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AI-driven self-service for enhanced customer experience outcomes in the banking sector

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ABSTRACT

This study examines the influencing value factors of Artificial Intelligence (AI)-based self-service technology delivery, self-service customer experience, and outcomes based on customer value theory and trust-commitment theory. This study adopted a quantitative research approach. Four hundred and twenty-two bank customers who use AI-based self-service technology were sampled for the study. Structural equation modelling was employed to analyse the data. The study reveals that personalisation influences AI-based self-service customer experience, and convenience significantly and positively predicts AI-based self-service customer experience. Time spent, and AI-based self-service customer experience yielded significantly positive results. AI-based customer trust and self-service customer brands also had a significant positive relationship. However, the study did not find support for aesthetic and AI-based self-service customer experience. This study's novelty is identifying the customer value factors that influence AI-based self-service experience in an emerging country using the Customer Value Theory (CVT) and Trust-Commitment Theory (TCT) frameworks.

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Artificial intelligence (AI); customer self-service experience; customer value theory (CVT); Trust-Commitment theory (TCT); trust; brand love

SUBJECTS

Consumer Psychology; Business, Management and Accounting; Technology

1. Introduction

Artificial intelligence and self-service technology concepts are transforming and reshaping business conduct (Campbell et al., 2020; Fiestas Lopez Guido et al., 2024; Rai, 2020; Wirtz et al., 2023) and are increasingly receiving scholarly attention (Ameen et al., 2021; Chen et al., 2021; Gao et al., 2022). AI is 'a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation' (Kaplan & Haenlein, 2019, p. 17). Current trends in AI usage have improved customer experiences in several sectors, particularly the service sector, such as retail, hotels, tourism, public service delivery, and banking (Ameen et al., 2021; Gao et al., 2022; Lee & Chen, 2022).

AI has also increased the number of self-service technologies (SST). These technologies are constantly increasing in marketing, especially in retail markets (Park et al., 2021). Self-service technologies have changed service provision by eliminating the customer-employee experience with customer-technology experience (Barua et al., 2018; Cui et al., 2021; Djelassi et al., 2018). SSTs are technological interfaces with which customers interact and come in the form of self-check-in kiosks, self-ticketing machines, and those that customers can access remotely via the Internet (Cui et al., 2021). With the support of AI, SST technologies offer several benefits to organisations, such as increasing the number of customers they serve

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daily, increasing firms' efficiency, offering customers greater accessibility, and improving efficient decision-making (Djelassi et al., 2018).

SST is widespread in service sectors, and there is a current trend of integrating artificial intelligence (AI) into SST (Ameen et al., 2021; Gao et al., 2022; Lee & Chen, 2022). AI-based SST has unique features such as natural language processing, machine learning, face recognition, and recommendation algorithms, which provide personalised and improved customer experience.

Past studies have made progress in studying the SST service (Lien et al., 2021; Sohn et al., 2024) and AI-based SST (Chen et al., 2021; QianTing et al., 2021) experience of customers separately. However, it is observed that only some studies have examined AI-based SST in the current literature (Chen et al., 2021; QianTing et al., 2021). For example, Chen et al. (2021) examined how the public sector in China is using AI-based SST to improve work efficiency and user experience to reduce service costs and workers' workloads. The current literature reveals that AI-based SST is a new technology and is being used in the service sector, especially in retail (Ameen et al., 2021), hotels (QianTing et al., 2021) and public sector service delivery (QianTing et al., 2021). Currently, banks have also started using this technology in service delivery, and there needs to be a clear understanding of the factors influencing AI-based SST customer experience and trust in this technology in providing services in emerging Sub-Saharan African countries, where such studies are lacking in the current literature.

Hence, the study aims to identify the factors influencing customers' experiences of AI-based SST and customers in Ghana's banking sector to enhance customer experience, trust and love for banks. Specifically, this study examines the impact of value factors on customer self-service experience and the role of customer trust in linking this experience to brand love. The banking sector is increasingly using AI-based SST in service delivery, and studying the influencing factors and trust of this new customer service experience, especially from a sub-Saharan African country, enriches our understanding of this technology and adds to the existing literature on SST and AI-based SST and service literature in general. Further, the study extends previous studies by looking at how AI-based SST customer experience would influence trust and lead to brand love in the banking industry, which also provides scholars with a better understanding of how this technology in the banking industry, which is a different industry compared to previous studies focusing on industries such as retail, hotel and public sector services delivery brings the perspective of a different industry experience which enrich the current literature.

The current study contributes to the current literature in several ways. Departing from previous studies, this study developed a conceptual framework (see Figure 1). It tested the factors influencing AI-based SST in a different service sector (banking). It added a new perspective, especially in an emerging sub-Saharan African country, to the current AI-based SST customer experience literature. In addition, the study draws on consumer value theory and trust commitment theories to understand factors influencing customer experience of this technology and how that influences their trust and eventually leads to brand love, contributing towards a better insight into these theories and scholars understanding of how these theories can be applied in various sectors in the service sector. This investigation adds to our existing knowledge of these constructs in the service sector. The consumer value theory explains that customers assess different values before using a product or service, including functional, emotional, epistemic, social, and conditional (Chen et al., 2021; Sheth et al., 1991). The study applies this theory to argue

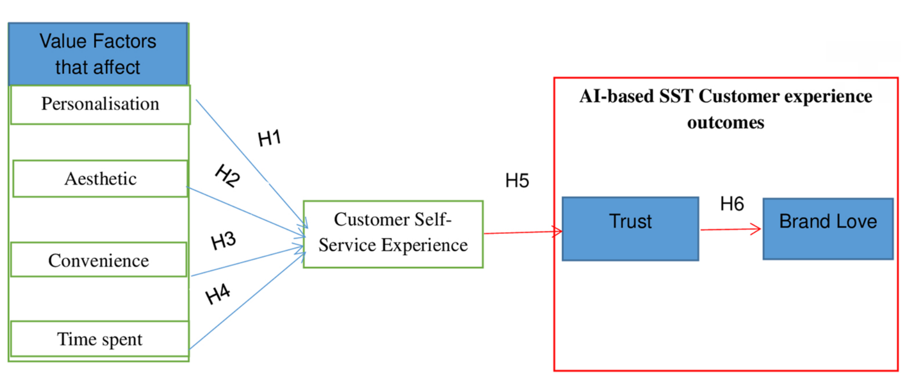

Figure 1. Proposed research framework.

that AI-based factors such as personalisation, aesthetics, convenience, and time spent can enhance customers' self-service experience (Wang, 2017).

