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Customer Perceived Quality of AI-Driven Digital Financial Service Platforms (DFSPs) in Saudi Arabia

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Abstract **- This study aims to examine customer perceived quality of AI-driven digital financial service platforms (DFSPs) in Saudi Arabia. The study is grounded in the Technology Acceptance Model (TAM), the DeLone and McLean Information Systems Success Model, and trust theory to establish the study's constructs. The study developed a structural model comprising seven latent constructs: AI-Driven Service Quality (AISQ), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in AI (TR), Perceived Risk (PR), Customer Perceived Quality (CPQ), and Customer Satisfaction (CSAT). To test the model, an online survey was conducted with 226 active users of digital financial service platforms in Saudi Arabia. The postulated relationships were examined using covariance-based structural equation modeling (CB-SEM). The results revealed that AI-driven service quality had a positive but nonsignificant direct impact on customer perceived quality, while it had a positive and significant impact on customer satisfaction. Perceived usefulness and trust had positive and significant direct impacts on customer perceived quality, while perceived ease of use influenced customer perceived quality indirectly through perceived usefulness. Perceived risk had a negative but non-significant impact on both customer satisfaction and customer perceived quality. Customer satisfaction partially mediated the relationship between AI-driven service quality and customer perceived quality. A cross-sectional research design is a major limitation of this study because it precludes generalizable conclusions about the dynamic evolution of customers' perceptions of digital financial services. The study's conceptual model provides a better understanding of customer-perceived quality of AI-driven in the context of digital financial service platforms. The study's implications help service providers implement appropriate measures to improve digital financial services and reshape platforms' quality past AI and emerging technologies.**

Keywords: Artificial Intelligence; Digital Financial Service Platforms; Customer Perceived Quality; Structural Equation Modeling; Saudi Arabia; TAM; Trust; FinTech.

I. Introduction

Financial services have been transformed in ways that would have seemed hard to imagine at the start of the century. Digital Financial Service Platforms (DFSPs), including everything from mobile wallets and payment apps to AI-powered investment-management boots and algorithmic peer-to-peer lending providers, have placed the smartphone screen at the center of most consumer finance engagements (Gomber *et al.*, 2018; Mention, 2019). The difference is that AI has now become a key part of how the algorithms at the heart of these platforms determine recommendations, flag fraud, and curate the interfaces users see every day.

Nowhere is this faster than in Saudi Arabia, where digitally driven financial transformation has been made a priority national agenda item as part of Vision 2030. This explicitly includes the shift to a cashless society and embedding new technologies across the core of the mainstream financial services ecosystem (Financial Sector Development Program, 2022). The results are impressive. According to the Saudi Central Bank (2026a), 85 percent of retail transactions in Saudi Arabia were made electronically were 14.6 billion were digital non-cash transactions in 2025. Hence, digital financial platforms such as STC Bank, Mobily Pay, D360, Barq, Urpay, Tamara, Tabby, Halalah, and others are rapidly becoming popular among users in Saudi Arabia. These digital wallets are powered by AI, providing customized spending insights, fraud detection in real-time, and automated credit decision making at the core of everyday financial activities (Aldaarmi, 2024). Moreover, the Saudi Central Bank has issued over than 150 licensed fintech companies were operating in Saudi Arabia (Saudi Central Bank, 2026b).

Despite the high adoption rates, research has not yet caught up, especially when it comes to what happens after customers adopt DFSPs. Most scholarly literature focuses on the drivers of digital banking adoption (Alalwan *et al.*, 2017), the drivers of mobile payment adoption (Dahlberg *et al.*, 2015), and the drivers of FinTech adoption in general (Hu *et al.*, 2019; Bommer *et al.*, 2023). However, rarely study focuses on how customers assess the quality of the AI-based

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services they use daily. Prior studies have mainly focused on advanced western economies (Belanche *et al.*, 2019; Cao, 2022), and their findings may not be applicable to Saudi Arabia, where cultural values, regulatory environments, and digital adoption rates can differ vastly from such nations.

A systematic review by Firmansyah *et al.* (2023) about FinTech adoption research outlines the Gulf Cooperation Council (GCC) region as being particularly under-studied. Alotaibi (2024) noted a similar lack of empirical research into AI and customer satisfaction in the Saudi banking sector. In fact, Al-Baity (2023) argued the same in their review of AI research in Saudi digital financial services in general, calling for the kind of systematic empirical work which this paper sets out to achieve.

Hence, service quality management becomes a rather different task when the service is an AI based financial services solution rather than a branch visit or even an online banking session. Classical service quality models (Parasuraman *et al.*, 1988) typically focus on human–human interaction, such as a teller's politeness, a financial advisor's expertise, or the branch's atmosphere. In contrast, an algorithm in place of the human, signaling quality amounts to how well the AI predicts spending behavior, how fast it learns user behavior, and how interpretable its recommendations (Davenport *et al.*, 2020; Wirtz *et al.*, 2018).

