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AI in Banking: What Drives Generation Z to Adopt AI-Enabled Voice Assistants in Saudi Arabia?

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Abstract: The aim of this study is to examine the factors that drive Saudi Arabian Generation Z's intention to use voice assistants (VAs) in banking. The Technology Acceptance Model (TAM) was extended by incorporating three additional constructs: subjective norms, which capture the social influence of close relationships, including family and friends; personal innovativeness, which reflects the openness to new technologies that is characteristic of Generation Z; and perceived trust, which addresses concerns related to security and reliability that are critical in financial contexts, thereby enhancing our understanding of this phenomenon among Generation Z. A survey of 292 Generation Z respondents was collected and structural equation modeling (SEM) was employed for data analysis. The findings of the study reveal that factors such as perceived usefulness, attitude, subjective norms, personal innovativeness, and perceived trust all have a significantly positive impact on Generation Z's intention to use AI-enabled VAs in banking. Additionally, the results indicate that perceived usefulness is influenced by ease of use, while attitude is affected by ease of use, perceived usefulness, personal innovativeness, and trust. Despite the Saudi government's support and initiatives for the development of the AI-fintech industry, there is still a lack of understanding about consumer behavioral intention toward AI-enabled VAs in Saudi Arabia and, particularly among Generation Z. This study contributes to the existing literature and provides valuable recommendations for policymakers and fintech service providers seeking to implement effective AI-enabled VAs that enrich consumers' engagement and experience.

Keywords: artificial intelligence (AI); fintech; banking; finance; voice assistant; adoption; consumer; Generation Z; TAM

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1. Introduction

The accelerated evolution of technology, particularly in the realms of Artificial Intelligence (AI), is revolutionizing the way businesses and industries operate, with the financial industry being at the forefront of this transformation. Fintech is a crucial component for financial institutions (Belanche et al., 2019; Nguyen & Pham, 2024), offering innovative tools to meet consumers' financial needs beyond e-banking. Hence, AI employment in fintech services can be a significant chance to revolutionize the industry by delivering greater benefits to consumers and increasing firms' profitability (Jambulingam et al., 2023). The utilization of AI in fintech services has resulted in the development of AI-enabled voice assistants (VAs).

Voice assistants (VAs) in banking can be defined as AI-powered interfaces that enable users to conduct banking transactions through intuitive voice commands, thereby enhancing financial accessibility and fostering greater financial inclusion (Malodia et al., 2021).

Among various AI technologies, VAs are gaining attention for their ability to boost customer engagement and streamline banking operations inclusion (Malodia et al., 2021). Unlike other AI applications, VAs offer a more intuitive and user-friendly experience, effectively bridging the gap in financial access and personalization that consumers desire inclusion (Malodia et al., 2021). VAs utilize advanced algorithms, Natural Language Processing (NLP), machine learning, and real-time processing to facilitate seamless communication with customers in their preferred language, thereby delivering high-quality, personalized, accurate, and expedient services that improve consumers' overall experience inclusion (Malodia et al., 2021; Iovine et al., 2023) AI-enabled VAs provide a unique value proposition, offering customers informational, transactional, and advisory services to inform their financial decisions (Iovine et al., 2023).

In the midst of the fintech revolution, Saudi Arabia has been recognized in the global fintech landscape as a key player. The country's fintech industry has shown rapid growth, determined by the government's initiatives to modernize financial systems and its ambitious vision for the future. The Saudi Vision 2030 aims to establish 525 fintech companies by 2030 (Fintech Saudi, 2022), a testament to the sector's immense growth potential. Furthermore, the government has prioritized the integration of AI and machine learning, with a significant proportion of its objectives centered around their adoption. The Arab Monetary Fund (Arab Monetary Fund, 2021) reports that 70–96% of these objectives are focused on AI and machine learning, highlighting the importance of these technologies in shaping the country's future. When comparing Saudi Arabia's fintech advancements with those of its regional peers in the GCC and the broader Middle East, it is evident that Saudi Arabia holds a unique and leading position, being the largest market in the region, driven by strong government support and demographic factors that influence its approach to fintech development.

Despite this progress, there is a significant gap in empirical research on banking VAs from the consumer perspective. Jambulingam et al. (2023) note that there is a scarcity of studies on this topic, with no single study specifically focused on Saudi Arabia to the best of our knowledge. Moreover, existing research has not addressed the critical issue of behavioral intention to adopt VAs among Generation Z individuals, who are uniquely poised to harness the potential of AI services.

The importance of understanding Generation Z's adoption intentions lies in their potential to disrupt traditional financial services and significantly contribute to the growth of the fintech industry. Born between the middle of the 1990s and the 2000s (White, 2022), this generation is characterized by their digital nativity, prioritizing speed, efficiency, and personalization in their financial interactions. They are accustomed to a hyper-connected and digitally driven world (White, 2022), where AI-powered services are an essential part of their daily lives. As a result, fintech companies that fail to accommodate these preferences risk being left behind. Furthermore, adopting AI-powered services, including VAs, can also help banks and financial institutions meet the growing expectations of Generation Z, who demand seamless, user-friendly, and secure financial experiences.