On the other hand, trust commitment theory emphasises the importance of trust in automated services. The study argues that better self-service provision based on AI-based SST can lead to customer trust and brand love. Applying these theories adds value and enriches researchers' understanding of how these theories can be applied in different contexts and industries. Enhancing the applicability and robustness of these theories adds value to the scholarship. Further, this study provides practical insights for bank managers and financial institutions in emerging countries where AI-based self-service technology is still in its early stages. The study identifies AI-based factors that significantly influence the customer self-service experience, which can lead to customer trust and brand love. This information can help banks develop strategies to improve their AI-based self-service provision, making the experience more enjoyable for customers and enhancing their love towards the banks, ultimately positively impacting their performance.

The rest of the paper proceeds as follows: Section 2 reviews the literature on AI and self-service technologies, AI-based customer self-service experiences, trust, and brand love and develops the hypotheses and conceptual framework. Section 3 deals with the methodology and results. The final section, 4, looks at the discussions, implications, limitations, and directions for future studies and provides the conclusion.

2. Literature review and hypothesis development

2.1 Artificial intelligence, self-service technologies, and AI-based customer self-service experience

As an innovative and cutting-edge technology, AI is drastically revolutionalising several fields, such as finance and banking, marketing, retailing, insurance, and tourism and hospitality (Lee & Chen, 2022 Omoge et al., 2022; Shang et al., 2024; Vaidyanathan & Henningsson, 2023). AI is an example of disruptive technology that impacts and transforms business conduct (Omoge et al., 2022). Scholars have provided several definitions of AI (Kaplan & Haenlein, 2019). For example, Kaplan and Haenlein (2019, p. 17) defined AI as 'a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation'. AI is a goal-focused technology that allows devices to take advantage of their environment and improve performance (Russell, 2016). Thus, AI deals with cognitive mapping (CM), machine learning (ML), and natural language processing (NLP) (Kshetri, 2024; Liddy, 2001).

Prentice et al. (2019) added that AI technology behaves like humans undertaking activities through computers and machines based on automation, big data, and machine learning to reach a specific objective and activity. AI technology involves voice interaction, personalisation, and face recognition (Chen et al., 2021). The voice assistant installed in the machine processes the user's language in real time and allows the user to interact (Hoy, 2018). Personalisation refers to the supply of essential personal information, products, and services depending on the users' peculiar characteristics and needs (Chiu et al., 2024; Xiao & Benbasat, 2007). According to Chen et al. (2021), personalisation is becoming very important to users as they deal with every individual differently and lessen the cognitive problems of users. For example, the face recognition feature recognises individual characteristics, such as eyes, mouth, forehead, nose, or other spatial geometry features that separate one user from another (Jayaraman et al., 2020).

Before the integration of AI into SST, the traditional SST was extensively applied in the service sector (Kim, 2024; Shin & Perdue, 2019; Wexler & Oberlander, 2021). Early research recognised SST as a platform for value co-creation (Chandra & Rahman, 2024; Chen et al., 2021; Lee & Allaway, 2002). For instance, Kelly et al. (2017) employed service-led logic to investigate SST's role in tourism. The results show that customers' value creation experiences better explain the experience scale of customers. Additionally, scholars have studied the factors influencing the adoption of orthodox SST (Meuter et al., 2003). For instance, Meuter et al. (2003) noted that perceived usefulness, reliability, and ease of use influence the use of conventional SST. Likewise, personal attributes, technical readiness, and situational and demographic factors influence customers' adoption of SST (Bitner et al., 2002; Dabholkar et al., 2003; Song et al., 2024). The extant literature reveals that Dabholkar (1996) introduced 'technology-based self-service' first but failed to clarify its definition (Guan et al., 2021). Later, Meuter et al. (2000) introduced the term 'self-service technology' (SST) and defined it as a 'technological interface that enables customers to produce a service independent of direct service employee involvement' (p. 50). Scholars have universally adopted the definition of Meuter et al. (2000) to constitute self-service technology that enables customers to attend to themselves (Chen et al., 2021). The integration of orthodox SST and AI technology occurred in the banking sector, referred to as the AI-based self-service machine for improving customers' experience (Hassan & Farmanesh, 2022). AI-based SST creates new opportunities and possibilities for customer-computer interaction, customer experience improvement, and cost reduction to employees' expenses, which are some of the benefits banks derive from using AI-based SST.

In the banking sector, banks employ the use of AI-supported services which uses advanced algorithms, machine learning, and natural language processing to automate processes, enhance customer service, and provide personalised financial solutions (Bhatnagr & Rajesh, 2024; Tóth & Blut, 2024). For example, chatbots, a prominent AI application, assist customers in real time by answering questions, helping with transactions, and resolving common banking issues by streamlining the customer experience while reducing the workload for human agents (Sawant et al., 2023; Thowfeek et al., 2020). Predictive analytics, another AI-supported service, processes vast amounts of customer data to offer insights into spending habits, creditworthiness, and risk management (Sawant et al., 2023; Tóth & Blut, 2024). This enables banks to tailor their services based on each customer's unique financial behaviour and needs, improving customer satisfaction and financial outcomes. In the study context, some examples of AI-based SST services banks provide are ATMs, online banking, and mobile banking (Iqbal et al., 2017; Zarifhonarvar, 2024).

2.2. Customer/user self-service experience

Customer experience is associated with constructs such as functional, emotional, affective, experiential, hedonic, and aesthetic aspects of the interaction between humans and products or services (Boczko, 2024; Lallemand et al., 2015; Law et al., 2009). Customer experience has three key factors: the user, the system, and the context (Chen et al., 2021). According to Chen et al. (2021), the International Organization for Standardisation defines customer experience as 'the perception and responses a customer holds emerging from the use of a product or service, and system' (p. 3). Law et al. (2009, p. 727) define experience as 'products, systems, services, and objects that a person interacts with through a user interface'.

