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From Intelligence to Trust: Evaluating AI-Powered Service Quality for User Satisfaction and Continuance in mHealth

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Abstract Mobile health (mHealth) applications are increasingly integrating artificial intelligence (AI), transforming digital health technologies by making them more convenient, accessible, and personalized. This research addresses the gap in understanding how AI functionalities influence user behavior, guiding the design of effective mHealth solutions. This study examines the correlation between AI-powered service quality, user satisfaction, and continuous usage, using the Sehhaty app in Saudi Arabia as a case study. We collected data via an online survey and analyzed it using Partial Least Squares Structural Equation Modeling (PLS-SEM) to test seven hypotheses. Results revealed that system quality significantly enhances both user satisfaction (β=0.462, $p < 0.05$) and continuous usage (β=0.344, $p < 0.05$). Interaction quality strongly influences user satisfaction (β=0.753, $p < 0.05$) but not continued usage (β=0.165, $p > 0.05$), while information quality negatively affects satisfaction (β=-0.324, $p < 0.05$) and does not directly impact continued usage (β=-0.216, $p > 0.05$). User satisfaction emerged as a crucial predictor of continued usage (β=0.587, $p < 0.05$). These findings emphasize the need for user-centric design in mHealth apps to enhance satisfaction and sustain long-term usage. For developers, healthcare organizations, and policymakers, this research underscores the importance of balancing system efficiency, interaction quality, and information relevance to maximize the potential of AI-powered mHealth solutions. Further research is needed to explore how these dimensions collectively shape long-term usage.

Keywords AI-powered mHealth, Artificial Intelligence, User Satisfaction, Continued Use, Service Quality, PLS-SEM Analysis

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1. Introduction

The mobile health (mHealth) industry is projected to reach $150 billion by 2028, underscoring the need for rigorous evaluation of mHealth app service quality [1]. Globally, governments and the healthcare industry recognize the transformative potential of artificial intelligence (AI) in enhancing digital healthcare. The landscape of digital healthcare, encompassing a broad range of technologies. While e-health generally refers to computer-based applications, mHealth encompasses portable devices, such as smartphones, tablets, and wearables, to deliver and improve healthcare services. Compared to e-health applications, mHealth apps incorporate more advanced features to enhance healthcare quality [2], [3].

mHealth apps serve diverse purposes, including disease diagnosis [4], drug references, medical calculators [5], [6], decision support [7], clinical communication [8], [9], medical education [10], hospital client applications [11], medical training [12], general healthcare applications, and applications for patients focusing on disease management for chronic illnesses [13], [14], [15]. These applications play a crucial role in delivering personalized and accessible healthcare

In Saudi Arabia, with a population exceeding 37 million and 83.7% residing in urban areas, mHealth has significant potential. With more than 54 million mobile phone subscriptions, the country presents a significant

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opportunity for the adoption of mHealth. Despite the proliferation of mHealth apps, their usage remains low, with many Saudi users engaging with these apps only briefly after downloading them [16], [17]. Research indicates that up to 80% of mHealth users access services fewer than twice, and 30% of mHealth apps are uninstalled within a month [18], [19]. Within the framework of Saudi Vision 2030, e-health has been identified as a pivotal sector for economic diversification, with a strong emphasis on expanding access to health information and delivering personalized services through digital platforms [20]. AI in healthcare aims to enhance patient experiences, deliver personalized care, support informed clinical decision-making, improving security and dependability without replacing medical personnel [21], [22].

The influence of mHealth apps services on user satisfaction and continued usage has been extensively studied in various developing countries, including Ghana [23], [24], South Africa [25], Indonesia [26], Bangladesh [27], [28], Pakistan [29], China [30], Iran [31], Korean Republic [32], and Brazil [33]. Research has also examined this topic in the broader context of developing nations [34], [35], [36] particularly within business-to-consumer (B2C) mHealth services [37], [38], and during the COVID-19 pandemic [39]. Despite the breadth of these studies, findings on factors influencing the sustained use of mHealth applications remain inconsistent [27]. This study seeks to address this gap by examining the impact of AI-powered mHealth service quality on user satisfaction and continued use. understanding the behavioral impact of AI-powered functionalities in mHealth can inform the design of more effective, user-centric applications. Such advancements not only have the potential to enhance mHealth adoption rates but also support broader national objectives by contributing to economic development and improving the overall quality of healthcare delivery.