This paper takes up that challenge. It asks the seemingly simple but largely disregarded question: what shapes customer perceptions of DFSP quality driven by AI in Saudi Arabia? In addressing this research question, the study develops and empirically tests a structural model with seven constructs: AI-driven service quality, perceived usefulness, perceived ease of use, trust in AI, perceived risk, customer perceived quality, and customer satisfaction. Insights are drawn from the Technology Acceptance Model, DeLone and McLean IS Success Model, and trust theory. The study analyzes primary data from 226 active DFSP users via CB-SEM through AMOS software. This is realized through three steps: first, identifying the contextual factors that determine platform quality in this context; second, mapping the direct, indirect, and mediating pathways through which these factors operate; and third, offering recommendations to platform providers, regulators, and policymakers to support their engagement with the next stage in this industry.

The remainder of this paper is organized as follows. Section 2 outlines a literature review with hypotheses and conceptual models. Section 3 highlights the research methods applied in this study. Section 4 presents the data analysis. Finally, Section 5 discusses the results and contrasts them with extant literature, while the study limitations and avenues for future research are also outlined. Practical and managerial recommendations are interspersed throughout.

II. Literature Review

A substantial body of scholarship has examined the conceptual foundations of digital financial service platforms (DFSPs), the application of artificial intelligence in financial services, and customer-perceived quality of AI-driven services. However, these strands have largely developed in isolation, leaving the relationships among platform characteristics, AI capabilities, and the perceptual mechanisms such as trust, perceived risk, and perceived usefulness that shape customer evaluations only partially understood. This review synthesizes these literatures and organizes the discussion around the constructs central to the present study, thereby establishing the theoretical basis for the structural model proposed in the following section.

Digital Financial Service Platforms: Conceptual Foundations

DFSPs do not have a linear trajectory of development but instead exhibit an accelerating pace of development (Gomber *et al.*, 2018). Those phases have taken place in a much shorter timespan in Saudi Arbia than most other countries, as the preconditions for adoption of mobile-first financial services have been met. Additionally, one of the initiatives of Saudi Vision 2030 is the "Financial Sector Development Program" (FSDP), which set a target of 70% cashless transactions by 2025 (Saudi Central Bank 2022a). Also, Saudi Central Bank issued atypical regulator activity, creating an Open Banking Framework and launching the Fintech Saudi initiative, which lowered the barriers to entry for new entrants in the Saudi Arabian fintech ecosystem (Saudi Central Bank 2022b).

Consequently, the literature about the FinTech domain is developing in Saudi Arabia. Meanwhile, Aldaarmi (2024) investigated the relationship between fintech service quality and customer satisfaction in Saudi Arabia. The study findings established that tangibles, reliability, and empathy were important predictors. Furthermore, the dimensions of quality related to technology-mediated service products might differ in terms of their relationship with satisfaction when compared to face-to-face banking. Alkhowaiter (2020), who reviewed studies related to digital payment in the Gulf countries, found no studies assessing quality perceptions, trust, and risk concurrently. Al-Baity (2023) proposed a conceptual model for the application of AI in Saudi finance and the study's finding reveled that integrating critical components and algorithms help to improve financial services simultaneously. On the other hand, Alzahrani and Bhunia (2025) confirmed that trust plays a mediating role between perceived ease of use and adoption intention among Generation Z Saudi users, underlining the role of trust in this area.

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Artificial Intelligence in Financial Services: Rethinking Quality

AI in financial services is a continuum of supervised and unsupervised machine learning, deep neural networks, natural language processing (NLP), and reinforcement learning algorithms that enable computer systems to perform tasks that previously required human judgment (Cao, 2022). In the context of DFSPs, these are personalization engines for product recommendations, fraud detection engines to identify and flag suspicious transactions in real-time, chatbots to answer basic and commonly asked questions, and predictive algorithms to understand a user's financial needs before the user articulates them (Davenport *et al.*, 2020).

The employment of AI in these domains requires the rethinking of service quality measurement. The SERVQUAL model (Parasuraman et al., 1988), the dominant model of service quality, was developed with the tacit assumption that humans perform services to other humans. Its five dimensions—tangibles, reliability, responsiveness, assurance, and empathy—implicitly assume that a human service provider is involved in the service delivery. When assessing algorithmic services, however, some dimensions need to be reconceptualized. For instance, responsiveness would be measured by processing speed and adaptiveness, assurance by algorithms' accuracy and explainability, and empathy by AI's level of personalization (Wirtz *et al.*, 2018). This reconceptualization is more a work in progress than a done deal and barely begun in emerging markets such as Saudi Arabia.

Recent studies offer useful reference points about FinTech throughout the world. Roh *et al.* (2024) found that system, information, and service quality all predicted customer trust and behavioral attitudes, and that security and privacy mediated the effects of the qualities on trust in China. Balaskas *et al.* (2024) found that government support and trust are important drivers for adoption in Greece. Alkhwaldi *et al.* (2022) found that uncertainty avoidance moderates the influences of TAM constructs on digital payment adoption, which would be relevant for Saudi Arabia. Moreover, Bommer *et al.* (2023) conducted a meta-analysis based on 42 samples and found that hedonic motivation, price value, performance expectancy, and social influence had the strongest relationships with FinTech use intention, with few studies moving past adoption to consider perceived quality. Furthermore, Sharma *et al.* (2024) integrated SERVQUAL and TAM in their study of FinTech payment services. Contrary to existing literature, they found that perceived ease of use does not always dominate perceived usefulness of FinTech in determining intention to adopt.