Consistent with the three primary key customer experience factors, scholars have investigated dynamic, context-dependent, and subjective customer experience. The dynamic factor deals with customers' instrumental and non-instrumental needs (Chen et al., 2021), while the context-dependent focuses on the interaction's affective and emotional aspects, such as customer's expectations, motivation, and mood (Baloch & Gzara, 2024; Chen et al., 2021; Ma et al., 2024). Finally, subjective customer experience refers to situatedness, the temporality of the experience, or the context within which the interaction occurs (Chen et al., 2021; Darmody & Zwick, 2024). According to Hassenzahl and Tractinsky (2006, p. 95), blending these three perspectives illustrates the value of 'a customer's internal state (e.g. predispositions, expectations, needs, motivation, and mood), the characteristics of the designed system (e.g. complexity, purpose, usability, and functionality), and the context within which the interaction occurs (e.g. organisational, social setting, the meaningfulness of the activity, and the voluntariness of use)'. As a result, improving customer experience has become an important marketing strategy and is receiving increasing interest from practitioners and scholars (Chen et al., 2024; Gao et al., 2020; Rajaobelina et al., 2018). In addition, researchers such as Mclean et al. (2018) have noted that customer experience has been the foundation of human-computer interaction for some years now, and technological innovations such as the Internet of Things, AI, and interactive technologies have further deepened the interest of researchers in customer experience.

2.3. Trust in self-service

Customer trust is a multidimensional construct from various perspectives in current literature. Researchers across many disciplines use Mayer et al.'s seminal definition (1995). Mayer et al. (1995, p.

712) defined trust as 'the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party'. They further noted that human-like trust comprises ability, benevolence, and integrity. In a related study, Mcknight et al. (2011) noted that system-like trust consists of reliability, functionality, and helpfulness. This study focuses on system-like trust, which deals with technology features and customer expectations of the technology (Hanantyo & Mahmudi, 2024; Mcknight et al., 2011; Mulyawan, 2024). In addition, literature records studies examining trust and technology attributes (Chen et al., 2016; Kim et al., 2021; Prakash et al., 2023; Wong et al., 2024). The role of technology in service provision is increasing in the banking sector, making trust issues significant. According to Nyadzayo and Khajehzadeh (2016), trust is essential for building customer relationships and influencing the future use of a particular technology. Other scholars posit that trust in a service or technology influences a customer's behaviour towards the service or the technology (Dimitriadis & Kyrezis, 2011; Huang et al., 2024; Mulcahy et al., 2019). For example, Kim et al. (2021) found trust to mediate the relationship between the preciseness of information and evaluation and behavioural intentions of AI usage.

2.4. Brand love

Brand love has been extensively studied in marketing and brand relationship literature (Ali et al., 2021; Amegbe et al., 2021; Rauschnabel et al., 2024; Trivedi, 2019). Brand love refers to a satisfied customer's passion and emotional attachment towards a particular brand (Carroll & Ahuvia, 2006; Ghorbanzadeh, 2024). Scholars have noted that brand love positively impacts an organisation's tangible and intangible assets (Mostafa & Temerak, 2024; Reimann et al., 2012). This study argues that customers tend to develop brand love for banks when they have a good experience with AI-based self-services, which leads to trust in these services. Furthermore, the study highlights the importance of brand love in understanding customer-brand relationships in the banking and service sectors (Cho & Hwang, 2020; Zhang & Xu, 2024) observed that customers exhibit love toward a brand if it is driven by technology because of its reputation when it comes to technology. Therefore, brand love helps better understand customer-brand relationship building in the banking and service sectors (Trivedi, 2019).

2.5 Influencing value factors of AI-based self-service technology

This study operationalised the value factors that affect the self-service customer experience: personalisation, aesthetics, convenience, and time spent using AI-based SST machines. Personalisation refers to 'the degree to which information is tailored to the needs of a single user and thus constitutes an important determinant of positive experiences' (Bilgihan et al., 2016, p. 110). According to Zanker et al. (2019), personalisation is a critical factor often linked to AI-enabled services. They also indicated that the objective of the AI and machine learning (ML) domains is to make the best out of personalisation applications and create suitable algorithms to enhance decision-making and forecasting.

Scholars identify three dimensions of personalisation: customer interface, content, and interaction processes (Zanker et al., 2019). Customer interface refers to the layout of screens. Whether the size suits all customers (Findlater & McGrenere, 2010), content involves providing personalised information to customers (Zanker et al., 2019), and interaction processes involve AI-based system autonomy in deciding how to interact with customers (Chen et al., 2021; Zanker et al., 2019). Personalisation strategies that contribute to positive attributions build customer commitment to the brand.

According to Rafaeli and Vilnai-Yavetz (2004), customer aesthetics experience refers to the sensory customer experience a product or service creates and the level at which it matches the customers' objectives and desires. Aesthetics impact customer perception and behaviour when using innovative services (Chen et al., 2021) by positing that ensuring product or service uniqueness (Postrel, 2002). Coursaris and Van Osch (2016) examined customer satisfaction's aesthetics and usability dimensions from a cognitive-effective perspective and further divided aesthetics into classical and expressive aesthetics. Their findings reveal that classical aesthetics have a significant impact on customer satisfaction. Sheng and Teo (2012) held a similar position. They noted that aesthetic values influence customer decisions regarding a product or service. The current study investigates aesthetics in AI-based SST of banks since researchers (Li & Yeh, 2010) have noted that aesthetics are critical in developing a better relationship between customers and products or services, influencing customer trust and loyalty.