This paper is structured as follows: the introduction outlines the research context, identifies research gaps, and defines objectives. The methodology describes the research design, establishes a theoretical framework, data collection, and analytical methods to ensure reproducibility. The results and discussion section presents the findings, links them to the research questions, and critically interprets them within the context of existing literature. Finally, the conclusion summarizes the study's contributions and suggests directions for future research.

2. Method

A structured methodology comprising two key phases was adopted: literature review, and empirical data collection and analysis.

2.1. Literature Review

A comprehensive literature search was conducted using PubMed, Scopus, IEEE Xplore, and Web of Science. Keywords such as mHealth,e-service quality,end user satisfaction,and continued usage were employed to identify relevant studies. The inclusion criteria were restricted to peer-reviewed articles published in English that examined the relationship between mHealth service quality, user satisfaction, and continued usage. This approach ensured the inclusion of high-quality studies addressing the core themes of the research.

To supplement the traditional database search, the AI-research tool Connected Papers was utilized to visualize the relationships among studies. Connected Papers employs co-citation similarity and bibliographic coupling to generate a force-directed graph, a visual map illustrating connections between studies. The studies by by Oppong et al. [23] and Akter et al. [40] were used as seed papers to generate two separate graphs for exploration. While Connected Papers highlighted study interconnections, the graphs lacked discernible patterns, clusters, or relationships between foundational and derivative works. Thus, they were excluded from further analysis. Nevertheless, the tool facilitated the identification of additional relevant papers, significantly expanding the body of literature reviewed.

While numerous frameworks and models assess healthcare service quality, few are specifically tailored to mHealth. A comprehensive review of relevant literature [23], [41], [42], [43], [44], [45], [46] identified overlapping dimensions across frameworks, though their focus varied by research objectives and target populations. Akter et al. [42] proposed a model for evaluating mHealth service quality based on marketing, information systems, and health management theories. Their model links service quality to customer satisfaction and loyalty. Oppong et al. [23]

tested Akter et al's model in rural Ghana, identifying three key dimensions: system quality, interaction quality, and information quality. Their analysis revealed that only interaction quality significantly influenced user satisfaction, which in turn positively affected continued usage. Similarly, Sharma and Sharma [47] investigated mHealth continuance among older adults in rural Bangladesh, analyzing data from 400 individuals with prior mHealth experience. Their findings revealed that system quality, performance expectancy, facilitating conditions, and social influence significantly influenced satisfaction and continued usage, whereas service level and information quality had minimal impact.

Considering another perspective, Alzaharani et al. [39] proposed a model based on established theoretical frameworks, identifying perceived ease of use, perceived usefulness, trust, and user satisfaction as key predictors of continuance intention. This highlights variability in determinants of mHealth satisfaction and continuance across populations and contexts. However, limitations such as small sample sizes and cultural/contextual biases were acknowledged [48], constraining the generalizability of their findings.

Existing literature identifies over 20 indicators of service quality in mHealth. The relative importance of core dimensions (e.g., information quality, interaction quality) varies contextually, influenced by demographic and geographic factors. Addressing these gaps requires the implementation of methodologies that account for geographic disparities (e.g., urban vs. rural access), cultural norms, and uneven technological infrastructure (e.g., internet reliability, device affordability) to design more effective mHealth interventions that encourage long-term usage. Building on this foundation, we propose evaluating the quality of AI-powered mHealth services using the three primary dimensions identified in [23], [42], each comprising three sub-dimensions and several measurement variables. This evaluation will involve 29 observational variables.

2.1.1. AI-powered mHealth services quality: The integration of AI in mHealth applications has redefined the conceptualization of service quality, offering insights into its impact on user satisfaction and continued usage. While Akter et al. [49] defined mHealth service quality as a user's assessment of a mHealth app's overall excellence, this study expands the definition to emphasize AI's role: In the user's overall evaluation of the service excellence, prioritizing AI-enabled effectiveness, personalized healthcare delivery, and decision-making capabilities. This refined definition captures the transformative influence of AI in improving service quality and decision-making

2.1.2. AI-powered system quality: System quality pertains to the technical aspects of a system, including reliability, efficiency, and privacy [49]. Chatterjee et al. [50] highlighted the importance of data processing capabilities and integration from diverse sources in enhancing system performance and user satisfaction. AI significantly elevates system quality by enabling real-time data processing, predictive analytics, autonomous problem-solving, and 24/7 monitoring. These features improve reliability, optimize workflows, and simplify complex processes through adaptive interfaces. In terms of privacy, AI technologies such as differential privacy and federated learning enhance user data protection, ensuring secure and resilient systems [51]. Consequently, system quality in AI-powered mHealth services can be defined as "the user's perception of the services enhanced performance, seamless real-time data integration, and robust privacy safeguards, facilitated by AI algorithms." This definition encapsulates the reliability, efficiency, and privacy improvements AI introduces to mHealth apps.

