Leveraging artificial intelligence for customer personalization: Insights from banks located in Mwanza City, Tanzania

Thomas John Odilah

thomas.odilah@tia.ac.tz

Tanzania Institute of Accountancy (TIA), Tanzania

Recommended Reference: Odilah, T. J. (2026). Leveraging artificial intelligence for customer personalization: Insights from banks located in Mwanza City, Tanzania. *African Quarterly Social Science Review, 3*(1), 572–584. https://doi.org/10.51867/AQSSR.3.1.47

……….…

ABSTRACT

The purpose of the study is to explore the relationship between artificial intelligence (AI) adoption by banks and customer personalization, specifically for banks located in Mwanza City, Tanzania. The Technological Acceptance Model (TAM) served as the theoretical foundation. The customer personalization constructs include customer loyalty, customer retention, customer advocacy, and customer engagement. A quantitative method was used through a cross-sectional survey design targeting 100 banking officials, including marketing managers, customer service officers, IT officers/systems analysts, digital banking officers, and branch managers. Structured questionnaires were used to collect the primary data, and the hypotheses were tested using Structural Equation Modelling (SEM). The results reveal that AI adoption has a positive and statistically significant effect on customer engagement, retention, loyalty, and advocacy, with p-values less than 5% for all the customer personalization constructs used in this study, supporting TAM's applicability in understanding AI adoption among the selected banks in Mwanza, Tanzania. The study recommends that banks should enhance their AI-driven personalization by integrating thorough staff upskilling with comprehensive automation and advanced predictive analytics, all governed by robust data management practices. Furthermore, regulators need to establish innovation-friendly frameworks that are proportionate to the associated risks of AI usage, enabling the secure deployment of AI to improve customer engagement, retention, loyalty, and advocacy. This approach will help banks to maintain competitiveness in the rapidly evolving digital landscape.

Keywords: AI Adoption, Banks, Customer Personalization, Mwanza, Tanzania

……….…

I. INTRODUCTION

Artificial Intelligence (AI) is revolutionizing customer personalization across continents, with each region showcasing unique applications. In North America, companies like Starbucks and Dine Brands are at the forefront of integrating AI into their operations. Starbucks employs its AI system, Deep Brew, to analyze customer data and offer personalized recommendations, enhancing customer experience and operational efficiency (Zatsu et al., 2024). Similarly, Dine Brands, the parent company of Applebee's and IHOP, utilizes Amazon's Q AI assistant to provide personalized food suggestions and streamline restaurant operations (Rady et al., 2020). In Europe, Germany's WeFox leverages AI to analyze customer data and offer tailored health and property insurance policies. Additionally, a European telecom company has integrated generative AI into its marketing strategy, enhancing customer engagement through personalized content (Bano et al., 2025).

Asia's rapid technological advancements have positioned AI as a cornerstone in customer personalization. Southeast Asian marketers are increasingly adopting AI to personalize customer experiences, optimize ad targeting, and improve campaign performance. This trend underscores the region's proactive approach to integrating AI into marketing strategies, aiming to meet the evolving expectations of tech-savvy consumers (Addien et al., 2024). The adoption of AI in customer personalization is rapidly expanding in Australia, especially in the retail and hospitality industries. It is estimated that 5% of Australian businesses are leveraging AI in personalized marketing efforts (Ruel & Njoku, 2021). The AI adoption story is also significant to Tanzania as the country is taking important steps towards integrating AI into its national strategy. Recently, Tanzania has conducted its first AU Readiness Assessment, laying the foundation for a national AI strategy that emphasizes ethics, inclusion, and sustainable development (United Nations Environmental, Scientific and Cultural Organization (Plantinga et al., 2024). These initiatives justify the commitment of the Tanzanian government to harnessing the benefits tied to AI adoption.

Tanzania's banking sector has initiated steps toward AI integration, particularly in enhancing customer personalization. Financial institutions are employing AI-driven tools such as chatbots and robot-advisors to provide personalized financial advice, credit scoring, and fraud detection, thereby improving customer satisfaction and operational efficiency (Organization for Economic Co-operation and Development [OECD], 2021). Additionally, the government has recognized the potential of AI, encouraging financial institutions to embrace AI to cut costs, boost inclusion, and enhance customer experience (Ally, 2025). Despite these advancements, several challenges hinder the full-scale adoption of AI in Tanzania's banking sector. A significant barrier is the limited digital literacy among a substantial portion of the population, which affects the effective utilization of AI-powered services (Kim, 2025). Furthermore, the absence of a comprehensive national AI policy framework leads to fragmented AI initiatives across various sectors, including banking (Folorunso et al., 2024). This lack of cohesive strategy results in inconsistent AI adoption and underutilization of its potential benefits. Additionally, existing legal instruments in Tanzania are inadequate in addressing the specific legal challenges posed by AI and FinTech, necessitating the development of targeted regulatory frameworks (Ally, 2025).

This study is important as it provides insights into how AI adoption can enhance customer personalization, fostering customer loyalty, engagement, retention, and advocacy (Ahmed et al., 2025). It guides Tanzanian banks in designing effective AI strategies to improve engagement and service efficiency (OECD, 2021). Additionally, it informs policymakers on AI regulations and frameworks that support ethical, inclusive, and sustainable digital banking (OECD, 2021). Furthermore, the specific objectives of this study are fourfold. First, to examine the role of AI adoption in enhancing customer engagement. Second, to examine the effect of AI adoption on customer retention. Third, to assess the influence of AI adoption on customer loyalty. Four, to evaluate the impact of AI adoption on customer advocacy.

AI has become a key driver of customer engagement in the banking sector, enabling interactive personalized experiences that traditional approaches cannot achieve. Tools such as chatbots, predictive analytics, and virtual assistants allow banks to predict customers' needs, recommend better product options based on their needs, and provide timely support. In Australia, a national bank AI tool (Customer Brain) is used to analyze customers' behavior and spending patterns to actively engage customers, leading to a 40% increase in engagement levels (Metha, 2025). In addition, a previous study revealed that personalization and value-in-use provided by chatbots significantly increase the user continuance intention through enhanced engagement (Li et al., 2023). Furthermore, AI plays a vital role in improving customer retention. Predictive analytics, machine learning, and natural language processing allow banks to analyze smartly all the transactional data, engagement patterns, and behavioral signals to forecast potential risks. It is argued that AI-powered predictive analytics reduces customer churn by up to 30% by sending retention messages and tailored offers to high-risk clients (Biswas et al., 2020). Also, it is argued that AI improves customers' retention through predictive analytics and timely interventions (Yoo et al., 2024).