Further, this study considers perceived convenience as a value factor in customer self-service experience with AI-based SST in the banking sector. Convenience is the ability to complete a task quickly and efficiently (Morganosky, 1986). Previous studies have shown that convenience is essential in predicting customer engagement, trust, and mobility (Roy et al., 2018). Past studies categorise AI-based SST convenience into three dimensions: availability, real-time information, and proactive discussion (Thiel, 2019; Walch, 2019). The authors suggest that these dimensions contribute to customers receiving timely satisfaction without the involvement of employees. Finally, this study considers time spent as an influencing factor in the customer self-service experience. While the impact of customers' willingness to spend time is still being determined (Chen et al., 2021), past studies suggest that less time spent positively impacts the customer experience (Mclean et al., 2018). Hence, the study believes that AI-based SST can help customers reduce the time spent using banks' AI-based SST.

2.6 Hypothesis development

This study used customer value and trust-commitment theories to investigate the factors influencing using AI-based self-service technology in Ghana's banking sector. The study focused on personalisation, aesthetics, convenience, and time spent as the influencing value factors of customer self-service experience. The study also applied the trust-commitment theory to suggest that a positive customer self-service experience leads to trust in banks' AI-based SST and ultimately to brand love. Figure 1 illustrates the study's conceptual framework.

2.6.1 Influencing value factors of AI-based self-service technology and self-service customer experience

Empirically, Dabholkar (1996) and Meuter et al. (2000) conducted seminal studies on the predictive role of self-service technologies on customer experience. Dabholkar's study found that speed of delivery, ease of use, expected reliability, and enjoyment are essential factors for technology-based self-service options. In contrast, Meuter et al.'s study revealed that ease of use, saving time, access, and availability were sources of customer satisfaction. Guan et al. (2021) also examined the factors influencing customers' use of self-service technology and found similar outcomes.

Further, a study conducted in Jordan by Hassan and Farmanesh (2022) discovered that customers' use of SST is influenced by performance expectancy, hedonic motivation, price value, and perceived risk. Another study by Chen et al. (2021) examined the user experience of AI-based SSTs in China and found that personalisation, aesthetics, and perceived time spent positively influence the user experience. Similarly, Ameen et al. (2021) found that trust plays a role in perceived convenience and personalisation toward the user experience of AI-based SSTs. Based on the above empirical evidence, this study argues that personalisation, aesthetics, convenience, and time spent positively influence customer self-service experiences in the banking sector in Ghana. Hence, the following hypotheses were formulated for testing:

H1: *Personalisation would significantly positively influence customers' AI-based self-service experience.*

H2: *There is a significant positive relationship between Aesthetics and customers' AI-based self-service experience.*

H3: *Convenience would significantly positively influence customers' AI-based self-service experience.*

H4: *Time spent would significantly positively influence customers' AI-based self-service experience.*

2.6.2. Self-service customer experience and trust

The literature suggests that there is a link between customer experience and trust. Several studies have confirmed this relationship, including studies on mobile banking (Rajaobelina et al., 2018) and travel agencies (Brun et al., 2020). Furthermore, positive customer experiences significantly impact trust, which suggests that the self-service customer experience can influence trust among bank customers. Hence, this study proposes that:

H5: *Positive self-service customer experiences in banking are positively related to the level of trust customers have in their bank.*

2.6.3. Trust and brand love

Trust and Brand love are essential constructs in banking and marketing literature. Salehzadeh et al. (2023) investigated the nexus of green brand love, image, trust, and attitude among 201 consumers of automobile brands in Iran. The result shows that trust significantly and positively affects brand love. Navaneethakrishnan and Sathish (2020) studied brand love through purchase intention, trust, and attitude. The results revealed that trust influences brand love. Further studies, such as those by Amegbe et al. (2021) and Kaufmann et al. (2016), have confirmed the relationship between trust and brand love. Based on these empirical reviews, the following hypothesis is proposed.

H6: *Self-service trust significantly and positively influences AI-based Self-service brand love.*

2.7. Conceptual framework

The conceptual framework (see Figure 1) is underpinned by two critical theories in the extant literature, namely, the consumer value theory (CVT) and the trust commitment theory (TCT). The study used CVT in the first part of the framework to claim that customers are influenced by AI-based factors such as personalisation, aesthetics, convenience, and time spent, which would influence their SST experience. The second part of the model draws insight from trust-commitment theory to argue that it could lead to customer trust and brand love when customers experience better self-service provision based on AI-based SST.

3. Methodology

3.1. Procedure and sample

This study used a quantitative research design. The target respondents were the customers of thirty-three universal banks in Ghana. The study employed Cochran's (2004) approach to determine the population, which was initially known, before using purposive sampling, a non-probability sampling technique, to select the respondents (Saunders et al., 2019). Purposive sampling was necessary to ensure that respondents with experience using AI-enabled banking services expressed their sense of personalisation, trust, brand love, time, aesthetics, and convenience. In addition, the information inviting the target respondents emphasised that only individuals who regularly use AI-enabled banking services should participate in the survey. Hence, respondents were asked to answer yes or no to an initial question: 'Do you frequently use any of the following: banking app, ATM, internet banking, cash recycler, voice assistant, or interactive kiosk?' Respondents who answered 'Yes' had access to the remaining items.

Data were collected through a survey using an online questionnaire. The questionnaire was administered via web links on social media platforms such as WhatsApp, Facebook, and LinkedIn. Respondents were also guaranteed anonymity and confidentiality of their data. A written statement of informed consent was included on the title page of the questionnaire. The Institutional Ethics Committee of Dominion University College granted the study's ethical approval under reference number IREC 03/22. Data was collected from May and July 2022. Six hundred and twelve responses were received at the end of the data collection. After data preprocessing, 422 responses were retained as valid datasets used for the study.

The demographic characteristics of the respondents are summarised in Table 1. The data showed that 54.73% ($n = 231$) of the respondents were male, and 45.26% ($n = 191$) were female. The dominant age group was 35–55 years ($n = 221$), constituting 52.37% of respondents. Respondents who had obtained a bachelor's degree constituted the dominant respondents in the education variable, representing 44.45%

Table 1. Demographic profile of respondents.

