated customer support systems, digital assistants, and intelligent communication platforms, to improve service delivery and customer interaction (Mijanur & Khatun, 2023). These technologies allow firms to respond more quickly to customer enquiries, enhance operational efficiency, and provide more personalised customer experiences. Consequently, AI-enabled digitalisation has become an important competitive strategy within the telecommunications sector worldwide.

In Zambia, the telecommunications industry has experienced significant growth due to increasing mobile phone penetration and internet usage. According to the Zambia Information and Communications Technology Authority (ZICTA), Airtel Zambia had approximately 8.3 million active mobile subscribers, MTN recorded 6.8 million subscribers, and Zamtel accounted for about 3.3 million subscribers (ZICTA, 2022). The competitive nature of the industry has compelled service providers to invest in advanced digital technologies aimed at attracting and retaining customers. However, despite these technological advancements, the sector continues to face challenges such as network failures, service interruptions, delayed responses to customer complaints, and inconsistent service delivery, which negatively affect customer satisfaction (Evangeline, 2025). As consumers can easily switch between service providers, understanding the factors that influence customer satisfaction and behavioural intention has become increasingly important for telecommunications companies seeking to maintain a competitive advantage (Mbilima & Phiri, 2025).

Although telecommunications firms in Zambia have adopted AI-enabled digital technologies, empirical evidence examining their influence on customer outcomes remains limited. Existing studies have primarily focused on digital marketing adoption, customer engagement, and digital service quality in e-commerce environments. For example, Katongo & Musawa (2022) examined digital marketing and customer engagement during the COVID-19 pandemic, while Mwiya et al. (2022) and Chawala et al. (2022) applied the E-SERVQUAL framework to investigate digital service quality and customer satisfaction in online platforms. While these studies provide valuable insights into digital service delivery, they do not explicitly examine how AI-enabled digitalisation influences customer satisfaction and behavioural intention within the telecommunications sector.

Furthermore, recent systematic literature reviews suggest that the role of AI in customer engagement and service delivery remains underexplored, particularly in emerging economies where digital transformation is still evolving (Gupta & Khan, 2024). This study examines the influence of AI-enabled digitalisation factors—specifically consumer experience, service quality, and trust—on customer satisfaction and behavioural intention among telecommunications customers in Kitwe, Zambia. The subsequent sections of this paper are structured as follows: a comprehensive review of the literature and development of hypotheses, a description of the research methodology, and a presentation and discussion of the results. Finally, the key findings are summarised, and directions for future research are proposed.

2.0 Literature Review

Customer satisfaction remains one of the most extensively researched constructs in marketing and service management because it influences customer loyalty, retention, and organisational performance. Customer satisfaction refers to the degree to which a product or service meets or exceeds customer expectations following consumption or usage (Guido, 2015; Mwiya et al., 2017; Oliver, 1980). According to Expectation-Disconfirmation Theory, satisfaction occurs when customers perceive that the actual performance of a service equals or surpasses their pre-consumption expectations (Oliver, 1980). Conversely, dissatisfaction arises when service performance falls below expected standards. In highly competitive industries such as telecommunications, customer satisfaction is particularly important because customers can easily switch service providers when their expectations are not met.

The rapid advancement of AI has transformed how organisations create and deliver value to customers. Artificial Intelligence refers to the capability of computer systems to perform tasks that typically require human intelligence, including learning, problem-solving, decision-making, and language processing. AI-powered technologies such as chatbots, virtual assistants, machine learning algorithms, predictive analytics, and automated recommendation systems have become increasingly prevalent in service industries. These technologies enable firms to analyse vast volumes of customer data, automate service processes, personalise customer interactions, and improve operational efficiency (Rane, 2023).

In the telecommunications sector, AI-enabled digitalisation has become a strategic tool for enhancing customer experience and strengthening customer relationships. Telecommunications companies increasingly utilise AI-driven customer support systems, automated complaint management platforms, intelligent network monitoring systems, and personalised marketing applications to improve service delivery (Mijanur & Khatun, 2023). These technologies allow firms to respond more quickly to customer enquiries, predict customer needs, and deliver tailored services based on individual preferences. Consequently, AI-enabled digitalisation has become an important determinant of customer satisfaction and behavioural outcomes in contemporary service environments.

Customer experience represents one of the most important dimensions of AI-enabled digitalisation. Customer experience refers to the overall perception formed through interactions between customers and organisations across multiple touchpoints during service consumption (Kuppelwieser et al., 2022). AI technologies enhance customer experience by facilitating personalised interactions, reducing waiting times, and improving service accessibility. Through machine learning and data analytics, organisations can better understand customer preferences and provide customised solutions that improve service encounters (Jarrahi, 2018). Previous studies conducted in developed economies have consistently reported that positive digital customer experiences contribute significantly to customer satisfaction and loyalty (O'Higgins & Fatorachian, 2025; Prentice, Dominique, et al., 2020).

Another important dimension of AI-enabled digitalisation is service quality. Service quality refers to customers' evaluations of the overall excellence and effectiveness of service delivery (Chawala et al., 2022; Mwiya et al., 2024). In AI-enabled environments, service quality encompasses responsiveness, reliability, accessibility, efficiency, and system functionality. AI technologies improve service quality by automating routine tasks, reducing human errors, and ensuring faster responses to customer requests (Akter et al., 2025). Studies conducted in various contexts suggest that improved service quality positively influences customer satisfaction and behavioural intention (Ali et al., 2023; Chinenye & Tochukwu, 2024). However, findings remain inconsistent across developing countries, where infrastructural challenges and network reliability issues may affect customer perceptions of service quality.

Trust is also recognised as a critical factor influencing customer evaluations of AI-enabled services. Trust refers to customers' confidence in the reliability, integrity, and competence of a service provider or technological system (Wanner et al., 2022). In digital environments, trust becomes particularly important because customers often share personal information and rely on automated systems to complete transactions and access services. AI-enabled trust is influenced by factors such as transparency, privacy protection, security, and system reliability (Toreini et al., 2020; Yu & Li, 2022). Customers who trust AI-powered systems are more likely to perceive service interactions positively and report higher satisfaction levels.