Customer Perceived Quality in AI-Driven Services

Customer Perceived Quality (CPQ) has been defined as the subjective evaluation of a product or service's overall excellence or quality by the customer (Zeithaml, 1988). In information systems research, CPQ is typically operationalized through the D&M model of information systems success's three quality components: system quality, information quality, and service quality (DeLone & McLean, 2003). For the purposes of this study, CPQ is defined as the user's overall evaluation of the extent to which an AI-enabled DFSP meets financial services expectations that, in addition to the customary IS quality dimensions, also include AI-related dimensions: recommendation accuracy, algorithmic decision consistency, process transparency, and platform learning (Davenport *et al.*, 2020).

Numerous studies have examined the relationship between quality of DFSPs and customer perceptions. Sharma and Sharma (2019) found that system quality features such as accuracy, reliability, and adaptiveness play a direct role in determining the overall quality perception of mobile banking services in Oman. Savitha *et al.* (2022) found that the impact of perceived quality on FinTech continuance intention is much stronger than its impact on initial adoption in India. Also, Chawla *et al.* (2023) confirmed that perceived trust influences the FinTech adoption of digital natives. Jafri *et al.* (2024) conducted a systematic literature review to identify the factors influencing FinTech adoption, and trust emerged as one of the most important yet under-researched factors in the FinTech adoption literature. Appiah and Agblewornu (2025) found that perceived benefit, perceived risk, and trust is a meaningful framework for FinTech adoption in emerging economies such as African countries.

Theoretical Framework

The current study develops a conceptual model that relies on three theoretical frameworks. First, the Technology Acceptance Model (TAM) supplies the constructs of perceived usefulness and perceived ease of use, developed by Davis (1989). Second, the IS Success Model provides the logic connecting system and service quality to user satisfaction and downstream outcomes (DeLone & McLean, 2003). Third, trust theory, anchored in McKnight *et al.* (2002) typology and Mayer *et al.* (1995) integrative model, offers the lens through which this study examines users' willingness to rely on AI-powered platforms that handle their financial data and provide financial suggestions.

The integration of these three perspectives is necessary because no single framework captures the full set of determinants relevant to AI-driven financial services: TAM addresses utilitarian perceptions, the IS Success Model

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addresses quality-to-outcome pathways, and trust theory discourses the vulnerability inherent in delegating financial decisions to opaque algorithms. Therefore, the following sections will be discussed regarding the proposed model constructs.

AI-Driven Service Quality and Customer Perceived Quality

AI-Driven Service Quality is composed of numerous facets of AI DFSPs performance: personalization, accuracy, responsiveness, reliability, and adaptiveness, which are based on both IS Success Model established by DeLone and McLean (2003) and E-S-QUAL e-service quality proposed by Parasuraman *et al.* (2005). The theoretical rationale behind these facets is that if the platform's AI is constantly providing accurate, personalized, and timely services that are deemed relevant by the user, the platform is more likely to be positively evaluated. Sharma and Sharma (2019) and Roh *et al.* (2024) found that system quality features can improve perceptions of platform quality. Correspondingly, Alotaibi (2024) found a positive and significant relationship between AI capabilities and customer satisfaction in the Saudi banking sector. One implication is that fintech service quality influence on customer satisfaction, as the fintech service quality are performing as or better than customer expected, a finding that is well established in the information systems continuance literature (Bhattacherjee, 2001; Aldaarmi, 2024). Hence, the current study developed hypotheses to scrutinize the relationships between AI-driven service quality, customer perceived quality and customer satisfaction which is followed by the conceptual framework which was adopted to achieve its objectives:

H1a: *AI-driven service quality positively affects customer perceived quality.*

H1b: *AI-driven service quality positively affects customer satisfaction.*

Perceived Usefulness and Customer Perceived Quality

Perceived usefulness refers to the belief that using a system enhances one's job performance (Davis, 1989). It has been recognized as one of the most consistent predictors of technology acceptance found in numerous studies (Venkatesh & Davis, 2000). A meta-analysis based on 42 samples by Bommer *et al.* (2023) found that performance expectancy conceptually analogous to perceived usefulness was among the strongest predictors of FinTech use intention, alongside hedonic motivation, price value, and social influence. In the context of DFSPs, perceived usefulness reflects whether AI features make financial decisions easier or smarter (e.g., making transactions faster, providing better budgeting and spending insights). When perceived usefulness is accentuated, how quality is perceived by the user is likely to follow suit. Sharma et al. (2024) confirmed that perceived usefulness affects FinTech usage beyond adoption. In addition, Alzahrani and Bhunia (2025) found that usefulness, along with ease of use and trust, sequentially mediated the relationship between user innovativeness and FinTech adoption intention among Saudi Gen Z users, suggesting a role for usefulness at multiple stages of the evaluation process. However, one hypothesis was developed to examine the relationships between perceived usefulness and customer perceived quality that trail by the conceptual framework to achieve study's objective:

H2: *Perceived usefulness positively affects customer perceived quality.*

Perceived Ease of Use and Customer Perceived Quality

Perceived ease of use refers to the extent to which a person believes that using a particular platform is easy (Davis, 1989). In the context of digital finance services in emerging markets, perceived ease of use has been found to be a direct driver, while in more mature contexts the effect has been shown to be mediated through perceived usefulness (Venkatesh & Bala, 2008). As digital payment systems have reached a certain degree of saturation in Saudi Arabia, it is an interesting case regarding usability principles. Although most users have been exposed to digital interfaces, there are still many who appreciate simplicity, such as the elderly and digitally less literate (Al-Somali *et al.*, 2009). A recent study in Saudi Arabia by Alzahrani and Bhunia (2025) highlighted that FinTech perceived ease of use operates mainly through trust and perceived usefulness. However, the current study established hypotheses to dissect the relationships between perceived ease of use, customer perceived quality and perceived usefulness:

H3a: *Perceived ease of use positively affects customer perceived quality.*

H3b: *Perceived ease of use positively affects perceived usefulness.*

Trust in AI and Customer Perceived Quality

Trust in this sense is the user's willingness to be vulnerable to the actions of the AI system based on positive expectations regarding its competence, integrity, and benevolence (McKnight *et al.*, 2002; Mayer *et al.*, 1995). Most financial services rely on trust and involve privacy-sensitive information and financially impactful decisions. Trust is even more critical when the service provider is opaque software rather than a service employee (Yousafzai *et al.*, 2003). Chawla *et al.* (2023) found trust to mediate the relationship between technology features and FinTech

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adoption intention of digital natives. Trust directly and indirectly influences FinTech attitude (Roh *et al.*, 2024). The influence of trust on quality seems to be prominent in Saudi Arabia, where underlying principles of trustworthiness are paramount to many commercial transactions. According to Saudi Data and AI Authority (2021), the government enacted the Personal Data Protection Law (PDPL), establishing the first comprehensive national framework for regulating the collection, processing, and protection of personal data. Furthermore, Jafri *et al.* (2024) and Appiah and Agblewornu (2025) suggest that further research concerning the impact of trust on FinTech quality in emerging markets is warranted. The subsequent hypothesis will test the relationship between Trust in AI and customer perceived quality:

H4: *Trust in AI positively affects customer perceived quality.*

Perceived Risk and Customer Perceived Quality

In contrast to the above constructs, perceived risk (PR) is expected to have a negative effect on quality perception. Based on Featherman and Pavlou (2003), perceived risk is defined as the user's perceived risk of financial loss caused by AI errors, privacy violations, inconsistency in quality, and unauthorized access to the account. Similar to the predictions of prospect theory (Kahneman & Tversky, 1979) regarding loss aversion, risk perception can weaken otherwise promising FinTech evaluations. Empirically, risk has been shown to reduce trust in and intention to adopt Islamic FinTech (Ali *et al.*, 2021) and to negatively affect attitudes toward FinTech platforms (Xie *et al.*, 2021). Jafri *et al.* (2024) identified risk, among other factors, as a key determinant of FinTech behavioral intention in their systematic review. Risk perceptions may be particularly relevant given Saudi Arabia's evolving legal framework for privacy and data protection. Hence, the following hypotheses developed to test the impact of perceived risk on customer perceived quality in the context of Saudi Arabia:

H5a: *Perceived risk negatively affects customer perceived quality.*

H5b: *Perceived risk negatively affects customer satisfaction.*

The Mediating Role of Customer Satisfaction

Customer satisfaction is defined as "the evaluative judgment resulting from the comparison of prior expectations with perceived performance" (Oliver, 1997). Following the American Customer Satisfaction Index framework (Fornell *et al.*, 1996), the specific service quality experience must first be subject to overall satisfaction before arriving at an aggregate service quality judgment. Bhattacherjee (2001) study findings suggested that customers' intention to continue using IS was shaped by satisfaction with using it and perceived usefulness. Correspondingly, numerous studies had provided evidence that customer satisfaction has a mediating effect on the relationship between online banking quality and customer loyalty (Albinalsheikh, 2022; Khan *et al.*, 2023; Hidayat *et al.*, 2024; Ajouz *et al.*, 2025). Thus, the current study proposed hypothesis to examination the mediating role of customer satisfaction on the relationship between AI-driven service quality and customer perceived quality:

H6: *Customer satisfaction mediates the relationship between AI-driven service quality and customer perceived quality.*

Although the proposed model constructs have been deliberated previously, Figure 1 illustrated the study model depicts the key variables and the presumed relationships, which will be explored in the current study.