2.1.3. AI-powered interaction quality: Interaction quality reflects the communication dynamics between users, doctors, healthcare providers, and mHealth apps. Key components include cooperation (promptness and reliability), confidence (trust and safety), and personalized care [23], [49]. AI enhances interaction quality by facilitating tailored and proactive responses. For instance, chatbots and virtual assistants provide 24/7 personalized health advice and immediate support. Natural Language Processing (NLP) technologies improve user inputs and responses, making interactions more intuitive and satisfying. In AI-powered contexts, confidence extends to trust in algorithmic decision-making, supported by explainable AI (XAI). This ensures transparency and user confidence in the system. Thus, interaction quality can be defined as "the extent to which AI-powered mHealth services facilitate intuitive, personalized, and trustworthy communication, enhancing user satisfaction and engagement."

2.1.4. AI-powered information quality: Motamarri et al. [52], define information quality as the degree to which a service aids users in achieving specific tasks. Chae et al. [32] decompose it into connection, content, interaction, and contextual quality, while Akter et al. [49] highlight utilitarian and hedonic benefits. These perspectives, however, may not fully capture AI's strengths in delivering accurate, reliable, and timely information. AI enhances information quality by providing contextually relevant data tailored to user profiles, performing real-time updates, and detecting patterns in health data. These capabilities facilitate informed decision-making and improve user satisfaction. Accordingly, information quality in AI-powered mHealth services can be defined as "the degree to which the service provides accurate, timely, and contextually relevant information tailored to users' health goals."

2.1.5. AI in Healthcare: Trust and User Acceptance: The successful integration of AI into healthcare is contingent not only on technological efficacy but also on user trust and acceptance. Trust is defined as the belief that an AI application will perform as promised, and it has emerged as a critical predictor of technology adoption in medical settings. However, AI adoption in healthcare has been slower than in other industries, largely due to a lack of trust among both clinicians and patients. This reluctance is often attributed to the black-box nature of many AI models, where the decision-making process is difficult for users to understand [53]. This challenge has given rise to the field of Explainable AI (XAI), which aims to make AI systems more transparent and interpretable without sacrificing performance. By providing justifications for its outputs, XAI can help build user trust, an essential condition for acceptance in high-stakes medical contexts [54].

A related challenge is algorithmic aversion, a phenomenon where individuals show a biased preference for human judgment over algorithmic advice, even when the algorithm is demonstrably more accurate. This aversion is particularly pronounced in decisions with serious consequences, such as medical diagnoses[55] . Understanding these psychological barriers is crucial for interpreting user responses to AI-powered information and interaction quality in mHealth services.

2.2. Proposed conceptual framework and hypotheses

The conceptual framework presented in Figure 1 illustrates the relationships between AI-powered mHealth service quality, user satisfaction, and continued usage. The application of this framework is driven by the transformative capabilities of artificial intelligence. Unlike traditional digital systems, AI introduces distinctive affordances, such as autonomy, adaptivity and intelligent decision-making, that substantially enhance service delivery and user experience. However, these advancements also introduce challenges related to system opacity, often described as the black box problem, which may influence users trust and acceptance of algorithmic outputs. The framework posits that mHealth applications integrating AI functionalities foster higher user satisfaction, which subsequently drives continued usage. Accordingly, the following hypotheses are proposed.

H1: AI-powered system quality, characterized by predictive analytics, autonomous error detection, and adaptive real-time processing, positively influences user satisfaction with mHealth applications by enhancing reliability and performance stability.

H2: AI-powered system quality, through intelligent automation, continuous performance optimization, and secure real-time data handling, positively influences the continued utilization of mHealth applications by improving operational trust and user confidence.

H3: AI-driven interaction quality, facilitated by personalized conversational agents, virtual assistants, and context aware communication, positively influences user satisfaction with mHealth applications by fostering trustworthiness.

H4: AI-driven interaction quality, through adaptive personalization and proactive, behavior-sensitive support, positively influences the continued use of mHealth applications by sustaining user engagement and relational continuity.