The research gap surrounding Generation Z's adoption intentions for VAs is particularly concerning, given the rapid uptake of AI technology among this demographic. To address this gap, this study aims to explore the determinants influencing Generation Z's behavioral intention to adopt VAs in the Saudi banking sector, providing critical insights for fintech industry practitioners. Specifically, the purpose of this study is to answer the following research question:

RQ1. *What are the main factors influencing Generation Z's behavioral intention to use voice assistants in the banking industry in Saudi Arabia?*

This study employs the Technology Acceptance Model (TAM) and integrates it with essential factors, including subjective norms, perceived trust, and personal innovation. The integration of subjective norms captures the significant social influence of family and friends on Generation Z's adoption decisions, reflecting the importance of interpersonal relationships within this age group. Perceived trust addresses the security and reliability concerns that are paramount in the banking industry, while personal innovativeness accounts for Generation Z's inherent openness to new technologies and willingness to experiment with innovative solutions such as VAs. Hence, integrating these factors adds a valuable contribution to this study, as, to the best of our knowledge, no study has integrated these factors with TAM to test AI-enabled VAs in the banking sector among Generation Z. Moreover, the aim of the integrated model is to improve understanding of Generation Z's perceptions toward AI-enabled VAs in banking, enabling banks, service providers, and policymakers to effectively utilize this technology in the fintech sector and enrich the literature related to AI adoption in the financial sector. By doing so, this study can inform the country's efforts to achieve its Vision 2030 objectives, particularly since around 37% of its population consists of Generation Z (The General Authority for Statistics, 2020).

The rest of the paper is organized as follows: Section 2 reviews the relevant literature. Section 3 outlines the theoretical framework and explains the development of the research hypotheses. Section 4 details the methodology utilized to conduct the study. The findings are presented in Section 5, while the discussion of these findings and their implications are outlined in Section 6. The paper then turns to limitations and potential avenues for future research in Section 7. Finally, the conclusion is presented in Section 8.

2. Literature Review

2.1. Research Reviewing the Adoption of AI in Banking

While reviewing the literature on the adoption of AI in Banking, a number of studies have conducted a systematic literature review. For instance, Lazo and Ebardo (2023) examined the present situation of AI adoption in the banking industry using a systematic review of related literature. Using the SCOPUS database, 35 studies were identified as relevant to this investigation. The usage of AI has invaded many elements of the banking function, going beyond chatbots. Banks utilize AI to improve consumer experience, revenue, and competitiveness, but human, technological, and regulatory compliance challenges impede banks from fully embracing AI. Transparency of algorithms, security of data, and fair use of data are the primary issues of authorities and consumers. The findings of Lazo and Ebardo (2023) highlight the need for additional theoretical and empirical studies on the legal aspects of the use of AI in banking, how to utilize the power of service providers to promote broader and more efficient adoption of AI, the way organizations may assist/boost the pool of talent for technologies powered by AI, and ways to improve the beneficial collaboration of different players in the implementation of AI in the banking sector. Furthermore, Fares et al. (2022) offered a comprehensive and systematic overview of the literature on the use of AI in banking since 2005. The researchers of this study analyzed 44 publications using a systematic literature review approach, and undertook thematic and content analyses on them. The review determines research themes suggesting the use of AI in banking, creates and defines sub-themes from previous research, and suggests a framework based on thematic outcomes and previous studies to bridge the gap between academic research and business knowledge. The findings show that the literature on AI and banking encompasses three main areas of research: strategy, process, and customer. Dewasiri et al. (2023) performed an in-depth literature review by investigating the use of two common robotic platforms in banking: chatbots and robo-advisors. However, this is diametrically opposed to traditional centralized digital banking, and the acceptance of

these technologies is still in the early stages. The most prevalent obstacles are employment, performance, security, privacy, and trust, as well as cost, ethical, and regulatory issues. To overcome these issues, they recommended that banks should focus on tactics such as collaborating with robotics, and improving platform performance.

2.2. Empirical Research Examining Consumers' Adoption of AI in Banking

While reviewing the literature on empirical research examining consumers' adoption of AI in banking, a number of recent research has been identified in different regions, including India (P. Singh et al., 2024; Priya & Sharma, 2023), China (Lee & Chen, 2022; Mei et al., 2024) Malaysia (Rahman et al., 2023), Palestine (Salem & Rassouli, 2024), and five Asian countries (Pakistan, China, Iran, Saudi Arabia, and Thailand) (Noreen et al., 2023) as well as potential insights from North America, Britain, and Portugal (Belanche et al., 2019). Most of the identified studies employed quantitative methodologies (e.g., P. Singh et al., 2024; Priya & Sharma, 2023) or mixed methods (Rahman et al., 2023). Regarding the theoretical frameworks, some studies have extended the Technology Acceptance Model (TAM) (Belanche et al., 2019; P. Singh et al., 2024; Rahman et al., 2023), while others used the Unified Theory of Acceptance and Use of Technology (UTAUT) (Salem & Rassouli, 2024), UTAUT2 (R. Singh et al., 2025), or other theories and models (Lee & Chen, 2022; Mei et al., 2024). Table 1 presents the theory-based empirical research examining consumer adoption of AI in the banking sector, detailing both significant and non-significant factors.

Table 1. Theory-based empirical research examining consumer adoption of AI in banking.