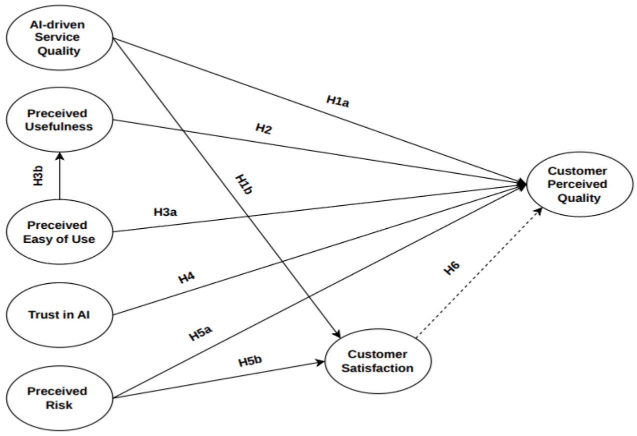

Figure 1: Conceptual Model

III. Methodology

The study follows a quantitative, cross-sectional survey design grounded in a positivist research philosophy (Creswell & Creswell, 2018). This approach suits the study's central aim, which is to test a set of theoretically derived hypotheses about causal relationships among measurable latent constructs. Hence, the current study employed CB-SEM due to its ability to test theoretical models and depict the relationships between latent constructs (Igbaria *et al.*, 1995). The study employed the convenience sampling technique because of the lack of a sampling frame in Saudi Arabia (Malhotra *et al.*, 1996). Convenience sampling is one of the most widely used non-probability sampling techniques in social science research (Taherdoost, 2016).

The analysis proceeded in two stages, following Anderson and Gerbing's (1988) well-established protocol. In

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the first stage, confirmatory factor analysis (CFA) was used to evaluate the measurement model. In the second, the structural paths were estimated. Model fit was judged against a set of widely accepted benchmarks: χ^2/df below 3.0, CFI and TLI at or above 0.90, RMSEA at or below 0.08, and SRMR at or below 0.08 (Hu & Bentler, 1999; Hair *et al.*, 2019). Common method bias was checked via Harman's single-factor test and a common latent factor (CLF) approach. All statistical work was carried out on SPSS 28 and AMOS 28.

A 5-point Likert scale was employed for the measurement items. The questionnaire consists of 30 measurement items spread across seven constructs; all adapted from previously validated scales. AI-driven service quality (5 items) draws on Parasuraman *et al.* (2005) E-S-QUAL and DeLone and McLean (2003) system quality dimensions. Perceived usefulness (4 items) and perceived ease of use (4 items) come from Davis (1989). Trust in AI (4 items) is based on McKnight *et al.* (2002) and Lankton *et al.* (2015). Perceived risk (4 items) follows Featherman and Pavlou (2003). Customer satisfaction (4 items) adapts scales from Fornell *et al.* (1996) and Bhattacherjee (2001). Customer perceived quality (5 items) relies on Zeithaml (1988) and Parasuraman *et al.* (2005). The instrument was originally drafted in English, then translated into Arabic by a bilingual expert and back translated to check for semantic drift. A pilot test with 15 respondents led to minor wording adjustments and confirmed adequate preliminary reliability.

IV. Data Analysis

A total of 226 valid survey responses were collected and used as the sample for this research. Nominal variables were generated to represent the demographic characteristics of respondents. The study used a five-point Likert scale for assessing the research variables related to customer perceived quality of AI-driven digital financial service platforms (DFSPs) in Saudi Arabia. The 30 items used in the survey measured the seven constructs: AI-Driven Service Quality (AISQ), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Trust in AI (TR), Perceived Risk (PR), Customer Satisfaction (CSAT), and Customer Perceived Quality (CPQ).

Response Profile

Respondents' profiles sought in the study included gender, age, education level, and household income. Table 1 provides the sample distribution, which shows that the majority were males at 58%, whereas females comprised 42% of the sample.

Table 1: Respondents' Profiles

Variable	Category	Frequency	Percentage
Gender	Male	132	58
	Female	94	42
Age	18–24	5	2
	25–34	43	19
	35–44	84	37
	45–54	77	34
	55+	17	8
Education	High School	22	10
	Diploma	37	16
	Bachelor	80	35
	Master	67	30
	Doctorate	20	9
Household Income	Below 5,000	20	9
	5,000–10,000	52	23
	10,001–15,000	68	30
	15,001–20,000	48	21
	Above 20,000	38	17

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DFSP	STC Bank	110	49
	Mobily Pay	14	6
	D360	25	11
	Barq	36	16
	Urpay	7	3
	Tamara	12	6
	Tabby	10	4
	Halalah	0	0
	Other	12	5
FrequencyUse	Daily	79	35
	Weekly	84	37
	Monthly	49	22
	Rarely	14	6
Experience	< 1 Year	37	16
	1–3 Years	107	47
	3–5 Years	52	23
	> 5 Years	30	14

In terms of age, the plurality (37%) of respondents was in the 35–44 age range. In terms of education, nearly three-quarters of respondents indicated they held a bachelor's degree or higher. Over one-third of respondents (38%) earned SAR 15,000 or more monthly. The leading DFSP was STC Bank with 49%, being the first and most established DFSP in the market. Most users of a DFSP used it weekly (37%) and had used a DFSP for one to three years (47%).