Empirical evidence supports the relationship between AI-enabled digitalisation and customer satisfaction across various contexts. Daqar & Smoudy (2019) found that AI adoption significantly enhanced customer experience and satisfaction in Taiwan's retail sector. Similarly, studies conducted in Australia and the United Kingdom reported that trust and AI performance positively influence customer satisfaction and engagement (O'Higgins & Fatorachian, 2025; Prentice, Weaven, et al., 2020). In India and Brazil, AI-driven digital marketing applications were found to improve customer experience, service efficiency, and overall customer satisfaction (Gabelaia & Hendieh, 2025; Singh & Singh, 2024). Within Africa, Manyanga et al. (2022) demonstrated that improved digital customer experiences significantly enhanced customer satisfaction and loyalty among consumers in Zimbabwe.

Despite growing international evidence, research examining AI-enabled digitalisation and customer satisfaction remains limited in Zambia. Existing studies have primarily focused on digital marketing adoption, customer engagement, and e-service quality within e-commerce contexts (Katongo & Musawa, 2022; Mwiya, Bwalya, et al., 2017; Mwiya et al., 2026). While these studies provide valuable insights into digital service delivery, they do not specifically examine how AI-enabled customer experience, service quality, and trust influence customer satisfaction and behavioural intention within the telecommunications sector. Furthermore, recent systematic reviews indicate that empirical evidence regarding AI-enabled customer engagement and service outcomes remains scarce in emerging economies where digital transformation is still developing (Gupta & Khan, 2024). This gap creates the need for further investigation into the role of AI-enabled digitalisation in influencing customer satisfaction and behavioural intention among telecommunications customers in Zambia.

2.1 Theoretical Background

This section focuses on the theoretical underpinnings and contexts of this study's conceptualisation, highlighting the most relevant and underpinning theories.

2.1.1 Theory of Planned Behaviour (TPB)

The Theory of Planned Behaviour developed by Ajzen (1991) provides an important theoretical foundation for understanding behavioural intention and has been widely applied in studies examining technology adoption and consumer behaviour. The theory evolved from the Theory of Reasoned Action developed by Ajzen & Fishbein (1975), which explains behaviour through attitudes and subjective norms. The TPB extends this model by incorporating perceived behavioural control, enabling researchers to explain behaviours that individuals may not fully control (Ajzen, 1991). Previous studies have applied TPB in analysing the adoption of digital systems and online services, including research by Mwiya et al. (2017), as well as studies by Kurniawati et al. (2023) and Nandre et al. (2020). However, limited studies have applied TPB to examine how AI-enabled digitalisation influences customer satisfaction and behavioural intention in telecommunications services within developing economies such as Zambia. Therefore, this study applies TPB to explain how attitudes toward AI-enabled services, social influence, and perceived behavioural control influence customers' behavioural intentions through the mediating role of customer satisfaction.

2.1.2 Expectation Disconfirmation Theory

Expectation Disconfirmation Theory, originally proposed by Oliver (1980), provides a theoretical explanation of how customer satisfaction is formed through the comparison between expectations and perceived performance. The theory suggests that consumers develop expectations before purchasing or using a service, and satisfaction occurs when the perceived performance confirms or exceeds those expectations, while dissatisfaction occurs when performance falls below expectations (Oliver, 1980). The theory has been widely applied in marketing and consumer behaviour research to explain customer satisfaction and post-purchase behaviour. For instance, studies by Mwiya et al. (2019) and Schiebler et al. (2025) demonstrated that expectation disconfirmation significantly influences customer satisfaction and loyalty. In the telecommunications sector, studies such as those by Kishore (2023), Dzivor et al. (2022), and Shafei & Tabaa (2016) applied the theory to explain customer retention and behavioural intention. However, limited research has examined expectation disconfirmation within AI-enabled digital services in telecommunications in developing countries. Therefore, this study uses disconfirmation theory to explain how customers evaluate AI-enabled service experiences relative to their expectations, which subsequently influences customer satisfaction and behavioural intention.

2.1.3 Marketing Automation Theory

Marketing Automation Theory provides another theoretical perspective for understanding how digital technologies influence customer engagement and satisfaction. The theory emphasises the use of automated systems and data-driven platforms to deliver personalised and relevant marketing communications to customers (Salonen et al., 2024). Marketing automation enables organisations to collect and analyse customer data in order to tailor content, recommendations, and services that meet individual customer preferences, thereby improving engagement and trust. Earlier studies by Heimbach et al. (2015) and Rolando (2025) demonstrate that marketing automation improves customer communication, enhances brand awareness, and increases conversion, cross-selling, and customer retention rates. Despite these contributions, existing studies largely focus on business-to-business environments and developed markets, with limited attention given to how AI-powered automation influences customer satisfaction and behavioural intention in developing economies. Therefore, this study integrates marketing automation theory to explain how AI-driven personalisation and automated communication enhance customer experience and satisfaction, which ultimately influences behavioural intention in the telecommunications sector.

2.2 Hypotheses Development

In light of the foregoing theoretical background and the identified gaps in the literature, this study proposes a conceptual model reflecting the interrelationships among consumer experience, service quality, trust, behavioural intention, and the mediating influence of customer satisfaction.

2.2.1 Artificial Intelligence-Enabled Consumer Experience and Customer Satisfaction

Customer experience refers to the cumulative interactions between customers and an organisation throughout the service process. According to Kuppelwieser et al. (2022), customer experience encompasses the overall perception formed during interactions with a firm's services and technologies. Previous studies indicate that customer experience involves cognitive, emotional, physical, and social dimensions that collectively shape customer perceptions and evaluations of a service (Mwiya et al., 2022). In the digital era, advancements in artificial intelligence have significantly enhanced customer experience by enabling organisations to analyse large volumes of customer data and interactions in real time. According to Jarrahi (2018), AI technologies can rapidly process consumer inputs and behavioural patterns, enabling firms to understand customer needs and preferences more effectively.

Artificial intelligence tools such as recommendation systems, chatbots, and predictive analytics enable companies to deliver personalised and efficient customer interactions. Studies by Rabby (2025) and Rakesh (2025) indicate that AI systems utilise customer data and profiles to provide customised experiences that improve service efficiency and responsiveness. Furthermore, AI-driven customer engagement can strengthen brand reputation and improve customer satisfaction (Wahid & Awad, 2025). Therefore, the first hypothesis is as follows:

H_1: Artificial intelligence–enabled consumer experience has a positive and significant effect on customer satisfaction.