H5: AI-enabled information quality, delivering explainable, contextually relevant, and clinically reliable insights, positively influences user satisfaction with mHealth applications by improving decision suppor.

H6: AI-enabled information quality, characterized by predictive accuracy, timely health recommendations, and explainable AI outputs, positively influences the continued use of mHealth applications by reinforcing perceived usefulness and confidence in AI-driven guidance.

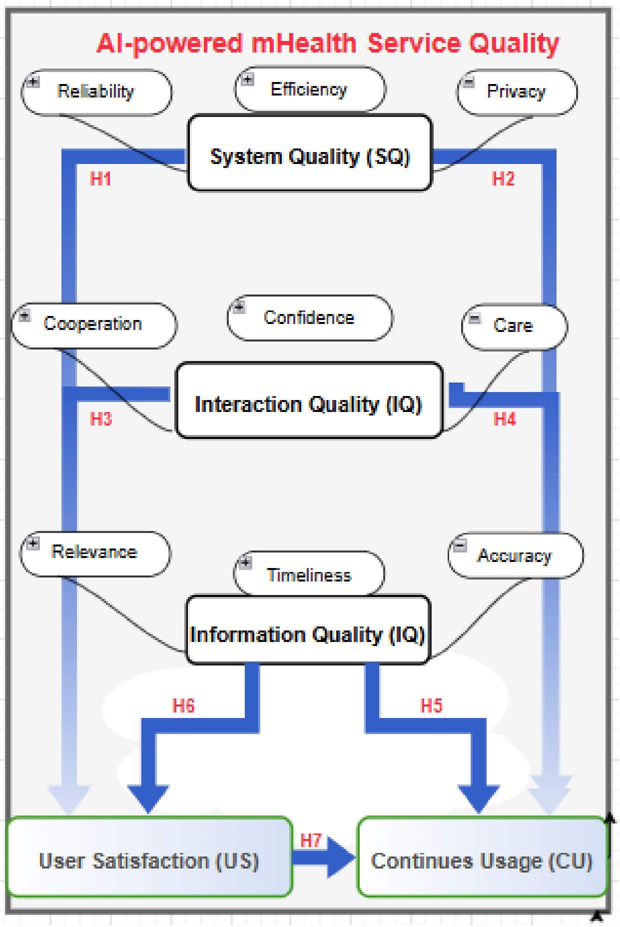

Figure 1. The Conceptual Framework. Source: Adopted from [23], [42]

H7: User satisfaction has a positive influence on mHealth applications' continued use.

2.3. Empirical Data Collection and Analysis

To empirically validate the proposed model, an online survey was administered to mHealth users in Riyadh, Saudi Arabia, focusing primarily on those familiar with the Sehhaty app. Developed by the Saudi Ministry of Health, Sehhaty integrates various health services into a unified platform for citizens and residents. According to the official website (https://www.seha.sa), the app has facilitated over 11 million online appointments and 31 million immediate consultations. Recent updates have incorporated AI-powered features such as intelligent virtual assistants, predictive analytics, personalized health recommendations, and real-time chatbot assistance. These functionalities aim to enhance accessibility, efficiency, and overall service quality, contributing to public health improvement.

Survey participants included undergraduate students and staff from Shaqra University, Inaya Medical Colleges, and Arab East Colleges. The questionnaire, validated in prior studies[23], [56], was adapted for the Saudi context using a rigorous forward-backward translation protocol to ensure linguistic and cultural validity. This process was reviewed by a multidisciplinary team, comprising experts in health management, data analysis, software engineering, and information systems, to confirm the instrument's conceptual equivalence, reliability, and validity. Furthermore, to ensure linguistic and cultural appropriateness, the instrument underwent a forward backward translation process by independent bilingual experts, followed by reconciliation and verification for conceptual equivalence. A total of 248 complete responses were collected. To ensure data quality, respondents who had never used the Sehhaty app were excluded through a screening question (Have you ever utilized the Sehhaty app?). Only participants who answered **YES** proceeded with the survey. The collected data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), a method chosen for its effectiveness in evaluating complex relationships between latent variables. PLS-SEM is particularly well-suited for exploratory research, such as technology adoption and service quality assessment [57], [58], [59].