Confirmatory Factor Analysis

Table 2 documents the findings for the revised CFA. Four items were deleted (AISQ3, PU4, TR3, and CPQ4) to enhance model fit indicators. The revised model had a chi-square of 322.54 with 278 degrees of freedom and a p-value < 0.05. The ratio of chi-square to the degree of freedom was 1.16. Since the ratio was within the recommended range of 1 to 3, the model met this fitness evaluation criterion (Hu & Bentler, 1999; Kline, 2016).

Table 2: Model Fit Summary for CFA

Indicators	
Model chi-square X^2	322.54
Degree of freedom	278
Probability level	0.00
X^2/df	1.16
Goodness-of-Fit Index (GFI)	0.90
Adjusted Goodness-of-Fit Index (AGFI)	0.88
Normed Fit Index (NFI)	0.88
Comparative Fit Index (CFI)	0.98
Root means square error of approximation (RMSEA)	0.02

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Adequate factor loadings were observed, with standardized coefficients ranging from 0.64 to 0.78. The critical ratio (C.R.) was used to examine the significance of factor loadings; coefficients were deemed significant if their C.R. exceeded ±1.96. The highest C.R. was 11.70, while the lowest was 7.81.

Convergent Validity

The reliability and validity of the measurement model were evaluated by calculating composite reliability, which assesses the internal consistency of construct scales (Hair *et al.*, 2019). Cronbach's alpha was also performed and compared with composite reliability. The reliability results in Table 3 indicate that composite reliability ranged from 0.76 to 0.85, exceeding the threshold of 0.70 recommended by Hair et al. (2019). Consequently, scale reliability was adequate. Average variance extracted (AVE) values fell between 0.50 and 0.60, clearing the 0.50 floor needed to establish convergent validity (Fornell & Larcker, 1981). As a check for common method bias, Harman's single-factor test was run; the first unrotated factor explained 30.01% of total variance, safely below the 50% warning threshold. Additionally, a common latent factor (CLF) was added to the CFA model; the comparison of standardized loadings with and without the CLF showed no difference exceeding 0.200, further confirming that common method bias is not a concern (Podsakoff *et al.*, 2003).

Table 3: Reliability for Research Constructs

Construct	Cronbach Alpha	C.R.	AVE
AI-Driven Service Quality	0.85	0.85	0.60
Perceived Usefulness	0.76	0.76	0.52
Perceived Ease of Use	0.83	0.84	0.56
Trust in AI	0.80	0.80	0.58
Perceived Risk	0.78	0.78	0.50
Customer Satisfaction	0.84	0.84	0.58
Customer Perceived Quality	0.82	0.82	0.54

Discriminant Validity

Discriminant validity was assessed using the Fornell and Larcker (1981) criterion, which compares the square root of the AVE for each construct against its correlations with other constructs. When the square root of the AVE is higher than the correlation estimates, discriminant validity is established. The results shown in Table 4 confirm discriminant validity, as the square root of AVE (shown in bold on the diagonal) exceeds all inter-construct correlations.

Table 4: Discriminant Validity

	AISQ	PU	PEOU	TR	PR	CSAT	CPQ
AISQ	**0.77**						
PU	0.40	**0.72**					
PEOU	0.42	0.57	**0.75**				
TR	0.46	0.51	0.37	**0.76**			
PR	-0.31	-0.39	-0.24	-0.35	**0.69**		
CSAT	0.50	0.42	0.27	0.52	-0.26	**0.76**	
CPQ	0.48	0.56	0.35	0.60	-0.35	0.58	**0.73**

Note: Bold diagonal values represent the square root of AVE.

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Structural Equation Modeling

As presented in Table 5, the goodness-of-fit indicators for CB-SEM revealed a CMIN/DF ratio of 1.65, which is within the recommended range of 1 to 3. The GFI was 0.85 and AGFI was 0.83. RMSEA likewise achieved the suggested requirement of < 0.08 with a satisfactory value of 0.05. While some indices such as GFI and AGFI did not exceed the 0.90 threshold, the indicators still met the acceptable goodness-of-fit criteria for the SEM model. Baumgartner and Homburg (1996) and Doll et al. (1994) suggested that SEM models can be acceptable when the indicator values are above 0.80.

Table 5: Model Fit Summary for CB-SEM

Indicators	
Model chi-square X^2	479.57
Degree of freedom	290
Probability level	0.00
X^2/df	1.65
Goodness-of-Fit Index (GFI)	0.85
Adjusted Goodness-of-Fit Index (AGFI)	0.83
Normed Fit Index (NFI)	0.82
Comparative Fit Index (CFI)	0.92
Root means square error of approximation (RMSEA)	0.05

The structural equation modeling results, as shown in Table 6, revealed that there was a positive but non-significant relationship between AISQ → CPQ ($\beta = 0.14$, C.R. = 1.66, $p > 0.05$); thus, H1a was rejected. Furthermore, there was a positive and significant relationship between AISQ → CSAT ($\beta = 0.47$, C.R. = 5.93, $p < 0.001$), so H1b was supported. Moreover, there was a positive and significant relationship between PU → CPQ ($\beta = 0.29$, C.R. = 2.89, $p < 0.001$), and this result supported H2.