2.2.2 Artificial Intelligence-Enabled Service Quality and Customer Satisfaction

Artificial Intelligence-enabled service quality refers to an organisation's ability to utilise intelligent technologies, such as automated systems, predictive analytics, and digital assistants, to enhance the efficiency, accuracy, and responsiveness of service delivery (Prentice, Dominique, et al., 2020). According to Malik et al. (2020), evaluating service quality involves assessing consumer perceptions of how effectively a firm delivers its service offerings. AI technologies have significantly transformed service operations by enabling organisations to predict customer needs, automate interactions, and personalise user experiences. Studies by Akter et al. (2025) and Chinenye & Tochukwu (2024) indicate that AI-driven tools allow firms to improve service quality by tailoring services to individual preferences, thereby enhancing operational efficiency and customer value.

The relationship between AI-enabled service quality and customer satisfaction is supported by Expectation Disconfirmation Theory, which suggests that customers evaluate services by comparing their expectations with actual performance. According to Ali et al. (2023), customers' perceptions of digital services are influenced by their expectations regarding the benefits that technology-based services can provide. However, previous studies have largely focused on human-delivered services, with limited research examining customer responses to AI-enabled services (Gong, 2026). Hence, the second hypothesis is that:

H_2: Artificial intelligence–enabled service quality has a positive and significant effect on customer satisfaction.

2.2.3 Artificial Intelligence-Enabled Trust and Customer Satisfaction

Trust refers to the confidence that customers place in a system based on perceptions of competence, reliability, honesty, and predictability. According to Wanner et al. (2022), trust in technological systems reflects a user's willingness to rely on a technology in situations involving uncertainty or potential risk. In the context of artificial intelligence, trust has become an important factor influencing users' acceptance and evaluation of digital services. Studies indicate that trust in AI is influenced by several factors, including system reliability, transparency, and the ability of users to understand how AI systems make decisions (Toreini et al., 2020; Yu & Li, 2022). Transparency and interpretability enable users to comprehend how AI systems function, which enhances confidence in the technology (Mathew et al., 2025).

Furthermore, issues such as privacy protection, data security, and system reliability play a critical role in shaping trust in AI technologies. Research by Cao et al. (2022) indicates that customers' perceptions of privacy and data protection significantly influence their level of trust in digital systems. Similarly, trust has been shown to strengthen relationships between customers and organisations in digital environments (Cao et al., 2022). When customers trust AI-enabled services, they are more likely to perceive the service positively and report higher satisfaction levels. Therefore, the third set of hypotheses is as follows:

H_3: Artificial intelligence–enabled trust has a positive and significant effect on customer satisfaction.

2.2.4 Customer Satisfaction and Behavioural Intention

Customer satisfaction plays a critical role in shaping customers' future behavioural intentions toward a firm's products or services. According to Mwiya et al. (2022), satisfied customers are more likely to maintain long-term relationships with organisations, leading to repeat purchases and stronger customer loyalty. In digital service environments, customer satisfaction is formed when the perceived performance of a product or service meets or exceeds customer expectations (Sutriani et al., 2024). A study done by Thakur (2019) indicates that organisations that provide high-quality services and positive customer experiences tend to achieve higher levels of customer satisfaction, which strengthens customer loyalty and retention.

Furthermore, customer satisfaction has been widely recognised as a key determinant of behavioural intention, including repurchase intention, positive word of mouth, and willingness to recommend services to others. According to Ribeiro & Prayag (2019), positive service experiences lead to favourable behavioural intentions, while poor service experiences result in negative behavioural responses. Empirical studies also show that satisfied customers are more likely to demonstrate loyalty and promote a firm through positive recommendations (Khan et al., 2022; Mwiya et al., 2019). Therefore, the fourth hypothesis is proposed:

H_4: Customer satisfaction has a positive and significant effect on behavioural intention.

2.2.5 The mediating role of Customer satisfaction

Customer satisfaction plays an important mediating role in explaining how service-related factors influence behavioural intention. With the advancement of information and communication technologies, the interaction between organisations and customers has become more dynamic, raising expectations regarding service delivery and quality (Alzaydi et al., 2018). When customers perceive that services meet or exceed their expectations, they are more likely to experience satisfaction, which subsequently influences their behavioural responses such as repeat purchase, positive word of mouth, and continued engagement with the service provider. Satisfied customers also tend to perceive lower switching risks, reducing the likelihood of searching for alternative service providers.

Previous studies have demonstrated that customer satisfaction mediates the relationship between service quality factors and behavioural outcomes. Research by Mwiya et al. (2022) shows that satisfaction indirectly influences customer retention and loyalty. Similarly, studies by Liang et al. (2018) and Mwiya et al. (2017) found that satisfied customers are more likely to develop repurchase intentions and maintain long-term relationships with organisations. Therefore, the fifth hypothesis is proposed:

H_5: The relationships between behavioural intention and its AI-enabled antecedents are mediated by customer satisfaction.

3.0 Research Methodology

Population, unit of analysis, and sample

This study adopted a quantitative cross-sectional survey design to examine the influence of artificial intelligence-enabled digitalisation on customer satisfaction and behavioural intention among telecommunications customers in Kitwe, Zambia. The unit of analysis comprised individual subscribers of mobile telecommunications services who actively utilise digital platforms and AI-enabled services offered by mobile network operators.

The target population consisted of customers of Airtel, MTN, and Zamtel operating within Kitwe. Due to the unavailability of customer databases from the service providers, the exact population size could not be established. Therefore, an estimated population of 20,000 mobile subscribers was adopted for sampling purposes. Using the Raosoft sample size calculator at a 95% confidence level and a 5% margin of error, the minimum recommended sample size was 377 respondents (Raosoft, 2026). To enhance reliability and minimise the effect of incomplete responses, a total of 401 valid questionnaires were collected and utilised in the final analysis.

Primary data were gathered through a structured questionnaire based on previously validated measurement scales and administered using both online and hard-copy formats. Responses were measured on a five-point Likert scale ranging from strongly disagree (1) to strongly agree (5). The demographic profile of the respondents is presented in Table 1.