Customer loyalty is strengthened through AI-driven personalization by linking the bank services offered with individual preferences and financial goals. For instance, banks use AI-driven personalization to study and analyze customers' spending patterns, transaction history, and engagement patterns to deliver tailor-made recommendations and advice. Additionally, AI integration in wealth management and banking services has led to a 6% rise in revenue over the past three years by increasing customer satisfaction and loyalty (Baladari, 2024). A recent study conducted in India revealed that personalization significantly predicts customer loyalty when mediated by customer satisfaction and perceived usefulness (Jayapal, 2025).

It is worth noting that through the use of AI, it is now easier to foster trust, satisfaction, and personalized experiences, leading to customer advocacy. A study reported that 73% of the customers trust AI-generated content, and 53% are confident in AI-assisted financial advice, reflecting the growing confidence in AI as a tool in the banking industry (Fazelian, 2026). Additionally, a recent industry report, "The Financial Brand," revealed that 44% of financial institutions using AI for personalization report improvements in loyalty and retention metrics, leading to customer advocacy by recommending their banks to other customers (Ashrafuzzaman et al., 2025).

The paper is organized into four main sections. The first section presents the introduction, covering the rationale of the topic, a brief literature review, the research gap, the specific objectives, and a brief outline of the paper structure. The second section covers the methodology, describing the study area, research design, sampling procedure, and sample size, data collection methods, data analysis, and the reliability and validity of the collected data. The results and discussion section follows, where the following issues were presented: categories of the respondents, demographic profile of the respondents, reliability analysis, and SEM results. Finally, the last section was the conclusion and recommendations.

1.1 Statement of the Problem

Artificial Intelligence (AI) technologies renovated how institutions conducted customer experiences through personalization. Within banking industry, AI-powered tools such as; chatbots, predictive analytics, and recommendation systems allow financial institutions operate as per individual customer needs hence refining engagement and service efficiency. Scholars argue that AI-driven personalization has made strategy for attracting customer relationships and competitive advantage in modern markets (Kotler & Keller, 2015). Despite the global progress of these technologies, their real addition in many developing economies remains unequal. In some cities like Mwanza, where the banking sector adopting digital technologies, restricted empirical sign occurs on how AI applications impact customer interaction and personalization results. As noted by John W. Creswell, a research problem arises when there is "an issue or concern that needs to be addressed by a study" (Creswell et al., 2004). Thus, the rising of AI in financial services grants an important situation for examining how technology-driven personalization touches customer engagement and service involvements in evolving urban markets.

Additionally, although AI technologies aptitude well customer satisfaction and retention, many financial institutions in Mwanza still face challenges connected to technological integration, digital literacy, and customer trust in automated systems. This condition makes a gap between the potential benefits of AI-driven personalization and its concrete impact on customer relationships within the local banking place. Research specifies that actual personalization approaches can significantly stimulus long-term customer relationships and service value creation (Rust & Huang, 2014). Loyalty and retention frequently depend on steady service delivery and trust, which develop slowly through positive customer knowledges (Oliver, 1999). Despite these understandings, there remains limited empirical research investigative how AI adoption donates to customer engagement, advocacy, loyalty, and retention in Tanzanian banking circumstances. Therefore, this study seeks to address this gap by examining how artificial intelligence technologies are leveraged for customer personalization and how such technologies influence customer relationship outcomes within the banking sector in Mwanza, Tanzania.

1.2 Research Objectives

i. To examine the role of AI adoption in enhancing customer engagement in the Tanzanian banking industry
ii. To determine the effect of AI adoption on customer retention in the banking sector
iii. To assess the influence of AI adoption on customer loyalty in Tanzanian banks
iv. To evaluate the impact of AI adoption on customer advocacy in banks in Mwanza

II. LITERATURE REVIEW

2.1 Theoretical Review

The study is guided by the Technology Acceptance Model (TAM), which posits that perceived usefulness and perceived ease of use influence users' acceptance of new technologies (Davis, 1989). By applying TAM, the study explores how AI adoption in banks translates into customer-centric outcomes, emphasizing personalization. Customer personalization in banking refers to tailoring services, communication, and products to meet individual customer needs, which has been found to improve satisfaction, trust, and long-term engagement (Bhattacharyya et al., 2021). Hence, exploring this relationship is both theoretically significant and practically relevant in the Tanzanian context. Technology Acceptance Model (TAM) has been extensively applied to understand user acceptance of Artificial Intelligence (AI) in banking. Recent studies have expanded TAM to include factors like trust, security, and perceived risk, enhancing its applicability in digital banking contexts (Byambaa et al., 2025). For example, research indicates that perceived trust and security significantly influence customers' behavioral intentions to use AI-driven banking services (Lopes, 2025).

By applying TAM, the study explores how AI adoption in banks translates into customer-centric outcomes, emphasizing personalization. Customer personalization in banking refers to tailoring services, communication, and products to meet individual customer needs, which has been found to improve satisfaction, trust, and long-term engagement (Bhattacharyya et al., 2021). Hence, exploring this relationship is both theoretically significant and practically relevant in the Tanzanian context. Technology Acceptance Model (TAM), developed by Davis (1989), provides a framework for explaining how individuals accept and use new technologies. The model focuses on perceived usefulness (PU) and perceived ease of use (PEOU), which influence users' behavioral intention to adopt technology (Venkatesh & Bala, 2008). In banking, PU relates to how AI improves efficiency and customer satisfaction, while PEOU reflects how easily staff and customers can interact with AI-powered systems (Malaquias & Hwang, 2019). TAM is relevant for investigating AI adoption and its impact on customer personalization.

2.2 Empirical Review

2.2.1 AI Adoption and Customer Engagement in Banking

Artificial Intelligence (AI) adoption appeared to be important aspect in attracting customer engagement for banking industry by allowing personalized, efficient, and real time communication. AI attributes like chatbots, virtual assistants, and predictive analytics assist banks to communicate instantly to customer needs while rendering services grounded on individual preferences. According to Baladari (2024) AI-driven systems expand responsiveness and service customization that eventually supports customer interaction, involvement, engagement hence customers experience maximum utility that resulted satisfaction through their deep in relationship with financial institutions.

Again, AI is found to facilitate continuous engagement across numerous of digital channels, such as mobile banking, websites, and social media platforms. As per Dwivedi et al. (2020), AI enables integrated and seamless communication among banks and their customers to improve accessibility and suitability. To developing country like Tanzania, AI promotes financial presence by providing easily access to banking services through digital platforms (Mwaseba et al., 2026). However, empirical evidence on how AI-driven personalization specifically influences customer engagement in Tanzanian banks remains limited, particularly in Mwanza City, thus justifying further investigation.