Study	Purpose	Country	Methodology	Theoretical Framework	Sample	Type of Analysis	Sig. Variables	Not Sig.
P. Singh et al. (2024)	Consumer's Adoption of AI in banking	India	Quantitative	Extended TAM	810	Structural Equation Modeling (SEM)	Awareness, Perceived usefulness, Attitude, Subjective norms, Intention	
R. Singh et al. (2025)	Decoding AI adoption in banking	India	Quantitative	UTAUT2	511	Artificial Neural Network modeling	Performance Expectancy, Effort Expectancy, Hedonic Motivation, Facilitating Conditions, Behavioral Intentions, Habit, Openness to Change	Social Influence, Perceived Risk, Knowledge
Priya and Sharma (2023)	Users' adoption intentions of intelligent virtual assistants in financial services	India	Quantitative		435	SEM	Perceived Intelligence, Perceived anthropomorphism, Perceived animacy, Attitude	Hedonic attitude
Lee and Chen (2022)	Users' adoption intention of AI mobile banking applications	China	Quantitative	Stimulus-organism-response theory	451	SEM	Perceived intelligence, Anthropomorphism, Trust, Task-technology fit	Perceived risk, Perceived cost
Mei et al. (2024)	AI adoption in sustainable banking	China	Quantitative	AI Device Use Acceptance model	435	SEM	Social influence, Hedonic motivation, Perceived anthropomorphism	
Rahman et al. (2023)	Adoption of AI in banking services	Malaysia	Qualitative and Quantitative	Extended TAM	302	SEM	Perceived usefulness, Perceived risk, Perceived trust, Subjective norms, Attitude	Perceived ease of use, Awareness
Salem and Rassouli (2024)	The impact of trust on consumer attitudes toward AI-powered online banking	Palestine	Quantitative	UTAUT	362	SEM	Performance expectancy, Effort expectancy, Social influence, Facilitating conditions, Attitude, Trust	
Noreen et al. (2023)	AI in banking industry and consumer's perspective	Pakistan, China, Iran, Saudi Arabia, and Thailand.	Quantitative	N/A	799	Regression analysis, ANOVA	Awareness, Attitude, Subjective norms, Perceived usefulness, Perceived risk, Knowledge of technology	
Belanche et al. (2019)	Robo-advisors adoption among Fintech customers	USA, UK, and Portugal	Quantitative	Extended TAM	765	SEM	Perceived usefulness, Mass media, Subjective norms, Attitude	

2.3. Research Examining AI Adoption in the Saudi Arabian Banking Sector

While reviewing the previous research examining AI adoption in the Saudi Arabian banking sector, Basri and Almutairi (2023) studied the basic principles of trust in artificial intelligence (AI), particularly in terms of its impact on individuals' financial self-efficacy, and examined the moderating effect of bank transparency in changing the nature of the Saudi banking industry. The fundamental goal of their study was to provide an innovative approach for developing trust and acceptance of AI-driven banking services by investigating the interactions between these variables. The study's research approach is based on quantitative techniques, with standardized surveys administered to both clients and workers in Saudi Arabia's banking sector. A total of 150 surveys were collected from employees, and 200 from customers. The study's findings confirm that the level of trust in AI acts as a mediator in the links between AI implementation in different industries (e.g., fraud detection and transaction monitoring) and consumers' financial self-efficacy. Furthermore, the effect of AI bank transparency in these relationships was identified, implying that increased transparency in AI operations boosts trust in AI technology. Furthermore, Mohammed (2024) investigated the impact of AI approaches on operational efficiency in Saudi banks. His aim was to assess the present situation of AI applications, investigate their impact on minimizing financial risks, and discover barriers to their use in banks. Data were collected using a descriptive-analytical methodology, using a questionnaire mailed to a simple random sample of Saudi private-sector employees. The sample size was 350 respondents. The findings showed a statistically significant association between the use of AI techniques and increased operational efficiency in Saudi banks. AI technology has been shown to improve decision-making processes, lower operational costs, and increase customer service efficiency. Challenges include high initial expenses, a lack of specialized expertise, and employee resistance to technological change. Suggestions are to invest in AI training for bank employees, ensuring ongoing updates to AI systems, and resolving technical and financial obstacles in order to promote a better adoption procedure within the banking sector.

Overall, the reviewed literature indicates that, to the best of our knowledge, only two empirical studies related to AI have been identified in the Saudi Arabian banking sector. Therefore, as recommended by Lazo and Ebardo (2023), there is a need for additional theoretical and empirical research on the use of AI in banking, particularly in Saudi Arabia, where fintech is rapidly growing and making significant contributions to the international fintech market.

3. Theoretical Framework and Hypotheses Development

The current research proposes a framework grounded in the Technology Acceptance Model (TAM) (Davis, 1989), which aims to examine the factors influencing consumers' behavioral intention toward adopting AI-enabled VAs. Since the TAM has been shown to accurately predict user acceptance of information technology (Belanche et al., 2019), it is considered an ideal model for investigating the reactions of users to innovative technologies over the past two decades, and has been widely employed to model consumers' intention to adopt several electronic services in banking, such as internet banking (Salimon et al., 2017) and fintech (Belanche et al., 2019). However, the literature shows that the TAM has been criticized for neglecting other important factors that influence user behavior, such as social processes, as it was initially designed to explain the factors influencing people's adoption of technology in general, rather than explaining their adoption of a specific type of technology (Rezaei et al., 2024). This limitation suggests that attitudes should be supplemented with subjective norms, as proposed by Fishbein and Ajzen (1975) in the Theory of Reasoned Action (TRA). Hence, to address this critique, our model extends the TAM by integrating it with subjective norms.

Furthermore, the current study makes a novel contribution by incorporating two additional factors that have been identified in the literature as influential in shaping behavioral intentions and adoption of AI: personal innovativeness and perceived trust.

The inclusion of personal innovativeness is justified by the propensity of Generation Z to embrace new technologies and innovations. This demographic's characteristics, marked by a strong inclination toward digital engagement (White, 2022), make personal innovativeness particularly pertinent in the context of the Saudi Arabian banking sector, where the adoption of fintech solutions is rapidly increasing (Fintech Saudi, 2022). Empirical evidence suggests that individuals with high levels of personal innovativeness are more inclined to adopt AI-powered services (Yang et al., 2012), thereby underscoring the importance of this factor.

Conversely, the consideration of perceived trust is essential due to its critical role in the banking sector (Lee & Chen, 2022; Salem & Rassouli, 2024), particularly in societies where relational dynamics and social norms significantly influence customer perceptions. In the context of Generation Z, whose concerns regarding digital security and financial reliability are paramount, perceived trust emerges as a key determinant in their intention to adopt VAs or other AI-based services in banking. By accounting for perceived trust, this study aims to provide a comprehensive understanding of the factors that drive behavioral intentions among Generation Z in the context of Saudi Arabian banking.