Table 1: Sample Profile

Variable	Responses	Frequency	Percent	Valid percent	Cumulative percent
Gender	Female	233.0	58.1	58.1	58.1
	Male	168.0	41.9	41.9	100.0
Age-group	Below 20 years	2	0.5	0.5	0.5
	21-30 years	111	27.7	27.7	28.2
	31-40 years	251	62.6	62.6	90.8
	41-50 years	30	7.5	7.5	98.3
	Above 51	7	1.7	1.7	100.0
Level of Education	Certificate and below	15	3.7	3.7	3.7
	Diploma	98	24.4	24.4	28.2
	Degree	263	65.6	65.6	93.8

	Master degree	24	6.0	6.0	99.8
	Doctorate	1	0.2	0.2	100.0
Marital Status	Married	213	53.1	53.1	53.1
	Single	188	46.9	46.9	100.0
	Student	12	3.0	3.0	3.0
Occupation	Self-employed/Entrepreneur	52	13.0	13.0	16.0
	Private sector	221	55.1	55.1	71.1
	Public sector	116	28.9	28.9	100.0
Monthly Income	Below K2,000	1	0.2	0.2	0.2
	K2,001-5,000	50	12.5	12.5	12.7
	K5,001-10,000	213	53.1	53.1	65.8
	K10,001-15,000	114	28.4	28.4	94.3
	Above K15,000	23	5.7	5.7	100.0
Mobile Network Operator (MNO) Used	MTN	8	2.0	2.0	2.0
	Airtel	32	8.0	8.0	10.0
	Zamtel	12	3.0	3.0	13.0
	MTN and Airtel	155	38.7	38.7	51.6
	MTN and Zamtel	75	18.7	18.7	70.3
	Airtel and Zamtel	51	12.7	12.7	83.0
	All Networks	68	17.0	17.0	100.0
	MTN	195	48.6	48.6	48.6
	Airtel	147	36.7	36.7	85.3

Frequently Mobile Network Operator Used	Zamtel	59	14.7	14.7	100.0
AI platforms	Yes	358	89.3	89.3	89.3
	No	43	10.7	10.7	90.0
Appreciate message sent	Yes	395	98.5	98.5	98.5
	No	6	1.5	1.5	100.0
Data charges affordable	Yes	224	55.9	55.9	55.9
	No	177	44.1	44.1	100.0

Alt Text: Sample Profile reflecting characteristics such as gender, age group, qualifications, marital status, occupation, income, MNO, AI platforms, and data charges affordable for the 401 respondents.

Data analysis method

Partial least squares structural equation modelling (PLS-SEM) was utilised to analyse the data and evaluate the hypotheses using SmartPLS. PLS-SEM is especially useful due to its robustness in undertaking measurement model assessment while concurrently testing structural models (Hair et al., 2019). The analysis method is appropriate when tackling complex models, small samples, and formative constructs where conventional covariance-based SEM (CB-SEM) might not be usable because of stringent assumptions on data distributions and inadequate sample sizes (Mwiya, 2012). Researchers in management and social sciences are increasingly embracing PLS-SEM, seeing that it is flexible in managing unbalanced datasets and latent variables (Ahmed et al., 2025).

PLS-SEM maintains strong discriminant validity as well as beta coefficients and frequently yields higher composite reliability and convergent validity than CB-SEM (Dash & Paul, 2021). Furthermore, it facilitates causal-predictive analyses, making it more suitable for developing and evaluating theoretical frameworks intended for explanation and prediction, in contrast to CB-SEM, which is primarily intended for theory confirmation using a covariance approach (Hair & Alamer, 2022).

The "10 times rule," which states that the sample size must be at least ten times the maximum number of path linkages directed at any latent variable in the model, governs the minimum sample size required for PLS-SEM (Marcoulides & Chin, 2013). With the sample size of 401, the current study much outstrips this, guaranteeing the validity and robustness of the PLS-SEM findings.

4.0 Results

Preliminary Statistical Checks for Data Distribution

The measurement model explains how endogenous and exogenous constructs are measured through observed indicators. To enhance internal and content validity, the study adapted measures from prior empirical publications. Particularly, the independent construct was consumer experience with 7 indicators, service quality with 4 indicators, trust with 6 indicators, the mediator construct was customer satisfaction with 4 indicators, and the dependent construct was behavioural intention with 4 indicators. Five constructs with 25 reflective indicators were assessed for reliability and validity using factor loadings, indicator reliability, internal consistency, and convergent and discriminant validity.

To minimise the potential effects of common method variance (CMV), several procedural measures were implemented during questionnaire design and administration, including clear wording of items, assurance of respondent confidentiality, and careful structuring of the survey instrument. Statistical assessment of CMV was conducted using Harman's single-factor test (Podsakoff et al., 2024). The results showed that the first factor accounted for 23.5% of the total variance, which is substantially below the recommended threshold of 50% (Pangarso et al., 2020). This suggests that common method bias was unlikely to pose a serious threat to the validity of the findings. Furthermore, exploratory factor analysis using principal component analysis confirmed the suitability of the measurement items. Table 2 states the results of the Harman single-factor test for CMV testing with Bartlett's Sphericity at Chi-square (χ^2) = 2554, df = 210, $p<0.001$ and KMO Measure of Sample adequacy at 0.820 in the acceptable range for factor analysis. In Bartlett's Sphericity, a significant result gives confidence that the correlations within the data are meaningful and not just random chance, making the dataset suitable for factor analysis. The KMO test assesses whether the data are suitable for factor analysis by comparing observed correlations to partial correlations. A high KMO value indicates strong correlations between variables, making factor analysis appropriate (0.80 to 1 is high, 0.70 middle, below 0.50 unacceptable) (Mwiya, 2012).

Table 2: Harman single-factor test, Total Variance Explained

Component	Eigenvalue	Variance proportion	Variance cumulative
1	4.943	0.235	0.235
2	2.449	0.117	0.352
3	1.978	0.094	0.446
4	1.217	0.058	0.504
5	1.109	0.053	0.557
6	1.046	0.050	0.607
7	0.880	0.042	0.649
8	0.763	0.036	0.685
9	0.727	0.035	0.720

10	0.713	0.034	0.754
11	0.645	0.031	0.784
12	0.595	0.028	0.813
13	0.563	0.027	0.839
14	0.546	0.026	0.865
15	0.520	0.025	0.890
16	0.506	0.024	0.914
17	0.501	0.024	0.938
18	0.416	0.02	0.958
19	0.411	0.02	0.978
20	0.326	0.016	0.993
21	0.146	0.007	1.000

Alt Text: Table of Harman's single-factor test showing total variance explained. Results indicate that a single factor does not account for the majority of variance, supporting the absence of common method bias.

Testing for normality may not be a strict requirement for variance-based structural equation modelling, but it was undertaken anyway to assess the distribution (Zulkifli et al., 2023). Deviations from normality may lead to biased results, unreliable estimates, and possibly incorrect conclusions, especially for covariance-based SEM. To improve the robustness and dependability of the analytical findings, thorough normality evaluations were conducted. The values of skewness and kurtosis, which ranged from -1.146 to -0.156 and -0.635 to 0.724, respectively, were within the acceptable limits of −2 to +2 for skewness and −7 to +7 for kurtosis, indicating a normal distribution of data (George & Mallery, 2024; Hair et al., 2021). These findings support the dataset's suitability for additional analysis, which is supported by PLS-SEM's robust handling of both normal and non-normal distributions (Henseler et al., 2015).