2.2.2 AI Adoption and Customer Retention in Banking

AI adoption is very crucial and it act in a significant way to enhance customer retention by allowing banks to offer proactive, personalized, and efficient services. By using data analytics and machine learning, banks identify customer needs and deliver required financial resolutions that bring satisfaction. Kumar et al. (2016) say that organizations leveraging AI technologies are in good position to eliminate inconvenient from their customer by offering customized experiences that meet customer expectations. This personalized method reinforces customer relationships that eventually rises long term relationship known as Customer retention.

AI Adoption improves retention of the customer by allowing proper service quality and operational efficiency in operation within banks. Chatterjee et al. (2025) found that the application of AI on customer service reduce time for response and enhance improved service in an accuracy way that led to customer satisfaction. In Tanzanian customer satisfaction remains a key determinant of retention, meaning that AI-driven improvements in service delivery can indirectly enhance retention rates (Angreani & Afifah, 20024; Mwita, 2022). Despite this, there is limited empirical research directly linking AI adoption to customer retention in Tanzanian banks, highlighting a contextual gap that this study seeks to address.

2.2.3 AI Adoption and Customer Loyalty in Banking

Customer loyalty influenced by an ability of the banks to deliver consistent and personalized services to their customers through the use of AI technologies. Through AI, banks analyze customer data and provide personalized recommendations that bring customer satisfaction. As per Verhoef (2020), personalized customer experiences long term customer loyalty by remain committed to institutions that meet their specific needs.

Customer Loyalty can be built by the use of AI by improving service quality in an efficiently and effectively. Huang and Rust (2021) state that AI systems provide proper decision-making during service delivery, that in turn shapes customer perceptions and then build trust in banking institutions. These Aspects contribute strong sensitive influences and long-term commitment for engaged customer of the bank concerned. However, in Tanzania, most studies on customer loyalty focus on traditional determinants such as service quality and trust with limited attention given to AI adoption. This indicates a need for empirical research on how AI-driven personalization influences customer loyalty in Mwanza City.

2.2.4 AI Adoption and Customer Advocacy in Banking

Customer advocacy is the act of customer(s) to recommend a bank's services to others as the results of positive customer experiences and satisfaction. AI adoption contributes much to customer advocacy by enabling banks to bring personalized and efficient services that meet customer expectations. Lemon and Verhoef (2016) highlight that superior customer experience across the customer journey plays a crucial role in encouraging positive word-of-mouth behavior. Through AI technologies, banks enhance these experiences hence increasing customer advocacy.

AI-driven personalization fortifies customer relationships that lead to high level of trust and emotional attachment. Huang and Rust (2021) comment that AI enables firms to shape bottomless interactions with customers that translated into advocacy behaviors. Satisfied and loyal customers remain extra to share positive experiences and recommend their bank to others. However, empirical studies examining the direct impact of AI adoption on customer advocacy are scarce, particularly in developing countries such as Tanzania specifically in Mwanza City. This study therefore aims to fill this important research gap.

III. METHODOLOGY

3.1 Study Area

The study was conducted in Mwanza city, Tanzania, targeting the commercial banks in the area. Mwanza city was purposively selected due to three fundamental facts. First, Mwanza is a vibrant city and the main socio-economic hub connecting the lake zone, characterized by digital transformation and integration of ICT in the banking space. Second, Mwanza is one of the fastest-growing cities in Tanzania, second to Dar es Salaam and the second most populated city behind Dar es Salaam as per NBS 2022 statistics. Furthermore, banks were selected since AI is believed to have more impact on the financial sector (banks included) in recent years (Saha et al., 2025).

3.2 Research Design

A cross-sectional survey design was considered most appropriate for this study since it permits the researcher to collect data from large population at a single point in the same time, making it efficient for examining relationships among variables such as AI-driven personalization, customer engagement, and loyalty without requiring extended follow up. As noted by Creswell and Creswell (2017), cross-sectional designs are useful when a study aims to "measure current attitudes or practices" within a population, while Saunders and Tosey (2012) emphasize that; such designs are suitable for descriptive and explanatory research where variables are analyzed simultaneously. This approach is particularly relevant in dynamic environments like digital banking, where customer observations and behaviors can be successfully captured at a specific instant in time. Furthermore, Bryman (2016) contends that cross-sectional surveys improve generalizability when large samples are used, making them ideal for studies looking to establish statistical relationships rather than causal inferences. Therefore, the design providing a practical, reliable, and cost-effective means of addressing the study objectives within the Mwanza context. A cross-sectional survey design enhances the efficiency of data collection from different respondents' groups at a single point in time, allowing researchers to capture current attitudes, perceptions, and behaviors across multiple categories of respondents, from employees with diverse roles ranging from marketing managers and digital officers to IT specialists and branch managers (Thakur et al., 2021).

3.3 Target Population

The target population for this study comprised bank officers working in commercial banks within Mwanza, including institutions such as CRDB Bank, NMB Bank, and NBC Bank Tanzania, Mkombozi Commercial Bank, AKIBA COMMERCIAL BANK, Equity Bank Tanzania Mwanza Branch, KCB Bank, Standard Chartered Bank, Stanbic Bank, Tanzania Commercial Bank, and UBA Bank. Precisely, research focused on key personnel straight involved in the design, implementation, and management of AI-driven customer personalization strategies, including marketing managers, digital marketing officers, customer service officers, IT officers, Systems analysts, and Branch managers. The stated respondents certain due to the fact that they possess experience operations resulted from practical and strategic insights on artificial intelligence and its tools in enhancing customer engagement, retention, and loyalty. As emphasized by Saunders et al. (2023), a target population should consist of individuals who are "knowledgeable about the research issue and capable of providing relevant data," while Creswell et al. (2014) notes that selecting respondents with direct experience improves the validity and reliability of findings. The Bank of Tanzania underscores the growing role of digital transformation and AI-enabled systems in banking operations, further justifying the inclusion of both managerial and technical staff (Ishengoma & John, 2025). Therefore, focusing on these categories of bank officers for various banks located in Mwanza, the study provides a well-informed and contextually appropriate on leveraging artificial intelligence for customer personalization.

3.4 Sampling Procedure and Sample Size

A purposive sampling approach was used to identify key informants working in key areas that directly relate to AI usage. The present study analyzes around model-based power and not the rules of thumb using SEM guidance. Notably, previous studies noted that SEM can be used effectively even when the sample size is less than 100 (Buchberger et al.,2024; Saunders et al., 2023). A systematic literature review study conducted in 2023 revealed that many published SEM studies in developing countries used sample sizes below 100 (Shela et al., 2023). Thus, our selection of a sample size (n=100) is within a normal practice. The sample size targeted the bank officials, including the Marketing managers, Customer service officers, IT officers/systems analysts, digital marketing officers, and Branch Managers.