3.1. The Technology Acceptance Model

The TAM suggests that two key factors influence a person's attitude toward technology; these are perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1989). As per the cost–benefit paradigm, an individual's attitude toward technology influences their intention to accept and adopt it (Davis, 1989). Attitude (ATT) is the degree to which a person considers a specific behavior to be desirable or undesirable, such as the adoption of new technology (She et al., 2024). In today's digital era, attitude has become an essential predictor of consumer behavior more than ever before (She et al., 2024). PEOU is the degree to which a person expects that using a particular technology would be effort-free, while PU is the extent to which a person expects that using a particular technology would make his/her performance better (Davis, 1989). Several studies on AI in banking examined the TAM factors (Belanche et al., 2019; P. Singh et al., 2024; Rahman et al., 2023). Hence, the following hypotheses are proposed:

H1. *PU has a positive influence on ATT toward AI-enabled voice assistants in banking among Generation Z.*

H2. *PEOU has a positive influence on ATT toward AI-enabled voice assistants in banking among Generation Z.*

H3. *ATT has a positive influence on the intention to use AI-enabled voice assistants in banking among Generation Z.*

H4. *PEOU has a positive influence on the PU of AI-enabled voice assistants in banking among Generation Z.*

Numerous studies have reported the significant influence of PU on behavioral intention (Belanche et al., 2019). Salimon et al. (2017) found a substantial and positive link between PU, perceived security, and e-banking acceptance. Furthermore, Alalwan et al. (2016) indicated that PU had a significant influence on behavioral intention while examining consumer acceptance of mobile banking in Jordan. Hence, we propose the following:

H5. *PU has a positive influence on the intention to use AI-enabled voice assistants in banking among Generation Z.*

Similarly, research has shown that PEOU is a significant predictor of consumers' intention to adopt electronic banking (R. Singh et al., 2025; Salem & Rassouli, 2024). When consumers perceive a particular system to be easier to use, they are more likely to have favorable feelings toward it and accept it. Therefore, the following hypothesis is proposed:

H6. *PEOU has a positive influence on the intention to use AI-enabled voice assistants in banking among Generation Z.*

3.2. Subjective Norms

In social psychology, normative influences refer to the perception that others believe an individual must or must not perform a behavior (Fishbein & Ajzen, 1975). Social norms rely on social information and pressure individuals to adopt a certain behavior based on others' opinions (Fishbein & Ajzen, 1975).

In digital finance, subjective norms (SNs) are often affected by both interpersonal and external information sources (Bhattacherjee, 2000). This aligns with research on technology-based innovations, where societal opinions shape behaviors through comments, behaviors, and media reports (Liao et al., 2023). Several studies suggest the positive influence of SNs on behavioral intention toward AI banking services (Belanche et al., 2019). Given the importance of social confirmation and incentives in the adoption of AI in banking, we propose the following hypothesis:

H7. *SNs have a positive influence on the intention to use AI-enabled voice assistants in banking among Generation Z.*

3.3. Perceived Trust (PT)

Trust can be referred to as a person's belief in a specific service's ability to consistently meet their expectations and their willingness to consistently rely on its features (Hassan et al., 2024). Trust is based on the service's timeliness, honesty, and customer focus (Hassan et al., 2024). In self-service technologies, such as mobile banking, trust is essential for customer loyalty and security perceptions (Alalwan et al., 2016). Several studies found that PT has a significant and positive impact on consumer adoption of AI in banking (Lee & Chen, 2022; Salem & Rassouli, 2024; Hassan et al., 2024). Hence, the existing study proposes the following:

H8. *PT has a positive impact on the intention to use AI-enabled voice assistants in banking among Generation Z.*

The technology adoption literature demonstrates that trust is an essential determinant of attitude, as it influences an individual's willingness to accept and use a new technology. For instance, Mashhour and Saleh (2015) found that trust significantly affects the adoption of mobile banking services, as it helps to reduce the uncertainty and risk associated with transactions. Hence, in the context of VAs adoption, we hypothesize:

H9. *PT has a positive impact on ATT toward AI-enabled voice assistants in banking among Generation Z.*

3.4. Personal Innovativeness (PIIT)

Previous research has shown that personal innovativeness in IT (PIIT) is a key factor in the acceptance of new technologies. PIIT has been defined by Agarwal and Prasad (1998) as a person's willingness to try out new information technologies and adopt new ideas. Studies confirm that PIIT influences technology adoption (Yoon et al., 2015), with individuals with higher innovativeness having positive intentions toward adopting new IT innovations (Yang et al., 2012). Given AI-enabled VAs' recent development in the banking sector, it is anticipated that PIIT will have a significant influence on customers' intention to adopt them. Therefore, the following is hypothesized:

H10. *PIIT has a positive impact on the intention to use AI-enabled voice assistants in banking among Generation Z.*

Moreover, studies show that the relationship between personal innovativeness and behavioral intention is influenced by the attitude and readiness to adopt a new technology (Thakur & Srivastava, 2014), which can affect a person's likelihood of adopting a new technology. Hence, the following hypothesis is formulated:

H11. *PIIT has a positive influence on ATT toward AI-enabled voice assistants in banking among Generation Z.*

The definitions of all constructs utilized in the current study's hypotheses are summarized in Table 2.

Table 2. Constructs' definitions.