Demography	Category	Frequency	Percentage
Gender	Male	231	54.73
	Female	191	45.26
Age	18–34	183	43.36
	35–55	221	52.37
	56 and above	18	4.26
Education	Diploma/HND	84	19.90
	Bachelor's degree	188	44.45
	Master's degree	137	32.46
	Doctoral Degree	17	4.03
	Others	13	3.08
Employment status	State institution	247	58.53
	Private institution	166	39.33
	Self-employed	7	1.65
AI-enabled services	ATM	422	100
	Banking App	136	61
	Internet Banking	97	23
	Voice assistants	37	8.76

($n = 188$). Most respondents were government employees (58.53%, $n = 427$). Additionally, the respondents use the ATM as an AI-enabled service more frequently than the other listed AI-enabled services. The data shows that 100% of respondents ($N = 422$) reported using the ATM. However, when considering other AI-enabled services such as banking apps, internet banking, cash recyclers, voice assistants, and interactive kiosks, it is evident that they also play significant roles in the banking context. While less prevalent than ATM usage, these services collectively contribute to the evolving landscape of AI-driven banking solutions.

3.2. Measures

The items measuring each construct were drawn from existing literature (see Appendix A). All items were measured using a five-point Likert scale ranging from 1(I do not agree at all) to 5 (I completely agree). Personalisation was rated using a 5-item scale by Lee and Rha (2016) and Roy et al. (2018). Aesthetics was assessed using five items developed by Sheng and Teo (2012). Convenience was rated using the items from Collier and Sherrell. The perceived time spent on AI-based SST was assessed based on the 3-item scale of McLean and Wilson. User experience was measured using a 9-item scale by Schmitt (1999) and Gentile et al. (2007). The respondents' views of their Trust in AI were measured using a 4-item scale adapted from Teo et al. (2008). The scale was initially developed to assess trust in the success of electronic government. Finally, brand love was measured using a 9-item scale adapted from Cho and Fiore (2015). The details of the items are presented in Appendix A.

3.4. Common method bias

Data on all constructs in this study were obtained from a single source. Self-reported data obtained using questionnaires with standard and consistent response scales are prone to bias (Podsakoff et al., 2003; 2012). To reduce the potential for common method bias (CMB), the wording of the items was short and straightforward to understand (Kock et al., 2021; Podsakoff et al., 2012). In addition, the items were mixed to avoid predictability. Subsequently, Harman's single-factor test was conducted to statistically check for the presence of CMB (Harman, 1976). The outcomes of Harman's test revealed that the total percentage of variance explained was only 48. 55%., which is less than 50%, indicating that CMB was not challenging in this study. See Appendix B for details.

Further data assessment was conducted to check for non-response bias, following the guidelines of Armstrong and Overton (1977). An assessment was performed to ensure that the data reflected the population. In checking for non-response bias, the first 25% of the responses were compared with the 25% of responses received at the end of the data collection (Armstrong & Overton, 1977). No significant variance was recorded ($p > 0.05$) among the constructs. The outcome indicated that non-response bias was not critical in this study.

3.5. Data analysis procedure

SPPS (version 27) was initially used for data preprocessing, mainly when accounting for a valid dataset and analysing the demographic profile of the respondents. Then, partial least squares structural equation modelling (PLS-SEM, 3.0) was used to evaluate the measurement and structural models (Hair et al., 2019a; 2022). PLS-SEM was used because it supports evaluating reliability and validity, complex models, and predictions and facilitates estimating and testing the hypothesised relationship between latent variables (Hair et al., 2017a; 2019a).

4. Results

The model fit of this study was assessed based on the saturated model fit in PLS-SEM: standardised root mean squared residual (SRMR), unweighted least squares discrepancy (d_ULS), geodesic discrepancy (d_G), and normed fit index (NFI). The results show that SRMR is 0.060, which is acceptable (Lohmöller & Lohmöller, 1989). The NFI was 0.804, which is adequate because it is close to the acceptable threshold of 0.9 (Lohmöller & Lohmöller, 1989). In addition, d_ULS (0.972) and d_G (0.952) are below the 99%-quantile (HI99) of bootstrap discrepancies (Henseler et al., 2016).

Table 2 offers a comprehensive view of the data's central tendencies and distribution characteristics for each construct. The constructs show strong factor loadings, reflecting their reliability in measuring their underlying constructs. The factor loadings exceeded the 0.708 threshold (Hair et al., 2019a; 2022). The lowest item indicator loading was 0.720. The skewness and kurtosis values provide insights into the distribution characteristics of the constructs, with most of them exhibiting slight negative skewness and slightly flatter tails. For example, customer Self Service Experience comprises 4 items and exhibits strong factor loadings in the range of 0.867 to 0.874, denoting a high relationship with the underlying construct. The mean score for customer Self Service Experience is 3.34, with a standard deviation of 0.743, indicating a moderate level of self-service experience among the respondents. The skewness value of −0.212 suggests a slight negative skew, indicating that the data distribution is slightly skewed to the left. In contrast, the kurtosis value of −0.212 indicates that the data has slightly flatter tails than a normal distribution. These values collectively suggest room for improvement in enhancing the self-service experience to make it more favourable for a broader range of customers.

The measurement model was assessed per Hair et al.'s guidelines. Table 3 presents various statistical measures for the constructs, including Cronbach's alpha (CA), Composite Reliability (CR), Averaging Variance Extracted (AVE), and the correlations among these constructs. These measures help assess the reliability and validity of the constructs in the research study. The CA ranged from 0.802 to 0.937, exceeding the threshold of 0.70 (Hair et al., 2022). CR assesses the extent to which the items within each construct are interrelated and contributes to the overall reliability of the construct. All constructs have high CR values, ranging from 0.883 to 0.960, well above the recommended threshold of 0.70, indicating that the items within each construct are highly reliable and consistently measure the underlying construct (Hair et al., 2022). Additionally, all constructs have AVE values above 0.70, which suggests good convergent validity (Hair et al., 2017b; Sarstedt et al., 2021).

Table 2. Constructs summary: factor loadings, descriptive statistics, and normality statistics.