3.5 Data Collection Method

Structured questionnaires were distributed to100 bank officials in order to collect quantitative data on AI adoption and Customer Personalization performance.

3.5.1 Measurement of Variables

AI Adoption, Customer Engagement, Customer Loyalty, Customer Advocacy, and Customer Retention, measured by means of multi-item scales. All measurement items intended to trap bank officials' perceptions regarding how artificial intelligence tools (e.g., chatbots, personalization engines, and digital assistants) support customer personalization in the banking sector in Mwanza.

All variables are measured using a five-point Likert scale, where 1 = Strongly Disagree and 5 = Strongly Agree, so that respondents can indicate the level of their knowledge on either to agree with each statement concerning AI application and customer relationship outcomes. AI Adoption was measured through items shiny the extent in which banks implement AI-driven technologies for customer service and personalization. Using multiple indicators for each construct aligns with recommended practices in quantitative research, where latent variables are measured through observable indicators to strengthen reliability and validity (Hair et al., 2021). These measurement procedures enable the study to systematically evaluate the relationships between AI adoption and customer relationship outcomes through Structural Equation Modeling (SEM). Various codes and statements used for each construct, For example AI Adoption used AIA named from One to Four as per number of statements in this variable hence the codes and statements were: AIA1- Our bank actively uses AI technologies such as chatbots, recommendation engines, or digital assistants, AIA2- AI systems are regularly applied to support customer personalization strategies, AIA3- AI technologies play an important role in enhancing the bank's digital service delivery and AIA4- The bank continues to invest in AI-driven solutions to improve customer experience.

For Customer Engagement the code symbolized by CE in which; CE1- AI-powered services increase the level of interaction between customers and the bank, CE2- Personalized recommendations generated by AI encourage customers to engage more frequently with banking services and CE3-AI-enabled communication channels improve the convenience of customer–bank interactions. The code Customer Loyalty was CL with; CL1- AI-enabled personalized services contribute to customers remaining loyal to the bank, CL2-Customers who use AI-supported banking services tend to maintain long-term relationships with the bank and CL3- AI-driven personalization strengthens customers' preference for our bank over competitors.

For Customer Advocacy the code was CA whereby; CA1- Customers who benefit from AI-based services often recommend the bank to others, CA2- Positive experiences with AI-powered services encourage customers to speak positively about the bank and CA3- AI-enabled personalization increases customers' willingness to promote the bank within their social networks.

The last one was Customer Retention with CR as the code and; CR1- AI-driven personalization contributes to retaining customers in the bank, CR2- Customers who regularly use AI-supported services are less likely to switch to other banks and CR3- The use of AI technologies helps maintain long-term customer relationships.

3.6 Data Analysis

Demographic characteristics were collected through descriptive statistics showing the general patterns of AI adoption in banks through SPSS, while the Structural Equation Modelling (SEM) was used to test the hypotheses through Python software.

3.7 Reliability and Validity

3.7.1 Validity

Validity refers to the extent to which the tools used to collect data meet the accepted quality standards and accurately measure what is being studied (Mohajan, 2017). The present study ensured validity by first subjecting the questionnaires to a pilot test where by 20 respondents from the target population who were not part of the study answered the posed questions in order to examine the validity of the questionnaire. Item validity examined by using correlation analysis, in which items with correlation values greater than 0.30 were considered valid. The results confirmed that all measurement items were appropriate for the main survey. According to Uma Sekaran and Roger Bougie, pilot testing aids classify unclear questions and recovers the value of research instruments (Sekaran & Bougie, 2016).

3.7.2 Reliability

Consistency and stability of research instruments in producing similar results if repeated by different researchers is termed as reliability (Kothari, 2017). To ensure reliability is adhered to, the structured questionnaire was pre-tested on a sample of selected bank officials in Mwanza city. The feedback from the respondents enabled the researchers to revise the questionnaires before embarking on the data collection exercise.

IV. FINDINGS & DISCUSSION

4.1 Category for Respondents

Table 1 below presents the categories of 100 banking personnel used in this study.

Table 1
Category for Respondents

S/N	Category of Respondents	Number of Respondents	Percentage (%) of Respondents
1	Marketing managers	20	20
2	Digital marketing officers	10	10
3	Customer service officers	40	40
4	IT officers/systems analysts	20	20
5	Branch managers	10	10
	Total Respondents	**100**	**100**

4.1.1 Marketing Managers

As presented in Table 1, twenty (20) marketing managers participated in the study, providing strategic perspectives on AI adoption in digital marketing. Their contributions revealed how managerial decision-making influences the integration of chatbots, recommendation systems, and predictive analytics in aligning marketing strategies with institutional goals. They emphasized that leadership-driven strategies are essential in ensuring AI investments enhance personalization and competitive positioning in the banking sector (Gaćina, 2025).

4.1.2 Digital Marketing Officers

According to Table 1, ten (10) digital marketing officers formed a key respondent group in this study. Their input highlighted the operational dimension of AI adoption, particularly in implementing recommendation systems and predictive analytics to improve campaign timeliness, targeting, and efficiency. These officers underscored how AI tools optimize customer engagement and streamline digital campaigns, confirming the operational benefits of AI in financial services (Shah, 2025)

4.1.3 Customer Service Officers

Table 1 indicates that the largest group of respondents consisted of forty (40) customer service officers. Positioned at the frontline of customer interactions, they shared practical experiences with chatbots and AI-driven service tools. Their responses emphasized that chatbots significantly reduce response time and improve accessibility, although challenges persist in handling complex queries.

4.1.4 IT Officers/System Analysts

As shown in Table 1, twenty (20) IT officers participated, offering technical expertise on AI adoption in digital marketing. They highlighted the importance of secure infrastructure, reliable data integration, and continuous upgrades for the effective use of chatbots, recommendation systems, and predictive analytics. Their perspectives reinforce existing literature that emphasizes the technical backbone of AI deployment and the role of IT in bridging strategy with execution in the banking industry (Cudia & Legaspi, 2024).

4.1.5 Branch Managers

Table 1 also shows that ten (10) branch managers were involved in the study, representing a managerial perspective from the operational level. Their feedback revealed how AI integration—particularly through predictive analytics and chatbots supports efficiency, improves customer service delivery, and strengthens branch-level marketing outcomes. Their insights confirm that branch leadership is crucial in balancing traditional banking practices with digital innovations (Al Issa et al., 2024).