Construct	Definition	Reference
Perceived Usefulness (PU)	The extent to which a person expects that using a particular technology would enhance their performance.	(Davis, 1989)
Perceived Ease of Use (PEOU)	The degree to which a person anticipates that using a particular technology would be effort-free.	(Davis, 1989)
Attitude (ATT)	The degree to which a person considers a specific behavior, such as the adoption of new technology, to be desirable or undesirable.	(She et al., 2024)
Subjective Norms (SNs)	The perception that others believe an individual must or must not perform a behavior, influenced by social information and pressures.	(Fishbein & Ajzen, 1975)
Perceived Trust (PT)	A person's belief in a specific service's ability to meet their expectations and their willingness to rely on its features consistently.	(Hassan et al., 2024)
Personal Innovativeness (PIIT)	A person's willingness to try out new information technologies and adopt new ideas.	(Agarwal & Prasad, 1998)
Behavioral Intention (BI)	An individual's intention to perform a specific behavior, in this case the intention to use AI-enabled voice assistants in banking.	(Davis, 1989),

Based on the developed hypotheses, the conceptual framework is shown in Figure 1.

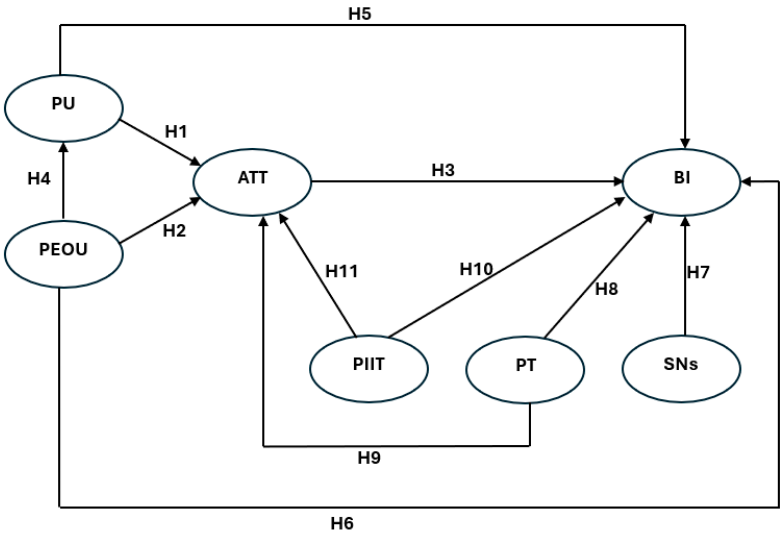


Figure 1. Conceptual framework.

4. Methodology

4.1. Sample Selection and Data Collection

The research employed a quantitative approach using a survey to examine the aspects affecting consumers' intentions toward AI-enabled VAs' adoption in Saudi Arabia's banking sector. The questionnaire consisted of close-ended questions valued on a 5-point Likert scale, similar to previous research on AI in banking (Salem & Rassouli, 2024; Noreen et al., 2023). The original English survey was translated into Arabic via the back-translation technique to ensure accuracy (Brislin, 1976). A pilot study with 35 Generation Z individuals in Saudi Arabia confirmed that the questionnaire was easy to complete and the language was clear.

Convenience sampling was used, which is a cost-effective method that allows for a different variety of participants (Alalwan et al., 2016). To enhance sample representativeness and address sampling bias, a larger sample size was required without imposing numerical restrictions on demographic factors such as gender, income, or place of residence (Bhattacherjee, 2012). The online survey was disseminated through Google Forms from January to March 2024. Potential biases in online data collection include technology familiarity bias, where respondents' comfort with technology may skew participation. To mitigate this, the survey was designed to be user-friendly and distributed across diverse platforms to reach a broader segment of Generation Z, ensuring a more representative sample.

The questionnaire targeted Generation Z members, resulting in 292 completed surveys from individuals aged 18–30, which were sufficient for validating the research methodology and testing hypotheses (Hair et al., 2019).

4.2. Measurements and Data Analysis Approach

The scale items were sourced from current literature to evaluate behavioral intention toward AI-enabled VAs in banking across seven constructs. PU, PEOU, ATT, and Behavioral Intention (BI) items were from Belanche et al. (2019), Davis (1989), and Rahman et al. (2023). SNs items were from Belanche et al. (2019), PT items were from Kim et al. (2009) and Payne et al. (2018). PIIT items were from Thakur and Srivastava (2014) and Yang et al. (2012). For data analysis, the Structural Equation Model (SEM) was used with SPSS 25 and SmartPLS 4 software, following a two-stage process recommended by Hair et al. (2019); the

first stage evaluated the measurement model, while the second stage tested the structural model and hypotheses.

4.3. Common Method Bias

The self-reported data may be susceptible to common method bias (CMB), as highlighted by Podsakoff et al. (2003). A Harman's single-factor test on all constructs was applied to address this concern and found that no single factor explains more than 48.87% of the variance, which is below the 50% threshold suggested by Podsakoff et al. (2003), thereby alleviating concerns about CMB. Furthermore, a variance inflation factor (VIF) test was conducted, revealing VIF values from 1.864 to 3.286, which are well below the threshold of 5 (Hair et al., 2019). Moreover, the tolerance values ranging from 0.304 to 0.536 indicate that all variables have acceptable tolerance levels, being above 0.2 (Hair et al., 2019). This indicates that the data meet the criteria for acceptable multicollinearity.

5. Results and Analysis

5.1. Descriptive Statistics and Respondents' Profile

To analyze the data, we began by conducting descriptive statistics and verifying the normality of the data, as non-normality can compromise the results' validity. According to Hair et al. (2019), a skewness and kurtosis range of ± 2.58 indicates normality, which was confirmed for our constructs.

The collected demographic data were analyzed, revealing that 91.1% of the respondents were female. Additionally, 86.3% of the total sample were not married. In terms of education, 79.8% held a bachelor's degree, whereas 19.2% held a high school degree and 3% held a diploma. The income level showed that 88.4% of them had an income below SAR 5000, whereas 7% earned between SAR 5000 and 9999. The remaining respondents reported higher incomes, up to SAR 30,000 or more.