Construct validity test results

The current study evaluated the reliability and convergent validity of constructs using several metrics. Composite reliability values for all constructs ranged from 0.774 to 0.853, indicating that internal consistency was within the acceptable range. The average variance extracted (see Table 3), which measures convergent validity by the squared loadings of items, displayed values between 0.403 and 0.625 for all variables, exceeding the threshold of 0.5 and confirming sufficient explanatory power of the constructs (Hair et al., 2019).

Table 3: Convergent Validity and Reliability

Construct	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
Behavioural Intention	0.768	0.853	0.595
Consumer Experience	0.734	0.799	0.403
Customer Satisfaction	0.700	0.833	0.625
Service Quality	0.639	0.774	0.462
Trust	0.631	0.780	0.472

Alt Text: Table reporting convergent validity and reliability results. Factor loadings are high, average variance extracted exceeds the threshold, and composite reliability values confirm internal consistency.

The final measurement model involved 21 reflective indicators. Before this, and based on factor loadings, some items were excluded to enhance model robustness: two items from trust, one item from consumer experience and one item from customer satisfaction. This refinement process sought to ensure that each item's loading exceeded the commonly accepted threshold of 0.5 (Benitez et al., 2020), thereby contributing positively to construct validity (see Table 4) since the loadings range from 0.501 to 0.844.

Table 4: Analyses of Outer loadings

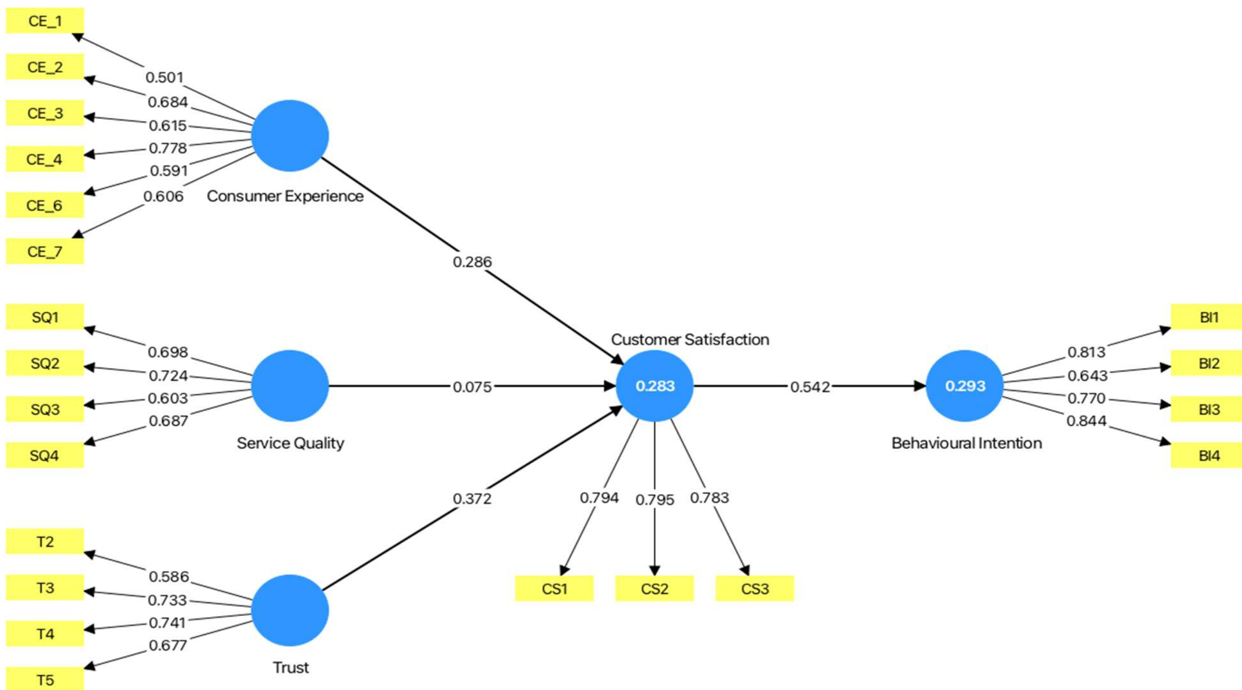
Construct	Items	Outer loadings
Behavioural Intention	BI1	0.813
	BI2	0.643
	BI3	0.770
	BI4	0.844
Consumer Experience	CE_1	0.501
	CE_2	0.684
	CE_3	0.615
	CE_4	0.778
	CE_6	0.591
	CE_7	0.606
Customer Satisfaction	CS1	0.794
	CS2	0.795

	CS3	0.783
Service Quality	SQ1	0.698
	SQ2	0.724
	SQ3	0.603
	SQ4	0.687
Trust	T2	0.586
	T3	0.733
	T4	0.741
	T5	0.677

Alt Text: Table presenting analyses of outer loadings for measurement items. All loadings exceed recommended thresholds, confirming indicator reliability and supporting construct validity.

The iterative process of refining the SEM models led to improved construct validity and model robustness, as items with weaker loadings were eliminated. This approach aligns with practices noted in the literature, where item reduction is often necessary to achieve a more valid and reliable measurement model (Chinnaraju, 2025; Hair et al., 2019; Magno et al., 2024).

Figure 1 illustrates the measurement model post-refinement, displaying the constructs after adjustments based on the PLS-SEM analysis. This visual representation confirms the structural integrity and validity of the refined model, ensuring that all remaining indicators robustly represent their respective constructs.



Alt Text: *Structural equation model diagram with five latent variables (Consumer experience, service quality, trust, customer satisfaction, behavioural intention) linked to their observed indicators with loadings between 0.501 to 0.844.*

Figure 1. Measurement Model

Cronbach's alpha measures the internal consistency of a group of items, indicating how closely related they are to one another. Values between 0.558 and 0.916 are considered valid to ensure internal consistency (Benitez et al., 2020; George & Mallery, 2024). Figure 1 shows the modified model after removing the indicators below the minimum accepted threshold (see also Table 4).