Constructs	No. of items	Factor loadings range	Mean	Std. Deviation	Variance Statistic	Skewness	Kurtosis
Customer self-service experience	4	0.867***–0.874***	3.34	0.743	0.552	−0.212	−0.212
Trust	4	0.820***–0.883***	3.73	0.911	0.831	−0.494	−0.494
Personalisation	5	0.852***–0.911***	3.70	0.911	0.831	−0.602	−0.602
Aesthetic	5	0.720***–0.885***	3.81	0.834	0.696	−0.605	−0.605
Convenience	3	0.930***–0.956***	3.58	0.828	0.685	−0.425	−0.425
Time spent	3	0.820***–0.883***	3.65	0.823	0.677	−0.206	−0.206
Brand Love	4	0.753***- 0.879***	3.60	0.904	0.816	−0.552	−0.552

*Note: ***indicate values significant at 95% confidence level.*

Table 3. Measurement model.

Constructs	CA	CR	AVE	1	2	3	4	5	6	7
Aesthetic (**1**)	0.890	0.919	0.695							
Brand Love (**2**)	0.838	0.892	0.674	**0.885**						
Convenience (**3**)	0.937	0.960	0.888	0.716	**0.703**					
Customer Service Exp (**4**)	0.890	0.924	0.751	0.773	0.781	**0.649**				
Personalisation (**5**)	0.933	0.949	0.789	0.877	0.876	0.671	**0.833**			
Time spent (**6**)	0.802	0.883	0.716	0.834	0.862	0.878	0.669	**0.788**		
Trust (**7**)	0.879	0.917	0.734	0.884	0.867	0.622	0.884	0.779	**0.758**	

Note: a. CA represent Cronbach's alpha; b. CR signifies composite reliability; c. AVE denotes average variance extracted; d. The square roots of AVEs are in bold format along the diagonal for each construct; d. The values in the correlation matrix demonstrates significance at a 95% confidence level.

Table 4. Path coefficient.

Predictor variable	Standardized beta coefficients	*t*-value	*p*-value	Decision
Personalisation -> Customer Service Exp	0.746***	8.009	0.000	H1 = Supported
Aesthetic -> Customer Service Exp	0.091***	0.973	0.331	H2 = Not Supported
Convenience -> Customer Service Exp	0.317***	4.379	0.000	H3 = Supported
Time spent -> Customer Service Exp	−0.264***	2.559	0.011	H4 = Supported
Customer Service Exp -> Trust	0.884***	53.037	0.000	H5 = Supported
Trust -> Brand Love	0.868***	56.075	0.000	H6 = Supported

***= $p < 0.00$.

Table 4 also presents correlations among the constructs. These correlations provide insight into the relationships between the constructs. For example, the correlations between Brand Love and other constructs (ranging from 0.716 to 0.885) suggest that Brand Love is distinct from other constructs in the study. Similarly, other constructs exhibit correlations, reflecting the interconnections among the variables (Henseler et al., 2015). Thus, a value below 0.90 based on the HTMT is a more robust means of assessing discriminant validity and satisfies the discriminant validity criteria (Henseler et al., 2015).

Further analysis shows that the explanatory power of the model was high. The dependent variable, brand love, recorded R^2 0.56 ($p < 0.05$). Customer service and trust explain the variation in the independent variables between 0.6 (60%) and 0.6 (60%).

Structural relationships were examined to determine the strength levels of significance and path coefficients (Hair et al., 2022; Sarstedt et al., 2021). The results of the consistent bootstrapping resampling procedure are shown in Table 4. As a rule of thumb, the *p*-values of path coefficients may range from +1 to −1, and the *t*-statistic must be 1.96 or greater (Sarstedt et al., 2021; Hair et al., 2021).

The results showed a positive and significant relationship between personalisation and customer service experience ($\beta = 0.746$; $t = 8.009$; $p = 0.000$). Therefore, H1 is supported. However, the hypothesis that aesthetics significantly affects customer service experience is not supported. The small beta coefficient of 0.091 and the low *t*-value of 0.973 yield a *p*-value of 0.331, more significant than the conventional significance level of 0.05. These values collectively indicate that aesthetics does not significantly impact customer service experience in this study. Therefore, H2 is not supported. H3 proposes a positive and significant relationship between convenience and the customer service experience. This study found a positive and significant relationship ($\beta = 317$; $t = 4.379$; $p = 0.000$), which supports H3. The results also revealed that the relationship between time spent on AI and customer service experience was positive and significant ($\beta = -0.264$; $t = 2.559$; $p = 0.011$), indicating support for H4. Similarly, customer service experience positively and significantly affects customer trust ($\beta = 0.884$; $t = 53.037$; $p = 0.000$). Thus, H5 is supported. Finally, customer trust in AI was found to have a positive and significant effect on brand love ($\beta = 0.868$; $t = 56.075$; $p = 0.000$), confirming H6.

5. Discussion of results

The study explores factors that influence customers' experiences with AI-based self-service technology in the banking sector in Ghana, which is an emerging market. AI-based SST is a novel technology that employs machine learning, big data mining, natural language processing, and other technologies to provide personalised suggestions and services to customers. The study aims to identify the factors influencing the customer experience with this technology and its outcomes. Six hypotheses were tested, with one hypothesis not supported. The results provide insights into how banks can improve the customer experience by personalising the service, improving convenience, and reducing the time customers spend.

The study first tested the relationship between personalisation and customer AI-based self-service experiences (H1). The findings revealed that personalisation predicts AI-based self-service experiences. This finding is consistent with previous studies' findings (Chen et al., 2021; Zhang & Sundar, 2019). For instance, Chen et al. (2021) noted in a similar study that personalisation influences the user experience of AI-based SST. Thus, through AI-based SST, banks can provide customers with interfaces, content, and information interactions tailored to their needs (Zanker et al., 2019). Hence, customers are influenced by banks' personalisation provision of AI-based SST, which contributes positively to their experience journey with the banks. Additionally, when banks' personalisation strategy drives significant positive attribution and reduces negative attribution, banks can build customers' commitment toward the brand.