5.2. Measurement Model Assessment

The measurement model was tested for reliability and validity by evaluating Cronbach's alpha and construct reliability (CR). Factor loadings for each item scale were also examined, and convergent validity was assessed by measuring the average variance extracted (AVE). The results are presented in Table 3.

Table 3. Reliability, validity, and loading values of the constructs.

	Factor Loading	Cronbach's Alpha	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
PU		0.854	0.902	0.697
PU1	0.873			
PU2	0.851			
PU3	0.865			
PU4	0.745			
PEOU		0.865	0.909	0.715
PEOU1	0.773			
PEOU2	0.834			
PEOU3	0.910			
PEOU4	0.858			
ATT		0.867	0.919	0.790

Table 3. *Cont.*

	Factor Loading	Cronbach's Alpha	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
ATT1	0.869			
ATT2	0.907			
ATT3	0.891			
SNs		0.806	0.885	0.720
SNs1	0.871			
SNs2	0.844			
SNs3	0.829			
PIIT		0.894	0.926	0.759
PIIT1	0.868			
PIIT2	0.836			
PIIT3	0.899			
PIIT4	0.879			
PT		0.902	0.932	0.773
PT1	0.898			
PT2	0.897			
PT3	0.888			
PT4	0.832			
BI		0.909	0.936	0.785
BI1	0.858			
BI2	0.907			
BI3	0.898			
BI4	0.881			

The analysis of Table 3 reveals that the constructs' Cronbach's alpha values topped the suggested threshold of 0.70 (Hair et al., 2019), with 0.806 for SNs and 0.909 for BI. All constructs met the CR measures (Mueller & Hancock, 2019), with CR values ranging from 0.885 to 0.936. The AVE values ranged from 0.697 to 0.790, above the suggested threshold of 0.50 (Hair et al., 2019). Furthermore, all factor loadings exceeded 0.50, with the lowest being 0.745.

For discriminant validity assessment, the Fornell–Larcker criterion was utilized to evaluate the correlation between constructs by comparing the square root of AVE values with inter-correlation values (Hair et al., 2019). The results show that the square root of AVE values exceeds the correlation values for each construct, suggesting that the scales and concepts used in this study are distinct and separate from one another, meeting the requirements for discriminant validity (Table 4).

The Heterotrait–Monotrait (HTMT) ratio of correlations was employed to further examine discriminant validity. Table 5 reveals that all values fall below the threshold of 0.90, as advised by Henseler et al. (2016). The measurement model assessment confirms that the chosen constructs are relevant and suitable for the research model, providing support for the study's conceptual framework.

Table 4. Discriminant validity: Fornell–Larcker criterion.

	ATT	BI	PEOU	PIIT	PT	PU	SNs
ATT	**0.889**						
BI	0.709	**0.886**					
PEOU	0.659	0.622	**0.845**				
PIIT	0.649	0.611	0.530	**0.871**			
PT	0.635	0.623	0.646	0.520	**0.879**		
PU	0.644	0.693	0.751	0.573	0.637	**0.835**	
SNs	0.587	0.650	0.771	0.555	0.599	0.773	**0.848**

Bold: square root of AVE.

Table 5. Discriminant validity: Heterotrait–Monotrait (HTMT) scores.

	ATT	BI	PEOU	PIIT	PT	PU	SNs
ATT							
BI	0.795						
PEOU	0.759	0.696					
PIIT	0.729	0.667	0.599				
PT	0.717	0.686	0.73	0.575			
PU	0.745	0.782	0.871	0.649	0.725		
SNs	0.651	0.697	0.888	0.603	0.697	0.862	

5.3. Structural Model Assessment

To assess the proposed hypotheses, the researchers employed a partial least squares (PLS) algorithm and bootstrapping analysis. Before testing the hypotheses, the structural model's overall fit was evaluated using the coefficient of determination (R^2) and predictive power (Q^2), as suggested by Hair et al. (2019) and Henseler et al. (2016). The outcomes in Table 6 show that the R^2 value for BI is 0.632, indicating that PU, PEOU, ATT, SNs, PIIT, and PT collectively explain 63.2% of the variance in BI. This can be considered a moderate explanation of variance, as R^2 values of 0.75, 0.50, and 0.25 are typically classified as strong, moderate, and weak, respectively (Hair et al., 2019; Henseler et al., 2016). Similarly, the R^2 values for ATT and PU are 0.598 and 0.563, respectively, indicating that these constructs are also significantly explained by their respective antecedents, with both values being considered moderate explanations of variance. Furthermore, the model's predictive ability, as reflected in the Q^2 values, exceeded the recommended threshold of 0.35 (Hair et al., 2019), indicating strong predictive power (Table 6).

Table 6. Model fit assessment: R^2 and Q^2 values.

	R^2	Q^2
BI	0.632	0.521
ATT	0.599	0.567
PU	0.563	0.550

Following Mueller and Hancock's (2019) guidelines, we analyzed the path coefficients using critical t-values and *p*-values. The results in Table 7 show that 10 out of 11 hypotheses were confirmed. While these findings support the expected relationships between the variables,

one hypothesis (H6) yielded insignificant results, indicating that PEOU does not significantly influence Generation Z's behavioral intention toward AI-enabled VAs in banking.

Table 7. Hypotheses testing.