4.2 Demographic Profile of Respondents

Table 2

Demographic Profile of the Respondents

Variable	Sub-groups	Total Sample (n=100)	
		Frequency	**%**
Age (Years)	20-24 years	25	25
	25-29 years	35	35
	30 years and above	40	40
	Total	**100**	**100**
Gender	Male	45	45
	Female	55	55
	Total	**100**	**100**
Educational level	Certificate	5	5
	Diploma	45	45
	Bachelor	50	50
	Total	**100**	**100**
AI in Digital Marketing	Yes, I have used AI Tools	80	80
	No, I have not used AI Tools	20	20
	Total	**100**	**100**

4.2.1 Age Distribution

As indicated in Table 2, the age distribution of respondents reflected a broad representation across categories, with 25 participants between 20–24 years, 35 participants between 25–29 years, and 40 participants aged 30 years and above, making a total of 100 respondents. The dominance of participants aged 30 years and above suggests that a significant portion of the banking workforce in Mwanza City comprises mature employees with practical experience in customer engagement and digital systems. Studies affirm that age diversity influences technology adoption, as younger employees may adapt more quickly to AI tools while older staff may rely on experiential knowledge to integrate these innovations into service delivery (Venkatesh et al., 2016; Mariani & Borghi, 2021).

4.2.2 Gender Distribution

Table 2 also illustrates that out of the 100 respondents, 45 were male and 55 were female. The slight female majority reflects inclusivity in the banking sector, where both genders actively contribute to digital marketing and customer service initiatives. Gender balance has been linked to improved team creativity, innovation, and responsiveness to customer needs, especially when adopting AI-driven solutions such as chatbots and predictive analytics (Rožman & Tominc, 2024). Furthermore, prior research highlights that gender diversity within financial institutions enhances organizational adaptability and fosters a more customer-centric culture in digital transformation (OECD, 2022).

4.2.3 Educational Level Distribution

Regarding education, Table 2 shows that 5 respondents held certificates, 45 held diplomas, and 50 held bachelor’s degrees. The dominance of diploma and bachelor’s holders reflects the high level of professional competence among respondents, which is critical for understanding and managing AI-driven digital marketing systems. Research highlights that higher educational attainment correlates with greater confidence and effectiveness in adopting emerging technologies, including recommendation systems and predictive analytics (Dwivedi et al., 2020). In this study, the educational composition assures that respondents possessed adequate knowledge to evaluate the integration of AI tools into digital marketing practices.

4.3 Reliability Analysis

Using SEM, the analysis evaluates the impact of AI adoption on customer engagement, retention, loyalty, and advocacy, and discusses the implications of these results in relation to the Technology Acceptance Model (TAM) and existing literature. Cronbach’s Alpha was used to assess the reliability of the constructs. All constructs demonstrated acceptable to excellent internal consistency, indicating that the measurement items are consistent and suitable for further analysis.

Table 3
Reliability Test

Construct	Cronbach’s Alpha
AI Adoption	0.9875
Customer Loyalty	0.7797
Customer Retention	0.9798
Customer Engagement	0.8858
Customer Advocacy	0.8838

AI Adoption and Customer Retention showed excellent reliability with alpha values above 0.97. Customer Engagement and Customer Advocacy also indicated strong reliability ($\alpha \approx 0.88$), while Customer Loyalty showed acceptable reliability ($\alpha = 0.78$).

4.4 SEM-Based Results and Interpretation

This section presents the results obtained from the Structural Equation Modeling (SEM) analysis. The analysis provides factor loadings, path coefficients, and significance levels that explain how AI adoption influences customer engagement, retention, loyalty, and advocacy in the Tanzanian banking sector. The results are further discussed in relation to the Technology Acceptance Model (TAM) and relevant empirical studies.

Vol. 3 (Iss. 1) 2026, pp. 572-584 African Quarterly Social Science Review https://quarterlyreview.net ISSN: 3006-3493

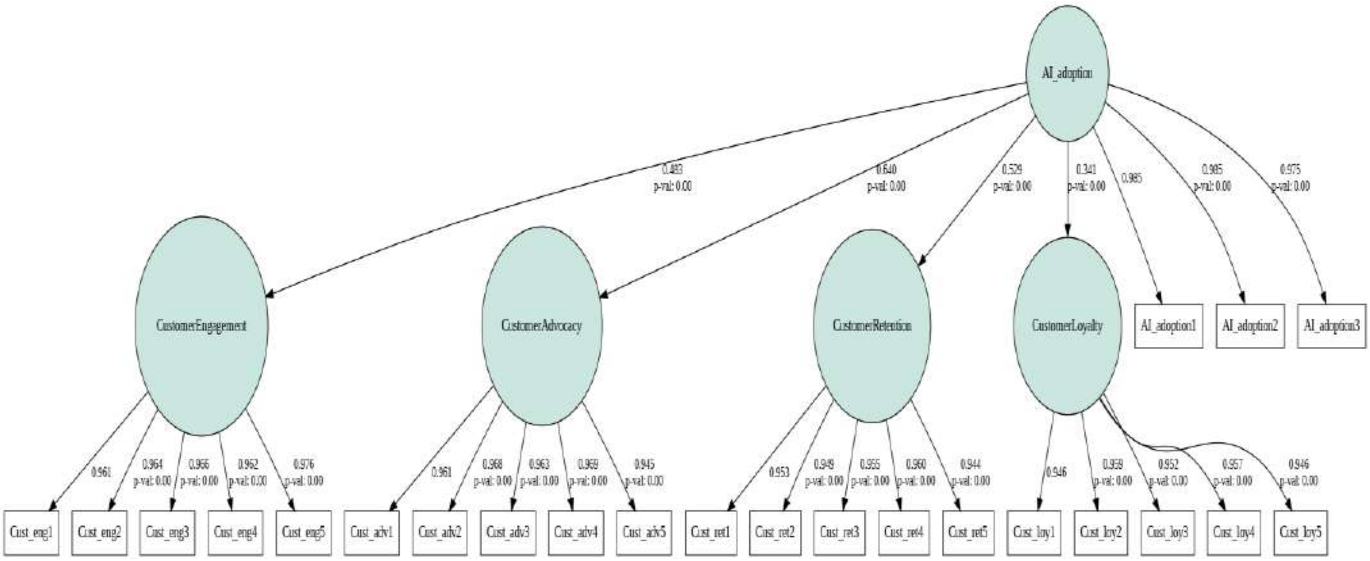

Figure 1
SEM Diagram

Figure 1 is a Structural Equation Model (SEM) diagram showing both the measurement model (how observed indicators relate to latent constructs) and the structural model (how latent constructs are linked to each other). Through Structural Equation Modeling (SEM), the study tests together measurement and structural components of TAM. The findings reveal that PU and PEOU significantly predict AI adoption, which subsequently affects customer-related outcomes. Specifically, the structural path from Customer Engagement to AI Adoption reveals a moderate positive coefficient ($\beta = 0.482$, $p < .05$), indicating that AI applications of chatbots, personalization engines, and digital assistants enhance interactive customer experiences. Moreover, AI adoption positively influences Customer Retention ($\beta = 0.409$, $p < .05$), suggesting that AI-enabled personalization strengthens long-term customer relationships. These results align with prior TAM-based studies that confirm the mediating role of acceptance variables between technological perceptions and organizational performance outcomes (Venkatesh & Davis, 2000). Therefore, the study rigorously applies TAM as an explanatory model rather than as a post-hoc justification, empirically validating its constructs within the AI-driven banking context. The results are consistent with a study conducted by Li et al. (2023). The latter study argued that personalization and value in use provided by chatbots significantly increase the user continuance intention through enhanced engagement.