Table 6: Structural Equation Modeling Results

H	Path	β	S.E.	C.R.	Sign.	Result
H1a	AISQ → CPQ	0.14	0.06	1.66	0.09	Rejected
H1b	AISQ → CSAT	0.47	0.07	5.93	***	Supported
H2	PU → CPQ	0.29	0.08	2.89	***	Supported
H3a	PEOU → CPQ	-0.02	0.07	-0.24	0.81	Rejected
H3b	PEOU → PU	0.57	0.09	6.57	***	Supported
H4	TR → CPQ	0.32	0.06	4.04	***	Supported
H5a	PR → CPQ	-0.08	0.06	-1.17	0.24	Rejected
H5b	PR → CSAT	-0.14	0.07	-1.88	0.06	Rejected
H6	AISQ → CSAT → CPQ	0.30	-	-	*	Partially

*Note: *** p < 0.001, * p < 0.05*

In addition, there was a negative and non-significant relationship between PEOU → CPQ ($\beta = –0.02$, C.R. = –0.24, $p > 0.05$), so H3a was rejected. There was a positive and significant relationship between PEOU → PU ($\beta = 0.57$, C.R. = 6.57, $p < 0.001$), so H3b was supported. There was a positive and significant relationship between TR → CPQ ($\beta = 0.32$, C.R. = 4.04, $p < 0.001$), so H4 was supported. There were negative and non-significant relationships between PR → CPQ and PR → CSAT, so H5a and H5b

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were rejected. It is worth noting that the PR → CSAT path ($p = 0.06$) approached conventional significance thresholds, suggesting a marginal effect that warrants further investigation in larger samples.

With respect to the mediating role of customer satisfaction, bootstrapping with 5,000 resamples was conducted in AMOS to assess the indirect effect of AISQ on CPQ through CSAT. The standardized indirect effect was 0.30 ($p < 0.05$), with a 95% bias-corrected confidence interval. Since the confidence interval does not include zero, the indirect effect is statistically significant. Given that the direct effect of AISQ on CPQ is non-significant ($\beta = 0.14$, $p = 0.09$) while the indirect effect through CSAT is significant, customer satisfaction partially mediates the AISQ–CPQ relationship. Hypothesis H6 is therefore partially supported.

V. Discussion

The following section provides the main findings, discussion and links the results of this study to those of prior studies on digital financial service platforms (DFSPs).

The current study developed a model to examine the effect of digital financial service platforms driven by AI on customer perceived quality in Saudi Arabia. Through the CB-SEM analysis, the results reveal that AI-driven service quality has a positive but non-significant direct effect on customer perceived quality, while it has a positive and significant effect on customer satisfaction. Thus, H1a is rejected and H1b is supported. This finding applies the DeLone and McLean IS Success Model to the AI-mediated financial services context and suggests that AISQ operates on overall quality perceptions indirectly through the satisfaction pathway rather than directly. This differs from the e-service quality literature, which has typically found direct effects of electronic service quality factors on customer perceived quality (Parasuraman *et al.*, 2005). This finding is consistent with Roh *et al.* (2024) finding that system quality is a driver of trust among Chinese FinTech customers and Alotaibi (2024) finding of a positive effect of AI-enabled banking on customer satisfaction in Saudi Arabia. As financial services become more algorithmic in nature, the algorithm becomes the product, which is rated like any other product.

The strong direct impact of perceived usefulness on customer perceived quality suggests that Saudi banks' users have moved beyond the early phase of application adoption. It is no longer enough to merely understand the functions of the application and know how to use it. Saudi banks' users expect AI features on platforms that deliver real value by saving time, easing decision-making processes, and tightening financial control. Meanwhile, perceived ease of use had a negative and non-significant direct impact on customer perceived quality. Nevertheless, perceived ease of use remains meaningful in influencing perceived usefulness. Thus, H2 and H3b are supported, while H3a is rejected. These findings are consistent with Venkatesh and Bala (2008) and with Bommer *et al.* (2023) meta-analytic findings, which identified performance expectancy as one of the strongest predictors of FinTech use intention. Furthermore, the study by Alzahrani and Bhunia (2025), which focused on Gen Z FinTech users in Saudi Arabia, highlighted the sequential relationship between perceived ease of use and perceived usefulness.

The analysis demonstrated that trust has a meaningful impact on customer perceived quality. This indicates that the moral and ethical principle of trustworthiness is a strong influence in Saudi financial practices. H4 is therefore supported. In effect, users cede their trust to the algorithm when they defer their financial decision making and the handling of sensitive financial information to an AI system. Platforms perceived to display competence, transparency, and benevolence in their use of AI receive considerably higher ratings of quality via path coefficients. This study extends the trust in technology research of Chawla *et al.* (2023) and Appiah and Agblewornu (2025) to the financial services industry in the Saudi context and closes the gap identified by Jafri *et al.* (2024).