Hypothesis	Path	Original Sample	Sample Mean	Standard Deviation	T Statistics	*p* Values	Empirical Evidence
H1	PU → ATT	0.134	0.131	0.076	1.776 *	0.038	Supported
H2	PEOU → ATT	0.239	0.240	0.080	2.971 **	0.001	Supported
H3	ATT → BI	0.328	0.334	0.094	3.491 ***	0.000	Supported
H4	PEOU → PU	0.751	0.752	0.034	21.868 ***	0.000	Supported
H5	PU → BI	0.234	0.230	0.079	2.962 **	0.002	Supported
H6	PEOU → BI	−0.050	−0.054	0.092	0.544 NS	0.293	Not Supported
H7	SNs → BI	0.164	0.169	0.088	1.866 *	0.031	Supported
H8	PT → BI	0.131	0.137	0.075	1.757 *	0.039	Supported
H9	PT → ATT	0.225	0.221	0.075	2.978 **	0.001	Supported
H10	PIIT → BI	0.131	0.126	0.075	1.745 *	0.040	Supported
H11	PIIT → ATT	0.327	0.332	0.067	4.854 ***	0.000	Supported

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, and NS: not significant.

As shown in Table 7, perceived ease of use has a strong effect on perceived usefulness (PEOU → PU: β = 0.751 ***). Among the two antecedents, PEOU has a larger positive significant effect on attitudes (ATT) (PEOU → ATT: β = 0.239 **), while PU has a lesser effect (PU → ATT: β = 0.134 *).

Personal innovativeness significantly influences attitudes (PIIT → ATT: β = 0.327 ***), as does perceived trust (PT → ATT: β = 0.225 **), although to a lesser extent.

Regarding the direct influence on behavioral intention (BI), the results show that attitudes have the highest influence (ATT → BI: β = 0.328 ***). Perceived usefulness also has a significant influence on BI (PU→BI: β = 0.234 **). Subjective norms also exert a significant influence on BI (SNs → BI: β = 0.164 *), followed by perceived trust and personal innovativeness, which have significant influences on BI, albeit to a lesser extent (PT → BI: β = 0.131 *; PIIT → BI: β = 0.131 *). Notably, perceived ease of use (PEOU) does not significantly influence BI, hence H6 was not supported.

The statistical significance levels for each relationship in the structural model, as well as the R^2 values for the dependent variables, are presented in Figure 2.

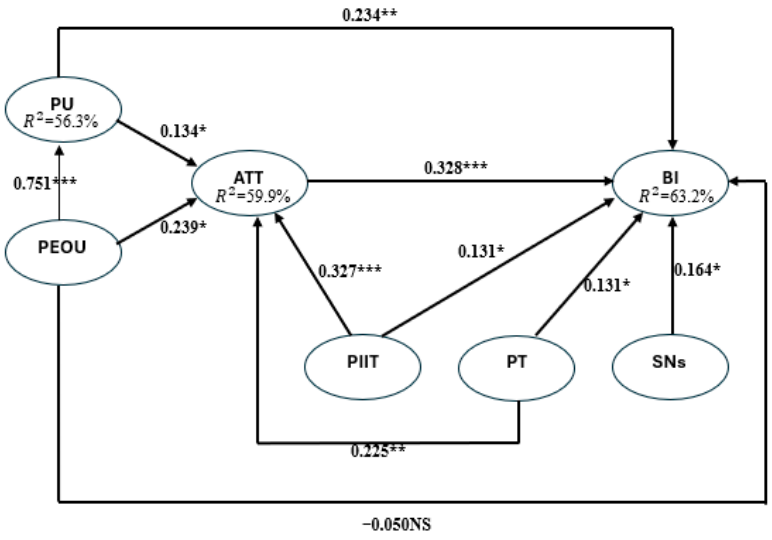


Figure 2. Structural model. Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, and NS: not significant.

6. Discussion and Contributions

This research employed an integrated model to assess the aspects affecting Generation Z's intention to use AI-enabled voice assistants (VAs) in Saudi Arabian banks. Generation Z in Saudi Arabia is characterized by their digital nativity, comfort with technology, and preferences for speed and personalized experiences. This demographic is particularly responsive to innovations that enhance convenience and efficiency in financial transactions, making them key drivers of technology adoption in the banking sector.

The model combined the TAM with subjective norms, personal innovativeness, and trust. PU and PEOU had a significant positive influence on attitude, supporting H1 and H2, and aligning with earlier studies (Belanche et al., 2019; Rezaei et al., 2024). These findings reflect the expectations of Generation Z users, who prioritize intuitive and efficient banking services, reinforcing the relevance of these constructs in their technology adoption behavior. Attitude had a highly substantial direct impact on behavioral intention (BI), supporting H3 and consistent with Rahman et al. (2023) and Noreen et al. (2023), among others.

The influence of PEOU on PU was also significant, supporting H4 and consistent with Belanche et al. (2019) and Rezaei et al. (2024). This indicates that when voice assistants are perceived as easy to use, Generation Z is more likely to recognize their usefulness. The direct influence of PU on BI was significant, supporting H5. However, the direct effect of PEOU on BI was insignificant (rejected H6), suggesting that while ease of use is important, it may not be a standalone driver of intention for this demographic in Saudi Arabia. This finding is in line with the results of previous studies, such as that of Rahman et al. (2023), which investigated the adoption of AI in banking services in Malaysia and reported a non-significant effect of PEOU on BI.

Subjective norms positively influence BI, supporting H7, and align with findings by Belanche et al., (2019); Rezaei et al., (2024) and Noreen et al. (2023). This indicates that the social circles of Generation Z, including peers and family, play a significant role in their technology adoption decisions in the industry. Furthermore, PT also has a direct and positive effect on BI (H8), consistent with studies by Lee and Chen (2022), Salem and Rassouli (2024) and Rahman et al. (2023). This emphasizes the importance of security and reliability for Generation Z, particularly in a digital-first world, where concerns about data privacy and security are paramount.

Moreover, perceived trust's influence on attitude was significant, supporting H9 and matching Mashhour and Saleh's (2015) findings. This reinforces the notion that to gain acceptance from Generation Z, banks must establish a strong foundation of trust. Additionally, personal innovativeness has a positive effect on both BI (H10) and ATT (H11), echoing the results of Thakur and Srivastava (2014) and R. Singh et al. (2025).