Furthermore, items and constructs exhibiting a Variance Inflation Factor (VIF) score higher than 5 would indicate potential multicollinearity concerns (Magno et al., 2024). However, as detailed in Table 5, the VIF scores for all constructs remained lower than the threshold of concern. Specifically, the VIF scores were between 1.000 and 1.079, which were comfortably within the acceptable range, suggesting that multi-collinearity was not an issue (Hair et al., 2019; Magno et al., 2024).

Table 5: Multi-Collinearity Test (VIF)

	VIF
Consumer Experience	1.079
Customer Satisfaction	1.000
Service Quality	1.011

Trust	1.068

Alt Text: Table displaying results of the multicollinearity test using VIF values. All variance inflation factors fall below accepted thresholds, indicating no multicollinearity concerns among the constructs.

Discriminant Validity Test Results

Discriminant validity (DV) measures the extent to which a given construct is distinct from other constructs within the model, i.e. it is vital to ensure that a construct uniquely represents specific phenomena not covered by other constructs (Benitez et al., 2020). In this regard, the Fornell-Lacker criterion (Table 6) shows that the squared AVE on each column is consistently greater than the correlations below, signifying discriminant validity (Magno et al., 2024).

Table 6: Discriminant Validity Fornell-Lacker Criterion

Construct	BI	CE	CS	SQ	T
Behavioural Intention	**0.771**				
Consumer Experience	0.549	**0.635**			
Customer Satisfaction	0.542	0.387	**0.791**		
Service Quality	0.160	0.102	0.103	**0.679**	
Trust	0.442	0.250	0.443	-0.002	**0.687**

Alt Text: Table presenting discriminant validity results using the Fornell–Larcker criterion. Diagonal values of average variance extracted are higher than inter-construct correlations, confirming discriminant validity among the constructs.

The Heterotrait-Monotrait (HTMT) ratio of correlations is a modern method for evaluating discriminant validity. It compares the correlations between measures of theoretically different constructs (heterotrait) with the correlations of measures within the same construct, i.e. monotrait (Hair et al., 2019). An HTMT value below 0.90 is typically recognised as evidence of discriminant validity (Benitez et al., 2020; Henseler, 2018). Table 7 outlines the HTMT ratios, which act as indicators of discriminant validity between constructs. The highest HTMT value was 0.578, remaining below the widely accepted cut-off point of 0.90. This result supports the constructs' uniqueness within the model, confirming their discriminant validity according to the heuristic benchmarks and reinforcing the constructs' definitional clarity in the research design (see Table 7).

Table 7 Discriminant Validity Via Heterotrait-Monotrait (HTMT)

	BI	CE	CS	SQ	T
Behavioural Intention					

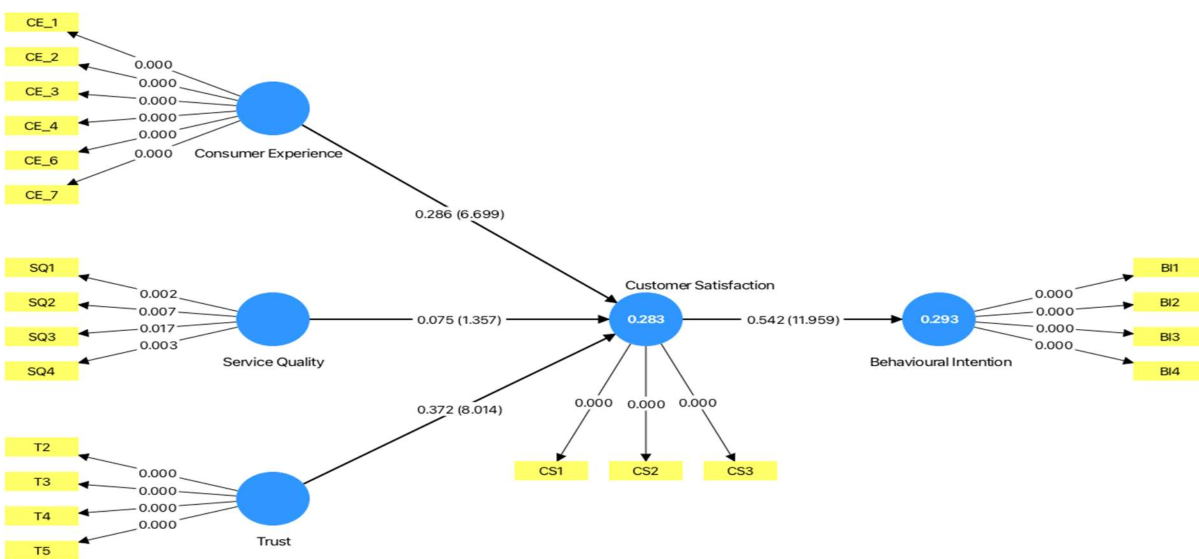
Consumer Experience	**0.578**			
Customer Satisfaction	0.739	**0.438**		
Service Quality	0.224	0.165	**0.141**	
Trust	0.605	0.318	0.646	**0.189**

Alt Text: Table presenting discriminant validity results using the Heterotrait–Monotrait (HTMT) criterion. All HTMT values fall below recommended thresholds, confirming discriminant validity among the constructs.

Lastly, to further check for discriminant validity besides the HTMT and Fornell-Lacker criterion in Tables 6 and 7, cross-loadings above 0.10 differences are usually good enough.

Interpretation of hypothesis testing outcomes

Having established the reliability, convergent validity, discriminant validity, and absence of multicollinearity concerns, the study proceeded to evaluate the structural model and test the proposed hypotheses. The hypothesis testing results, illustrated in Figure 2 and detailed in Table 8, conform to the standard that a hypothesis is supported when the t-value surpasses 1.65 or when the p-value falls below 0.10 (Hair et al., 2019).



Alt Text: Structural equation model diagram with five latent variables (AI Antecedent, Customer Satisfaction, Behavioural Intention) linked to observed indicators. Arrows indicate significant positive paths among consumer experience, service quality, trust, customer satisfaction, and behavioural intention.

Figure 2: Structural Model

Figure 2 shows that most t-values are greater than 1.65, indicating statistical significance, while service quality is below 1.65, indicating non-significance. The finding is consistent with the path coefficients presented in Table 8, showing that consumer experience positively influences customer satisfaction (β = 0.286, t = 6.699, p = 0.000). Similarly, the relationship between trust and customer satisfaction is statistically significant (β = 0.372, t = 8.014, p = 0.000). Customer satisfaction also positively influences behavioural intention (β = 0.542, t = 11.595, p = 0.001), while service quality is not statistically significant with customer satisfaction (β = 0.075, t = 1.357, $p < 0.175$). Overall, the results highlight the important role of customer satisfaction.