The analysis showed that perceived risk had negative but non-significant effects on both customer satisfaction and customer perceived quality. Hence, H5a and H5b are rejected. While the direction of the relationships aligns with theoretical expectations from prospect theory (Kahneman & Tversky, 1979) and prior FinTech risk research (Ali *et al.*, 2021; Xie *et al.*, 2021), the non-significance suggests that DFSP users may have developed a degree of risk tolerance, possibly owing to the strong regulatory environment established by Saudi Central Bank and Saudi Data and AI Authority. Alternatively, the prominent role of trust in the model may absorb some of the variance that would otherwise be attributed to perceived risk.

Finally, the current study examined whether customer satisfaction mediates the relationship between AI-driven service quality and customer perceived quality. The results revealed that customer satisfaction positively and significantly mediates this relationship. Consequently, H6 is partially supported. Hence, albeit this result is not fully supported, but it is consistent with Albinalsheikh (2022), Khan *et al.* (2023), Hidayat *et al.* (2024) and Ajouz *et al.* (2025) suggested findings. It confirms that the pathway from AISQ to CPQ runs through customer satisfaction: AI-driven service quality first generates satisfaction, which in turn elevates overall perceived quality. DFSPs executives should therefore develop strategies that attempt to enhance customer satisfaction as a mechanism

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for improving overall quality perceptions of AI-driven platforms.

VI. Practical Implications

The study outcomes have several managerial implications that would assist decision-makers in understanding issues about DFSPs. First, given that trust in AI emerged as the strongest direct predictor of customer perceived quality, platform providers should prioritize algorithmic transparency for example, by explaining how AI-driven recommendations are generated and how personal data is processed. Although, the enactment of the PDPL that established by Saudi Data and AI Authority provides a regulatory foundation (2021) for DFSPs; therefore, they proactively compliance and data governance practices stand to gain digital trust among their customers (Alaeaid *et al.* 2026).

Second, the significant role of perceived usefulness suggests that DFSP providers should focus on developing AI features that deliver tangible financial benefits to users—such as intelligent budgeting insights, real-time spending alerts, and personalized financial advice—rather than merely adding AI capabilities for their own sake. Third, while perceived ease of use did not directly affect perceived quality, its strong influence on perceived usefulness confirms that usability remains foundational. Platform builders should ensure that AI features are intuitively integrated into existing workflows rather than adding complexity to the user experience.

Fourth, the finding that AI-driven service quality affects perceived quality indirectly through customer satisfaction suggests that monitoring and improving customer satisfaction should be treated as a strategic priority. Continuous feedback mechanisms, responsive customer service powered by AI chatbots, and periodic satisfaction surveys can help platform providers identify and address service quality gaps promptly. Finally, although perceived risk was non-significant in this study, platform providers should not overlook cybersecurity systems, as risk perceptions may become more prominent as users engage with more complex AI-driven financial products. Implementing strong cybersecurity systems and clearly communicating security measures can help sustain the current low-risk perception among users.

VII. Limitations and Future Research

The limitations of this study relate to its research method. As a cross-sectional study, it captures the thinking of individuals at one point in time and does not explicitly capture whether their thinking changes as AI capabilities improve and the public becomes more familiar with using AI. Despite the appropriateness of the non-probability sampling method for active DFSP users, the findings of this study cannot be generalized to the entire population in Saudi Arabia. The sample was also concentrated on STC Bank users (49%), which may limit the applicability of the findings across all DFSP types. The study does not differentiate between types of DFSPs such as payments, lending, or investment, nor does it investigate the moderating effects of age, gender, and financial literacy on the quality evaluation criteria. Only one mediation path was tested (AISQ → CSAT → CPQ); future studies could examine whether satisfaction mediates other antecedent–quality relationships as well. Future research could also usefully develop cross-GCC comparisons, test which features of AI (chatbots versus recommendation engines versus fraud detection) drive quality perceptions most strongly and start to advance an understanding of the quality implications of generative AI in financial services as this emergent technology grows in use.

VIII. Conclusion

The current study aimed to discover the factors that influence customer perceptions of the quality of AI-driven DFSPs in Saudi Arabia. The study developed a framework based on the Technology Acceptance Model (TAM), the DeLone and McLean IS Success Model, and trust theory. A model of seven constructs and their relationships was tested using structural equation modeling in AMOS, with data collected from 226 active users of digital financial service platforms. The results demonstrated that trust in AI and perceived usefulness are the strongest direct drivers of customer perceived quality. AI-driven service quality, while not directly significant, exerts a meaningful indirect effect through customer satisfaction, which partially mediates the AISQ–CPQ relationship. Perceived ease of use operates as an enabler of usefulness rather than as a direct quality driver. Perceived risk, although negative in direction, was not statistically significant, suggesting a degree of risk tolerance among Saudi DFSP users. These findings collectively underscore the importance of algorithmic transparency, tangible usefulness of AI features, and data protection in shaping customer quality perceptions.

In addition, the study contributed to the understanding of the digital finance ecosystem practices regarding DFSPs. Its findings are important in that they would enable platform builders to gain a better understanding of customers' perceptions of quality. Therefore, this study highlighted managerial implications for assisting executives in designing effective strategies for improving service quality and thus enhancing customer experience. This study has provided a strong foundation by opening the potential for a more in-depth analysis of this important area of academic research.

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