These results collectively demonstrate that the study model accurately predicts Generation Z's intention to use VAs in Saudi Arabian banks. The findings not only enhance our understanding of Generation Z's unique preferences and behaviors but also contribute valuable insights for banks and policymakers looking to navigate the evolving landscape of fintech in Saudi Arabia. In comparing these results with existing literature, it becomes apparent that while some factors are universally influential in technology adoption, the specific cultural and social contexts of Saudi Arabia further shape Generation Z's interactions with technology.

6.1. Theoretical Contribution

This research makes several contributions to the field. First, it extends the TAM by incorporating subjective norms, personal innovativeness, and perceived trust—concepts that have been overlooked in the context of AI adoption in the Middle East and Saudi Arabian banking sectors. Second, we investigate Generation Z's adoption of VAs in financial

services, addressing a gap in the literature on the drivers of behavioral intentions among this digitally native segment. Third, by connecting practical outcomes to theoretical models, this study highlights the value of theory-based approaches in understanding consumer behavior and decision-making in AI-fintech. The results show that the extended TAM framework is effective in shaping consumer intentions toward voice assistant services in Saudi Arabia's dynamic fintech and AI landscape. Additionally, this research provides a foundation for future studies by identifying key factors influencing behavioral intentions toward AI-enabled VAs in banking.

6.2. Practical Implications

The presented model delivers insights for bank management and policymakers in developing countries on the behavioral intention to adopt AI-enabled voice assistant technologies in banking. The findings indicate that banks should focus on simplifying voice assistant navigation, enhancing user interfaces, and prioritizing usability to increase customer acceptance. Subjective norms, including the influences of social groups, family, and friends, significantly shape Generation Z's consumer behavior. This indicates that banks can effectively partner with public figures and influencers who resonate with this demographic to promote AI-enabled VAs. Additionally, banks can enhance their outreach by launching targeted campaigns and engaging with communities, creating a more relatable and impactful connection with Generation Z consumers. Personal innovation is also a key factor, emphasizing the need for banks to provide innovative features and updates that match consumer expectations. Online trust is a vital aspect for fintech providers, necessitating the development of strategies that foster strong connections with customers. Promoting a culture of Digital Corporate Responsibility (DCR) is a fundamental strategy for building trust (Aldboush & Ferdous, 2023). To achieve this, fintech providers should prioritize user education on online privacy and security measures, providing clear explanations of how customer data are protected and utilized. Transparency is essential; compliance with data protection laws and regular updates about security protocols can reassure customers, enhance their confidence in the platform, and ultimately drive long-term loyalty.

Policymakers can use the study's findings to inform their decisions, particularly in developing AI-fintech markets in banking. A positive attitude toward VAs can facilitate their strategies, while regulations supporting trust can further boost consumer confidence. For instance, regulatory frameworks should be established to ensure data protection and consumer rights, similar to the General Data Protection Regulation (GDPR) in the European Union, in order to bolster confidence in AI applications (Aldboush & Ferdous, 2023). In 2023, Saudi Arabia introduced the Personal Data Protection Law (PDPL) as a significant initiative aimed at protecting consumer rights and enhancing confidence in AI and fintech applications (Smida et al., 2025).

Overall, the study's findings support the development of AI-fintech markets in Saudi Arabia, aligning with the country's 2030 Vision goals. Other countries can also benefit from these insights.

7. Limitations and Directions for Further Research

Every research has its limitations, which opens the door for future studies. The survey responses in this study were exclusively gathered from Generation Z consumers in Saudi Arabia, which could limit the findings' generalizability to other countries and cultures. Future research could benefit from incorporating more diverse samples. Researchers could also explore other older generations, such as Millennials or Generation X. Additionally, conducting cross-cultural comparisons among different generations regarding their adoption of AI-enabled VAs in banking could provide a more comprehensive understanding.

Furthermore, as this study was limited to examining Generation Z consumers in Saudi Arabia, future studies could compare differences in Generation Z's adoption of AI in banking across different countries. Additionally, this study used convenience sampling, which might constrain the generalizability of the results. Future research ought to explore alternative sampling techniques, such as simple random sampling or probability sampling, to enhance the generalizability of the findings.

While this study integrated essential external factors with the TAM, future research can consider additional factors, including AI-related factors such as perceived intelligence and anthropomorphism. Considering this, moderating variables such as gender and socioeconomic status could also be discovered in further studies. To address the limits of the cross-sectional design used in this study, further research may explore longitudinal studies to track changes in attitudes toward VAs in banking over time.

8. Conclusions

As AI-powered banking services become more widespread, it is crucial to identify the factors driving their adoption. This study examines the aspects affecting Generation Z's intention to use AI-enabled voice assistants in the Saudi banking sector, combining the TAM with other key factors, including subjective norms, personal innovativeness, and perceived trust. Our findings show that the perceived usefulness of AI-enabled voice assistants, overall attitude toward them, subjective norms, personal innovativeness, and perceived trust all have a positive impact on the intention to use these services. Furthermore, ease of use has a positive effect on perceived usefulness, and attitude is positively affected by ease of use, perceived usefulness, personal innovativeness, and trust. These insights provide valuable guidance for policymakers and banks looking to implement AI-enabled voice assistants. They also enrich the existing body of knowledge on AI tool adoption within the banking industry and establish a robust foundation for future innovations in the AI-driven fintech landscape.

Looking ahead, the implications of this research are profound; it calls upon fintech providers and policymakers to prioritize trust, innovation, and user experience, aligning their strategies with the diverse needs of each consumer segment. This not only fosters greater acceptance of AI technologies in banking but also positions the industry to effectively adapt to the rapid technological changes ahead.

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