This study also supports convenience and AI-based self-service experiences (H3). This result supports the findings of previous studies (Ameen et al., 2021; Chen et al., 2021; Walch, 2019). For example, studies have indicated that AI-based SST can assist customers by providing answers without depending on the availability of employees, which helps save time and positively impacts customer satisfaction (Walch, 2019). This finding indicates that bank customers find it convenient to use AI-based SST. In addition, scholars (Roy et al., 2018) have noted that convenience motivates customers to engage more with the brand experience. Thus, because of its convenience, Ghanaian bank customers are likelier to engage in AI-based SST. In addition, banks stand to gain trust in AI-based SST and their brands, as suggested by scholars.

Time spent is another customer-value factor that influences AI-based SST. The results of this study support the relationship between time spent and AI-based self-service experiences (H4). This result is consistent with previous studies (Chen et al., 2021; Mclean et al., 2018) that examined the time spent in a similar study. For instance, Mclean et al. (2018) noted that if customers spend too much time during service provision, it negatively impacts their experience with the brand. This finding indicates that banks' customers are conscious of time during service provision, and AI-based SST provides alternative means of maximising their time.

The study also tested the relationship between aesthetic customer experiences and AI-based self-service experiences (H2). This relationship does not support the claim of previous studies that aesthetics influence user experience with AI-based SST (Chen et al., 2021). The finding suggests that more than a visually appealing design is needed to significantly impact customer satisfaction or engagement in AI-driven banking or service contexts. For managers and designers, investing solely in enhancing the visual appeal of AI-based self-service tools may not yield the expected benefits in customer experience. Instead, they may focus more on functionality, ease of use, and the practical value of AI-based interactions, such as personalisation and problem-solving efficiency. This insight also implies that customers may prioritise AI self-service tools' efficiency, accuracy, and convenience over aesthetics. Therefore, banks should concentrate on optimising the usability and effectiveness of these tools, ensuring that they meet customer needs swiftly and accurately. While aesthetics still plays a role in overall brand perception, this finding suggests that the tangible benefits of AI-based self-service, like speed and reliability, are likely more influential in shaping customer experiences and loyalty. According to Li and Yeh (2010), aesthetics is essential because they build relationships between customers and products, leading to trust and loyalty. Thus, banks must examine AI-based SST's aesthetic nature to provide their customers with the necessary benefits.

The subsequent interest of this study was to examine AI-based SST customer experience outcomes among bank customers. This study examines the relationship between AI-based SST customer experience and trust in AI-based SST (H5). The results support AI-based SST customer experience and trust in AI-based SST (5). This is consistent with previous studies that established customer experience and trust in brand linkage (Rajaobelina et al., 2018). This means that the experience of bank customers with AI-based SST tends to influence their trust in AI-based SST and the bank brand. The study also examined the relationship between AI-based SST trust and brand love. The study revealed a significant positive relationship between AI-based Trust and AI-based brand love, providing support (H6). This finding parallels Navaneethakrishnan and Sathish (2020) and Salehzadeh et al. (2023). Banks can use the study findings by enhancing their AI systems to build stronger customer trust through transparency, security, and personalised service. AI-powered chatbots and recommendation engines can improve customer experiences by offering efficient, reliable, and personalised interactions. As trust in AI systems grows, customers will likely develop stronger brand love with the bank, increasing loyalty and customer retention. The findings also allow future researchers to consider exploring how AI-based trust and brand love differ across various customer segments, such as different age groups or levels of tech-savviness, to help banks tailor their AI strategies more effectively.

5.1. Theoretical implications

This study significantly contributes to the theoretical landscape by building upon and extending previous research in several ways. This research bridges the existing gaps and expands our understanding of the adoption of AI-based self-service technology, particularly within the context of emerging markets and the service sector, such as banking. Previous research on AI-based SST adoption has predominantly focused on developed economies (Campbell et al., 2020; Rai, 2020). This study, situated in Ghana, an emerging economy, extends the geographic scope of research. Doing so provides insights into how AI-based SST is perceived and utilised in a different economic context, offering a more comprehensive understanding of its global implications.

Moreover, while prior studies have explored AI and SST adoption in various sectors, including banking (Ameen et al., 2021; Chen et al., 2021; Gao et al., 2022), research on AI-based SST in the Ghanaian banking context remains limited. This study enriches the literature with novel contextual insights by elucidating factors influencing customer experiences with AI-based SST in Ghana. The findings add to the breadth of knowledge and allow for comparisons and contrast with findings from other regions, ultimately enhancing the generalizability of the research.

Furthermore, consumer value theory and trust commitment theory have been influential in understanding customer behaviour and trust in technology-driven services (Sheth et al., 1991; Wang, 2017). This study extends previous knowledge by applying these theories to the context of AI-based SST. It empirically validates and reinforces the applicability of these theories in a novel context, making them more robust and relevant for understanding customer behaviour and trust within the context of emerging markets and AI-driven services.

5.2. Practical implications

This study provides essential insights for managerial implications that address the specific findings. First, the study's identification of key influencing factors, notably personalisation, convenience, and time spent, provides managers with actionable insights. These factors have been highlighted as critical determinants of AI-based SST experiences. Building upon previous knowledge, this study reaffirms the significance of these factors and emphasises the need for continuous improvement in these areas. Bank managers can leverage this insight to refine their AI-based SST offerings and sustain their positive influence on customers.

Second, the study's confirmation that banks can gain customers' trust and promote brand love through AI-based SST extends knowledge in customer relationships. It underscores the potential for AI-based SST to go beyond transactional interactions and create emotional connections. This insight offers a strategic pathway for managers to invest in factors influencing AI-based SST customer experiences. Banks can strengthen customer trust and brand loyalty by prioritising these factors, improving their overall performance and competitive positioning.

Third, while the study focuses on the banking sector, its findings have broader implications for AI-based SST across various service sectors. The insights regarding personalisation, convenience, time spent, aesthetics, trust, and brand love are transferable to other industries such as tourism, hospitality, and insurance. This extension of knowledge underscores the universality of the identified factors and their relevance in diverse service contexts.