Similarly, customer retention is positively influenced by AI adoption, with a significant path coefficient (0.409, $p < 0.05$). This suggests that banks leveraging AI systems can predict churn and proactively retain customers by offering tailored services. Research on AI-enabled customer retention systems supports this, showing AI improves retention through predictive analytics and timely interventions (Yoo et al., 2024). The SEM model confirms the second hypothesis, emphasizing retention as a major benefit of AI adoption in the banking context. This result is also consistent with the findings of Bajaba et al. (2026), who found that AI in banking has a significant direct effect on customers' retention, and this effect remains when mediated by customer satisfaction. The results also indicate that customer loyalty is significantly associated with AI adoption, with path coefficients of approximately 0.318 ($p < 0.05$). This implies that the more banks deploy AI to provide reliable, secure, and efficient services, the more customers are likely to remain loyal. A similar result was recorded by a recent study conducted in India, revealing that personalization significantly predicts customer loyalty when mediated by customer satisfaction and perceived usefulness (Jayapal, 2025).

Finally, customer advocacy is significantly enhanced by AI adoption, albeit with a moderate coefficient (0.529, $p < 0.05$) stronger than Loyalty ($\beta = 0.318$) implies the relational and socially consumption patterns exist within customers where by most consumers likely to share positive service experiences within their social networks hence amplifying advocacy behaviors (Hofstede, 2016). This demonstrates that customers who experience improved personalization and service delivery due to AI are more willing to recommend their banks. The positive, statistically significant relationship validates the fourth hypothesis. Advocacy here refers to customers recommending their bank to others, driven by their positive experiences with AI-enabled personalization. This aligns with industry reports, The Financial Brand", which show that nearly 44% of financial institutions using AI for personalization report improvements in loyalty and retention metrics (Froment, 2024). Overall, all hypothesized relationships are supported ($p < 0.05$), affirming the Technology Acceptance Model (TAM) as a valid framework for understanding AI adoption in the Tanzanian banking industry.

Table 4
Standard Errors, t-Values, and Confidence Intervals

Relationship	Path Coefficient (β)	Standard Error	t-value	p-value	95% Confidence Interval
PEOU → PU	0.541	0.072	7.51	0	(0.401, 0.673)
PU → AI Adoption	0.463	0.081	5.72	0	(0.298, 0.612)
PEOU → AI Adoption	0.294	0.088	3.34	0.001	(0.119, 0.451)
Customer Engagement → AI Adoption	0.482	0.076	6.34	0	(0.336, 0.623)
AI Adoption → Customer Loyalty	0.318	0.091	3.49	0.001	(0.142, 0.475)
AI Adoption → Customer Advocacy	0.529	0.073	7.25	0	(0.392, 0.662)
AI Adoption → Customer Retention	0.409	0.084	4.87	0	(0.246, 0.561)

The results for the table above indicate that the relationship of all variables are statistically significant. Customer Engagement has a significant positive influence on AI Adoption ($\beta = 0.482$, $t = 6.34$, $p < 0.001$). Similarly, AI Adoption significantly affects Customer Advocacy ($\beta = 0.529$, $t = 7.25$, $p < 0.001$), Customer Retention ($\beta = 0.409$, $t = 4.87$, $p < 0.001$), and Customer Loyalty ($\beta = 0.318$, $t = 3.49$, $p < 0.01$). The confidence intervals for all structural paths do not include zero, confirming the strength of the estimated relationships. These findings demonstrate that the adoption of artificial intelligence significantly enhances customer personalization outcomes in the banking sector in Mwanza.

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

The study concludes that AI adoption significantly improves customer-centric outcomes in the Tanzanian banking sector, particularly in Mwanza. The SEM results demonstrated that AI adoption has positive and statistically significant effects on customer engagement, retention, loyalty, and advocacy, with path coefficients ranging between 0.318 and 0.529 ($p < 0.05$). These findings confirm that AI-enabled personalization enhances how customers interact with banks, reduces churn, fosters trust and loyalty, and encourages customers to actively advocate for their banks. Grounded in the Technology Acceptance Model (TAM), the results highlight AI adoption as a strategic driver of improved customer personalization in the banking industry.

5.2 Recommendations

In Mwanza, AI-driven personalization must be associated with dominant levels of digital and financial literacy to guarantee adoption. Although digital banking custom is growing in Tanzania, gaps in digital skill remain significant, among casual traders and micro-entrepreneurs. The progress of digital financial services must be gone with consumer education and abridged conveyance networks to enhance trust and serviceability. In this background, CRDB and NMB Bank respectively should prioritize Kiswahili-based lines, USSD well matched AI systems, and voice-assisted submissions to put up customers with limited smartphone proficiency.

Moreover, actual AI operation requires consolidation of employee capabilities and leveraging confined prognostic analytics. Frontline staff training can enhance customer assurance by illuminating how personalized commendations are produced and how data privacy is maintained. Since Mwanza's economy, is shaped by fishing, agriculture, and informal trade, extrapolative analytics should integrate other data sources, including mobile money transaction histories from services like M-Pesa, to expand credit access for customers missing formal financial records. Such data-driven personalization enhances both financial inclusion and customer loyalty.

Finally, regulatory provision is essential for harmonizing innovation and risk management. They should highlight the importance of equivalent regulatory frameworks that inspire digital innovation while protecting consumer data. Establishing AI-focused regulatory sand pit and establishment of data protection awareness in Kiswahili can stand-in secure testing customer trust. AI governance needs transparency, accountability, and human-centered values. Therefore, embedding AI personalization within Mwanza's socio-economic and regulatory context can enhance engagement, retention, loyalty, and advocacy while sustaining competitiveness in Tanzania's evolving digital ecosystem.