Thus, the hypotheses, according to the results, are confirmed as follows:

H_1: Artificial intelligence–enabled consumer experience has a positive and significant effect on customer satisfaction. The hypothesis is supported.

H_2: Artificial intelligence–enabled service quality has a positive and significant effect on customer satisfaction. This hypothesis is not supported.

H_3: Artificial intelligence–enabled trust has a positive and significant effect on customer satisfaction. The hypothesis is supported.

H_4: Customer satisfaction has a positive and significant effect on behavioural intention. The hypothesis is supported.

Table 8: Path Coefficients in the Structural Model

Path	**Original sample (O)**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
Consumer Experience -> Customer Satisfaction	0.286	0.294	0.043	6.699	0.000
Customer Satisfaction -> Behavioural Intention	0.542	0.543	0.045	11.959	0.000
Service Quality -> Customer Satisfaction	0.075	0.088	0.055	1.357	0.175
Trust -> Customer Satisfaction	0.372	0.372	0.046	8.014	0.000

Alt Text: Table presenting path coefficients in the structural model. Reported paths are all positive and statistically significant, indicating meaningful relationships among the latent constructs except for service quality, which is insignificant.

Table 9 presents the model fit statistics, including key measures such as R^2, f^2, and Q^2. These statistics offer valuable insights into the model's explanatory power and predictive relevance, highlighting its potential effectiveness in forecasting outcomes.

Table 9 R-Squared, Effect Size, Predictive Relevance and Model Fit

Path	R^2	R^2 adj	Effect Size F^2	Predictive Relevance Q^2	Model fit (SRMR)
Customer Satisfaction	0.283	0.292		0.253	
Behavioural Intention	0.293	0.278		0.272	
Consumer Experience -> Customer Satisfaction			0.105		
Customer Satisfaction -> Behavioural Intention			0.415		
Service Quality -> Customer Satisfaction			0.004		
Trust -> Customer Satisfaction			0.179		
Customer Satisfaction -> Behavioural Intention					0.089

Alt Text: Table presenting structural model results including R-squared values, effect sizes, predictive relevance (Q^2), and overall model fit indices. Reported values meet recommended thresholds, supporting explanatory power, predictive accuracy, and acceptable model fit.

The statistical analysis detailed in Table 9 offers insight into the model's explanatory power and predictive relevance concerning behavioural intention. The R^2 value quantifies the variance in dependent variables explained by the independent variables (Hair et al., 2019). Chin & Marcoulides (1998) proposed the rule of thumb indicating that R^2 =0.26 large, 0.13 moderate and 0.02 weak effect sizes. In the current study, the R-squared value of 0.28.3 signifies that 28.3% of the variance in the dependent variable is explained by the model, suggesting a large explanatory capacity. This figure is 0.292 in the adjusted R-squared value, which compensates for the number of predictors in the model while confirming its relevance (see Table 9).

Other effect sizes, as measured by f-squared, reveal varying influences of different factors within the model when a particular variable is removed; $f^{2,}$ as an effect size, measures how the removal of a predictor variable affects R^2 for an endogenous variable. Usually, 0.02 is small, 0.15 moderate and 0.35 large effect size (Cohen, 1988). In the current study, 0.105 was for consumer experience, indicating a significant and robust effect on customer satisfaction; 0.415 for customer satisfaction, revealing a large and strong influence on the relationship with behavioural intention; and 0.004 for service quality concerning customer satisfaction, suggesting a small effect size, while 0.179 for trust on customer satisfaction, suggesting a moderate effect size. These variations highlight the differing roles these elements play within the broader behavioural intention.

Similarly, the Q^2 values represent predictive relevance, which would be satisfactory if it surpasses zero (0), aligning with the guidance of Hair et al. (2019) and Henseler (2018). In the current study, the predictive relevance values are both Q^2>0 for the endogenous variables; customer satisfaction =0.253 and behavioural intention =0.272, signifying moderate effects since the guidelines are Q^2

= 0.02 small, Q^2 =0.15 moderate, and Q^2 = 0.35 large (Hair et al., 2019). The Q-squared values, exceeding the zero threshold, underscore the satisfactory predictive relevance of the model. This indicates that the model has strong predictive capabilities, crucial for its practical application. The differentiation in effect sizes among the variables studied underscores the need to consider the specific contributions and limitations of various antecedents. Lastly, in terms of model fit assessment, the study utilised the SRMR criterion. An SRMR value below 0.05 is considered excellent, while a value between 0.05 and 0.08 indicates an adequate fit (Grosemans et al., 2020; Kyndt & Onghena, 2014). In this study, the SRMR value of 0.089 is slightly above the recommended threshold of 0.08, suggesting a marginal model fit. However, this value is still below the conservative cut-off of 0.10, which is often considered acceptable in PLS-SEM, according to Hair et al. (2017).

Mediation results

Usually, when a variable affects another, scholars are interested in establishing how the influence is transmitted to the outcome variable. Mediation analysis is meant to establish whether, besides the direct path, an explanatory variable transmits its influence on the consequent variable indirectly through a mediator (Hayes, 2018). In this study, customer satisfaction was tested as a mediator between consumer experience, service quality, trust and behavioural intention. Based on the bootstrapping procedure for mediation in SmartPLS, Table 10 reveals that the total effect was statistically significant for consumer experience on behavioural intention (path c, i.e. CE-> BI, β=0.455, p=0.000, LLCI 0.383 ULCI 0.533), indicating a strong overall influence. The direct effect was significant (path c', i.e. CE->BI, β=0.378, p=0.000, LLCI 0.298 ULCI 0.450), while the indirect effect through customer satisfaction (path ab, i.e. CE->CS->BI, β=0.077, p=0.000, LLCI 0.041 ULCI 0.128) was also significant, suggesting partial mediation with a VAF of 16.9%.