Fourth, contrary to expectations, the study finds that aesthetics does not significantly impact customers' AI-based experiences. These findings challenge prior assumptions and extend existing knowledge by emphasising the importance of aesthetics in AI-based SST. It suggests that bank managers and service providers should reevaluate their AI-based SST solutions' design and visual appeal. While aesthetics may not be a primary driver of customer experiences in this context, it can still contribute to overall satisfaction by creating a more engaging and user-friendly interface.

5.3. Limitations and future research

While this study is insightful, it is essential to acknowledge its inherent limitations. A primary limitation is not extending beyond a single-country setting. This limitation raises questions about the generalizability of the findings. Future research endeavours could enhance the robustness of AI-based SST by exploring customers from various service providers, such as telecommunications and insurance, and considering a multi-country perspective. Furthermore, this study adopts a quantitative approach. A complementary mixed-method approach that incorporates qualitative perspectives could be employed to enrich and deepen the insights gained. This synergistic uncovers subtle dimensions that quantitative analysis alone might overlook.

6. Conclusion

This study examined the factors influencing AI-based SST customer experience and its outcomes among bank customers in the banking industry from an emerging context. This study draws insights into Customer Value Theory (CVT) and trust commitment theories to develop the conceptual framework. Next, this study tested six (6) hypotheses, one of which did not find theoretical support. Finally, the study presents the results and discussion of the findings and provides theoretical and practical contributions. The study further recommends introducing moderating variables in subsequent studies to provide an understanding of how moderating variables could play a role in the value-influencing factors, self-service customer experience, trust, and brand love of customers.

Ethical declarations and human participants

The authors confirm that this study adheres to the ethical standards of the country in which it was conducted. The research posed no risk to participants, and participation was entirely voluntary with no personal or identifiable information collected. Additionally, the Institutional Ethics Committee of Dominion University College approved the study under reference number IREC 03/22.

Author contributions

Hayford Amegbe Conceptualization, Data curation, Writing of Introduction, and theoretical implications. Charles Hanu, Writing of literature and hypotheses development and methodology. Nkululeko PraiseGod Zungu, Data curation, Writing of practical implications and results. Emmanuel Selase Asamoah, Data curator, Writing of limitations and future direction, conclusion, and proofreading.

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Data availability

Data requests can be directed to the corresponding author Dr Emmanuel Selase Asamoah via email at emmanuel.asamoah@upsamail.edu.gh.

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Appendix A

Constructs	Items	Sources
Personalisation	PSONA1. Using smart self-service machine provides me personalized services. PSONA2. Using smart self-service machine understands my specific needs. PSONA3. Using smart self-service machine offers recommendations that match my needs and the situation. PSONA4. Using smart self-service machine is customized to my needs. PSONA5. Using smart self-service machine, I can get personalized information that is tailored to my interests and needs. PSONA6 Smart self-service machine has best interest at heart PSONA7 Smart self-service machine has features that are personalized for me	Lee & Rha, 2016; Roy et al. (2018)
Aesthetics	AES1. The design of this smart self-service machine is appealing. AES2. I like the shape of this smart self-service machine. AES3. This smart self-service machine makes me happy. AES4. This smart self-service machine can give me a sense of superiority. AES5. The design of the smart self-service machine can inspire my positive emotions.	Sheng and Teo (2012)
Perceived time spent on the AI-based SST	PTS1. I spent more time than I should on the smart self-service machine. PTS2. It took longer than I expected to find the information on the smart self-service machine. PTS3. It took too long searching for the information on the smart self-service machine.	McLean and Wilson (2016)
User experience	UP1. This smart self-service machine tries to be emotional. UP2. This smart self-service machine tries to be affective. UP3. This smart self-service machine tries to intrigue me. UP4. This smart self-service machine tries to stimulate my curiosity. UP5. This smart self-service machine makes me think creatively. UP6. This smart self-service machine tries to make me think about my lifestyle. UP7. This smart self-service machine gets me to think about my behaviour. UP8. This smart self-service machine tries to make me think about bonds. UP9. I can relate to other people through this smart self-service machine.	Schmitt (1999) Gentile et al. (2007)
Convenience	CON1. The smart self-service machine has operating hours convenient to customers. CON2. It is easy and convenient to reach the banks smart self-service machine. CON3. It is easy and convenient to use the smart self-service machine	Collier & Sherrell
Trust	TRUS1. I feel that the bank will act in my best interests. TRUS2. I feel comfortable interacting with the smart self-service machine because the machine will perform its duties efficiently. TRUS3. I always feel confident about relying on the smart self-service machine to do its part when I interact with it. TRUS4. I am comfortable relying on the smart self-service machine to meet its obligations.	Teo et al. (2008)
Brand Love	BLOV1 My bank is marvellous BLOV2 My bank makes me feel good BLOV3 My bank is absolutely terrific BLOV4 I feel neutral towards my bank BLOV5 I am in love with my bank BLOV6 I have no particular feelings about my bank BLOV7 My bank gives me sheer pleasure BLOV 8 I am so passionate about my bank BLOV 9 I am extremely attached to my bank	Cho and Fiore (2015)

Appendix B

Total variance explained

Component	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	15.527	48.523	48.523	15.527	48.523	48.523
2	2.382	7.443	55.966			
3	1.679	5.246	61.212			
4	1.254	3.920	65.132			
5	1.096	3.424	68.555			
6	.867	2.710	71.266			
7	.846	2.644	73.910			
8	.792	2.475	76.384			
9	.683	2.135	78.519			
10	.612	1.912	80.431			
11	.568	1.776	82.207			
12	.541	1.691	83.898			
13	.486	1.518	85.416			
14	.479	1.497	86.913			
15	.448	1.399	88.312			
16	.399	1.248	89.561			
17	.345	1.078	90.639			
18	.334	1.043	91.682			
19	.307	.959	92.641			
20	.293	.915	93.555			
21	.254	.794	94.349			
22	.249	.778	95.127			
23	.221	.692	95.819			
24	.212	.664	96.483			
25	.181	.564	97.048			
26	.176	.549	97.596			
27	.163	.509	98.106			
28	.155	.485	98.591			
29	.146	.457	99.048			
30	.126	.395	99.443			
31	.097	.303	99.745			
32	.082	.255	100.000			

Extraction Method: Principal component analysis.