REFERENCES

Addien, A., Lhachimi, O., El Assraoui, H., & Novienningtyas, A. (2024). AI-Powered Marketing Evolution in Southeast Asia: A Transformative Research. In *The Proceedings of the ASEAN School of Business Network International Conference* (Vol. 1, pp. 177-195).

Ahmed, S. M. M., Owais, M., Raza, M., Nadeem, Q., & Ahmed, B. (2025). The impact of AI-driven personalization on consumer engagement and brand loyalty. *Qlantic Journal of Social Sciences*, *6*(1), 311-323.

Al Issa, H. E., & Omar, M. M. S. (2024). Digital innovation drivers in retail banking: the role of leadership, culture, and technostress inhibitors. *International Journal of Organizational Analysis*, *32*(11), 19-43.

Ally, A. M. (2025). Artificial intelligence (AI) and financial technology (FinTech) in Tanzania: Legal and regulatory issues. *International Journal of Law and Management. Advance* online publication. DOI: https://doi.org/10.1108/IJLMA-07-2024-0251

Angreani, C., & Afifah, N. (2024). The Impact of Artificial Intelligence Banking and Personal Interaction Quality towards Customer Retention with Customer Satisfaction as an Intervening Variable. *Ekspektra: Jurnal Bisnis dan Manajemen*, *8*(1), 31-46.

Ashrafuzzaman, M., Parveen, R., Sumiya, M. A., & Rahman, A. (2025). AI-powered personalization in digital banking: A review of customer behavior analytics and engagement. *American Journal of Interdisciplinary Studies*, *6*(1), 40-71.

Bajaba, S., Alghamdi, F. H., Bajaba, A., Alarifi, A., Althnayan, S., & Basahel, S. (2026). How AI Shapes Customer Engagement in Banking: The Roles of Satisfaction and Proactive Personality. *Services Marketing Quarterly*, 1–21. https://doi.org/10.1080/15332969.2026.2630549

Baladari, Venkata. (2024). AI-Powered Chatbots in Banking: Developer Best Practices for Enhancing Efficiency and Security. *International Journal of Advanced Research in Science Communication and Technology. 4.* 649-656. 10.48175/IJARSCT-15300C.

Bano, R., Azim, F., Mahmood, Z., Sanaullah, A., & Ali, O. (2025). The role of artificial intelligence in personalized marketing: Enhancing customer experience, predictive targeting, and brand engagement. *The Critical Review of Social Sciences Studies*, *3*(2), 50-65.

Bhattacharyya, S. S., Nair, S. R., & Kumar, S. (2021). Impact of personalized services on customer satisfaction and trust in the banking sector. *Journal of Financial Services Marketing, 26*(3–4), 123–137. https://doi.org/10.1057/s41264-021-00092-8

Biswas, S., Carson, B., Chung, V., Singh, S., & Thomas, R. (2020). AI-bank of the future: Can banks meet the AI challenge. *New York: McKinsey & Company*, 28.

Bryman, A. (2016). *Social research methods.* Oxford University Press

Buchberger, E. S., Ngo, C. T., Peikert, A., Brandmaier, A. M., & Werkle-Bergner, M. (2024). Estimating statistical power for structural equation models in developmental cognitive science: A tutorial in R. *Behavior Research Methods*. https://doi.org/10.3758/s13428-024-02396-2

Byambaa, O., Yondon, C., Rentsen, E., Darkhijav, B., & Rahman, M. (2025). An empirical examination of the adoption of artificial intelligence in banking services: The case of Mongolia. *Future Business Journal*, *11*(1), 76.

Chatterjee, R., George, S. R., Verma, J. S., Heggde, G., & Gadhavi, D. D. (2025). Impact of human and AI-agent services on customer learning, immersion and loyalty: the role of interactivity. *Journal of Service Theory and Practice*, *35*(5), 668-692.

Creswell, J. D., Pacilio, L. E., Lindsay, E. K., & Brown, K. W. (2014). Brief mindfulness meditation training alters psychological and neuroendocrine responses to social evaluative stress. *Psychoneuroendocrinology*, *44*, 1-12.

Creswell, J. W., & Creswell, J. D. (2017). *Research design: Qualitative, quantitative, and mixed methods approach*. Sage publications.

Creswell, J. W., Fetters, M. D., & Ivankova, N. V. (2004). Designing a mixed methods study in primary care. *The Annals of Family Medicine*, *2*(1), 7-12.

Cudia, C. P., & Legaspi, J. L. R. (2024). Strategic Management of Technological Frontiers in Banking: Challenges and Strategies for Cloud Adoption, Big Data Analytics, and AI Integration. *Library of Progress-Library Science, Information Technology & Computer*, *44*(3).

Davis, F. D. (1989). *Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Dwivedi, Y. K., Hughes, D. L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J. S., Gupta, B., Lal, B., Misra, S., Prashant, P., Raman, R., Rana, N. P., Sharma, S. K., & Upadhyay, N. (2020). Impact of COVID-19 pandemic on information management research and practice: Transforming education, work, and life. *International Journal of Information Management, 55*, 102211. https://doi.org/10.1016/j.ijinfomgt.2020.102211

Fazelian, S. (2026). Assessing Trust in AI-Driven Marketing: Factors, Implications, and Opportunities. *Digital Repository of Theses*.

Folorunso, A., Olanipekun, K., Adewumi, T., & Samuel, B. (2024). A policy framework on AI usage in developing countries and its impact. *Global Journal of Engineering and Technology Advances*, *21*(01), 154-166.

Froment, L. (2024): The Future of Banking: AI Personalization as a Catalyst for Customer Loyalty. Retrieved from https://thefinancialbrand.com/news/personalization/the-future-of-banking-ai-personalization-as-a-catalyst-for-customer-loyalty-174457

Gaćina, A. (2025). *The disruptive power of artificial intelligence and robotic process automation in business* (Doctoral dissertation, Sveučilište u Zagrebu, Sveučilište u Zagrebu Ekonomski fakultet, Katedra za informatiku).

Hair Jr, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2021). Evaluation of reflective measurement models. In *Partial least squares structural equation modeling (PLS-SEM) using R: A workbook* (pp. 75-90). Cham: Springer International Publishing.

Hofstede, G. (2016). Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations. *Collegiate Aviation Review*, *34*(2), 108.

Huang, M.-H., & Rust, R. T. (2021). A strategic framework for artificial intelligence in marketing. *Journal of the Academy of Marketing Science, 49*(1), 30–50. https://doi.org/10.1007/s11747-020-00749-9

Ishengoma, F., & John, E. (2025). Factors influencing the adoption of mobile-based AI services in Tanzanian manufacturing SMEs. *Vilakshan-XIMB Journal of Management*, *22*(2), 234-252.