For service quality, the total effect was significant (path c, i.e. SQ-> BI, β=0.134, p < 0.008, LLCI 0.030 ULCI 0.225), and direct effect was significant (path c', i.e. SQ->BI, β=0.118, p <0.015, LLCI 0.009 ULCI 0.203), while indirect effect (path ab, i.e. SQ->CS->BI, β=0.016, p < 0.292, LLCI 0.041 ULCI 0.128) was not statistically significant, indicating no mediation. In contrast, trust exhibited a significant total effect (path c, i.e. T-> BI, β=0.343, p =0.000, LLCI 0.253 ULCI 0.492). The direct effect was significant (path c', i.e. T->BI, β=0.246, p=0.000, LLCI 0.136 ULCI 0.351), while the indirect effect through customer satisfaction (path ab, i.e. T->CS->BI, β=0.097, p=0.000, LLCI 0.053 ULCI 0.153) was also significant, suggesting partial mediation. The VAF entails that 28.3% of the influence of X on Y is transmitted through the mediator (i.e., indirect effect divided by total effect). Consequently, the hypotheses, according to the results, are confirmed as follows:

H5a: The relationships between behavioural intention and consumer experience are mediated by customer satisfaction (p = 0.001). Supported.

H5b: The relationship between behavioural intention and service quality is mediated by customer satisfaction. This hypothesis is not supported.

H5c: The relationships between behavioural intention and trust are mediated by customer satisfaction (p = 0.001). Supported.

Table 10: Mediation results

Path	Total effect	Direct effect	Indirect effect	P-Values	boot LLCI	boot ULCI	VAF	Hypotheses
CE -> BI (c')		0.378		0.000	0.298	0.450		
CE -> BI (c)	0.455			0.000	0.383	0.522		
CE ->CS -> BI (ab)			0.077	0.000	0.041	0.128	16.9%	S
SQ -> BI (c')		0.118		0.015	0.009	0.203		
SQ -> BI (c)	0.134			0.008	0.030	0.225		
SQ ->CS -> BI (ab)			0.016	0.292	-0.015	0.045	11.9%	NS
T -> BI (c')		0.246		0.000	0.136	0.351		
T -> BI (c)	0.343			0.000	0.253	0.429		
T ->CS -> BI (ab)			0.097	0.000	0.053	0.153	28.3%	S

Alt Text: Table presenting mediation analysis results. Indirect effects are significant for consumer experience and trust, confirming mediating relationships among the constructs except service quality.

5.0 Discussion and Implications

The findings of this study largely support existing literature, which proposes that AI-enabled digitalisation factors influence behavioural intention through customer satisfaction. The results confirm that consumer experience and trust significantly enhance customer satisfaction, which in turn drives behavioural intention. This aligns with prior studies conducted in developed economies such as the United States, the United Kingdom, and Australia, where personalised digital interactions and system reliability were found to improve customer satisfaction and subsequent behavioural outcomes (Casaca & Miguel, 2024; Hardcastle et al., 2025; Latif, 2025). Similarly, the positive link between customer satisfaction and behavioural intention with findings from South Africa and Nigeria, where satisfied customers demonstrate higher loyalty, repurchase intention, and positive word-of-mouth behaviour (Abidin et al., 2025; Nqunqa & Msosa, 2025).

However, the findings also reveal some deviations from prior research. Contrary to many studies in developed and some emerging markets, service quality did not significantly influence customer satisfaction in this study (Gonu et al., 2023; Mwiya et al., 2019). This suggests that in the Zambian telecommunications industry, customers may perceive basic service quality as a minimum expectation rather than a differentiating factor. This finding may also reflect persistent network-related challenges reported in Zambia's telecommunications sector. According to ZICTA (2023), service providers have periodically faced customer complaints stemming from network outages, poor connectivity, and service disruptions, including the nationwide service interruptions experienced by MTN Zambia in 2023, which negatively affected customer experiences and perceptions of service quality. Similar patterns have been observed in countries such as Ghana and

Zimbabwe, where trust, system reliability, and perceived security play a more critical role in shaping customer evaluations of digital services (Makanyeza, 2017; Tetteh, 2022).

These findings imply that customer satisfaction acts as a central mechanism through which AI-enabled digitalisation influences behavioural intention. The partial mediation observed for consumer experience and trust indicates that both direct and indirect pathways are important. In contrast, the absence of mediation for service quality highlights its limited explanatory power. Overall, the results suggest that organisations must prioritise experiential value and trust-building strategies, as technology alone is insufficient to drive sustained customer behavioural outcomes.

The findings highlight important implications for multiple stakeholders; For practitioners, telecommunications firms should adopt a customer-centric strategy by prioritising AI-enabled consumer experience and trust to enhance satisfaction and behavioural intention. Continuous monitoring of customer satisfaction and the active collection of feedback are essential for refining AI-driven services.

For scholars, the study extends existing literature by confirming the mediating role of customer satisfaction in AI-enabled digital contexts within emerging markets. Policymakers should support AI adoption through training initiatives that enhance digital skills and service delivery capabilities. For consumers, improved AI integration promises more personalised, efficient, and reliable service experiences, ultimately leading to greater satisfaction and value creation in the telecommunications sector.

6.0 Limitations and future research

This study has several limitations.

First, it was conducted in Kitwe, Zambia, which may limit the generalisability of the findings to other regions or countries with different technological, economic, and market conditions. Second, the use of a cross-sectional research design restricts the ability to establish causal relationships among the variables. Although SmartPLS (PLS-SEM) was employed for data analysis, the findings remain largely predictive. Third, the study focused only on selected AI-enabled factors, potentially excluding other relevant variables that may influence customer satisfaction and behavioural intention. Future research should consider longitudinal research designs to better capture changes in customer perceptions over time and establish stronger causal inferences. Additionally, qualitative research approaches could be employed to gain deeper insights into customers' perceptions of service quality and their experiences with AI-enabled services.

Future studies should also utilise larger and more diverse samples across multiple regions and incorporate additional constructs such as perceived risk, customer loyalty, service recovery, and technology readiness to provide a more comprehensive understanding of AI-enabled digitalisation in the telecommunications sector.

7.0 Conclusion

This study examined the impact of AI-enabled digitalisation on customer satisfaction and behavioural intention in the telecommunications sector in Kitwe, Zambia, using data from 401 respondents. The findings indicate that AI-enabled consumer experience and trust significantly enhance customer satisfaction and directly influence behavioural intention. However, AI-enabled service quality was found to have no significant effect on customer satisfaction, suggesting that customers may view basic service performance as a minimum expectation.

The study further highlights that the mediating role of customer satisfaction varies across relationships, with significant indirect effects observed for consumer experience and trust. Overall, the results suggest that AI technologies alone are insufficient unless they enhance the user experience and build trust. This study contributes to theory and practice by providing context-specific insights and emphasising the need for customer-centric AI strategies to improve satisfaction, loyalty, and long-term customer engagement in the telecommunications sector.

Data availability statement

Upon request.**References**

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