Jayapal, J. (2025). Unveiling the impact of AI-driven personalization on customer loyalty in online shopping: the moderating effects of privacy concerns. *Journal of Promotion Management*, *31*(5), 865-894.

Kim, Y. (2025). The AI Inclusion Challenge: Assessing Digital Vulnerability in AI Adoption and Usage. In *The Art of Digital Governance: Navigating Platforms and AI Revolution* (pp. 389-406). Cham: Springer Nature Switzerland.

Kothari, C. R. (2017). *Research methodology methods and techniques by* CR Kothari. Published by New Age International (P) Ltd., Publishers, 91.

Kotler, P., & Keller, K. L. (2015). *Framework for Marketing Management, A*. BoD–Books on Demand.

Kumar, V., Dixit, A., Javalgi, R. R. G., & Dass, M. (2016). Research framework, strategies, and applications of intelligent agent technologies (IATs) in marketing. *Journal of the Academy of Marketing Science*, *44*(1), 24-45.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of marketing*, *80*(6), 69-96.

Li, C. Y., Fang, Y. H., & Chiang, Y. H. (2023). Can AI chatbots help retain customers? An integrative perspective using affordance theory and service-domain logic. *Technological Forecasting and Social Change*, *197*, 122921.

Lopes, J. M. (2025). The role of artificial intelligence in mobile banking. *Financial Technology Review, 9*(4), 45–59. https://doi.org/10.1186/s43093-025-00510-0

Malaquias, R. F., & Hwang, Y. (2019). Mobile banking use: A comparative study with Brazilian and US participants. *International journal of information management*, *44*, 132-140.

Mariani, M., & Borghi, M. (2021). Customers' evaluation of mechanical artificial intelligence in hospitality services: a study using online reviews analytics. *International Journal of Contemporary Hospitality Management*, *33*(11), 3956-3976.

Metha, S. (2025). Ai-driven promotion platforms: Increasing customer engagement in banking. *Journal of Artificial Intelligence Research & Advances*, *12*(01), 87-92.

Mohajan, H. K. (2017). Two criteria for good measurements in research: Validity and reliability. *Annals of Spiru Haret University. Economic Series*, *17*(4), 59-82.

Mwaseba, S. L., Mwang'onda, E. S., & Donald, W. R. (2026). Bridging the digital financial divide: the role of financial literacy in rural–urban disparities in mobile money account ownership in Tanzania. *Cogent Economics & Finance*, *14*(1). https://doi.org/10.1080/23322039.2026.2624866

Mwita, D. (2022). *The Effects of Information Technology on Marketing of Financial Services in Tanzania: A Case of Commercial Banks* (Doctoral dissertation, The Open University of Tanzania).

OECD (2021), *Artificial Intelligence, Machine Learning and Big Data in Finance: Opportunities, Challenges and Implications for Policy Makers*, OECD Publishing, Paris, https://doi.org/10.1787/98e761e7-en.

OECD. (2022). Gender diversity and organizational adaptability in financial institutions. *OECD Publishing.* https://doi.org/10.1787/finance-gender-2022

Oliver, R. L. (1999). Whence consumer loyalty? *Journal of marketing*, *63*(4_suppl1), 33-44.

Plantinga, P., Shilongo, K., Mudongo, O., Umubyeyi, A., Gastrow, M., & Razzano, G. (2024). Responsible artificial intelligence in Africa: Towards policy learning. *Data & Policy*, *6*, e72.

Rady, J., Baden, A., Ali, U., & Khan, M. (2020). IHOP and Applebee's: Stacking up more than pancakes!. *Journal of Hospitality & Tourism Cases*, *8*(1), 26-37.

Rožman, M., & Tominc, P. (2024). Navigating gender nuances: Assessing the impact of AI on employee engagement in Slovenian entrepreneurship. *Systems*, *12*(5), 145.

Ruel, H., & Njoku, E. (2021). AI redefining the hospitality industry. *Journal of Tourism Futures*, *7*(1), 53-66.

Rust, R. T., & Huang, M. H. (2014). The service revolution and the transformation of marketing science. *Marketing science*, *33*(2), 206-221.

Saha, B., Rani, N., & Shukla, S. K. (2025). Generative ai in financial institution: A global survey of opportunities, threats, and regulation. *arXiv preprint arXiv:2504.21574*.

Saunders, M. N. K., Lewis, P., & Thornhill, A. (2023). *Research methods for business students* (9th ed.). Pearson.

Saunders, M., & Tosey, P. (2012). *Research design*. Academia.

Sekaran, U., & Bougie, R. (2016). *Research methods for business: A skill building approach*. john wiley & sons.

Shah, T. (2025). Leadership in digital transformation: Enhancing customer value through AI-driven innovation in financial services marketing. *International Journal of Science and Research Archive, 15*(3), 618–627. https://doi.org/10.30574/ijsra.2025.15.3.1767

Shela, V., Ramayah, T., Aravindan, K. L., Ahmad, N. H., & Alzahrani, A. I. (2023). Run! This road has no ending! A systematic review of PLS-SEM application in strategic management research among developing nations. *Heliyon, 9*(12), e22476. https://doi.org/10.1016/j.heliyon.2023.e22476

Thakur, S., Choudhary, J., & Singh, D. P. (2021). A survey on missing values handling methods for time series data. In *Intelligent Systems: Proceedings of SCIS 2021* (pp. 435-443). Singapore: Springer Singapore.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision sciences*, *39*(2), 273-315.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management science*, *46*(2), 186-204.

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2016). Unified theory of acceptance and use of technology: A synthesis and the road ahead. *Journal of the Association for Information Systems, 17*(5), 328–376. https://doi.org/10.17705/1jais.00428

Verhoef, P. C. (2020). Customer experience creation in today's digital world. In *The Routledge companion to strategic marketing* (pp. 107-122). Routledge.

Yoo, Y., Henfridsson, O., Kallinikos, J., Gregory, R., Burtch, G., Chatterjee, S., & Sarker, S. (2024). The next frontiers of digital innovation research. *Information Systems Research*, *35*(4), 1507-1523.

Zatsu, V., Shine, A. E., Tharakan, J. M., Peter, D., Ranganathan, T. V., Alotaibi, S. S., Mugabi, R., Muhsinah, A. B., Waseem, M., & Nayik, G. A. (2024). Revolutionizing the food industry: The transformative power of artificial intelligence-a review. *Food chemistry: X*, *24*, 101867. https://doi.org/10.1016/j.fochx.2024.101867