2.3.1. Justification of the Measurement Instrument: A critical methodological decision in this study concerned the operationalization of the service quality constructs. Rather than developing a new scale, we adapted the well-established instruments of Oppong et al. and Akter et al. This approach aligns with established information systems research practices that emphasize theoretical continuity while allowing for the exploration of emerging technological contexts. The adoption of an existing, validated scale provided several methodological advantages, including leveraging the robust psychometric properties of the original instrument and ensuring that our findings remain comparable with, and contribute to, the broader body of literature on mHealth service quality.

Nevertheless, we recognize that an instrument originally developed in a pre-AI context may not fully capture the nuances of user perceptions shaped by AI-driven functionalities. To address this limitation, we employed a three-pronged strategy consistent with best practices in scale adaptation.

Conceptual Adaptation: As detailed in Sections 2.1.4, the constructs of System Quality, Interaction Quality, and Information Quality were conceptually refined to reflect AI-powered environments. For instance, System Quality was reframed around real-time data processing and predictive analytics,while Interaction Quality emphasized chatbots and virtual assistants.This theoretical reframing guided participants to interpret the measurement items through the lens of their AI-specific experiences.

Contextual Grounding: The empirical study was conducted with users of the Sehhaty app, a platform that prominently integrates AI-driven features such as virtual assistants and personalized health recommendations. This context provided a naturalistic environment in which participant's evaluations of service efficiency,care and relevance were intrinsically linked to the performance and reliability of these AI systems

3. Results and Discussion

This section presents and discusses the key findings, which highlight the complex connection between different dimensions of AI-powered mHealth service quality, user satisfaction, and continued usage within the Saudi Arabian context. The results underscore the importance of system quality in driving both satisfaction and sustained engagement, the critical role of interaction quality in fostering user satisfaction, and the potential negative impact of information quality on user satisfaction. These findings have significant implications for future mHealth service development and implementation.

3.1. Profile of the Respondents

Respondents were asked to indicate their gender, level of experience, and age (see Table 1). The majority were male (74%) and had over one year of experience using the app (87%). The age distribution showed an almost equal mix of young adults (18-36 years) and middle-aged participants (37-55 years).

An independent samples t-tests were performed to compare the mean scores for US based on gender, age, and experience level. The results of this analysis are presented in Table 2. The analysis revealed a statistically significant gender difference in user satisfaction, $t(98) = -2.39$, $p = 0.018$. Female users reported higher satisfaction ($M = 4.50$, $SD = 0.51$) than male users ($M = 4.14$, $SD = 0.70$). This suggests that female participants may perceive AI-driven mHealth features as more supportive, intuitive, or engaging, potentially due to differing health information-seeking behaviors or attitudes toward digital health technologies. These findings align with prior research [60], indicating that gender can moderate perceptions of usability and trust in health applications, where female users often exhibit higher engagement when the system offers personalized and empathetic interaction designs.

Table 1. Respondents' Background Information

Demographic variable		Percent
Gender	Male	74
	Female	26
Age	Yong	51
	Middle-aged	49
Experience	Less than one year	13
	More than one year	87

Table 2. T-Test Analysis of Demographic Groups

Group		N	Mean	SD	T	P
Gender	Male	74	4.14	0.704	-2.394	0.018
	Female	26	4.5	0.51		
Age	Young	51	4.32	0.618	1.317	0.191
	Old	49	4.14	0.726		
Experience	Less than one year	13	4.44	0.551	1.161	0.249
	More than one year	87	4.2	0.69		

In contrast, no significant differences were observed between younger (M = 4.32, SD = 0.62) and older (M = 4.14, SD = 0.73) participants, t(98) = 1.32, p = 0.191, nor between users with less than one year of mHealth experience (M = 4.44, SD = 0.55) and those with more than one year (M = 4.20, SD = 0.69), t(98) = 1.16, p = 0.249

These results indicate that age and usage experience did not significantly influence satisfaction, implying that once users adopt AI-powered mHealth tools, their satisfaction levels tend to converge regardless of age or experience level.

These findings highlight that gender plays a modest but statistically meaningful role in shaping user satisfaction, while age and experience exert limited influence. The results support the robustness of the proposed model by showing that key satisfaction determinants, such as system quality, interaction quality, and information quality, affect users consistently across demographic and experiential groups. Future studies employing larger, more balanced samples across Saudi regions could further validate these subgroup patterns and explore gender-related nuances in user trust and engagement with AI-driven mHealth systems.

3.2. Assessment of the Measurement Model (First Stage)

The study framework includes five reflective constructs: system quality (SQ), interaction quality (IQ), information quality (INQ), user satisfaction (US), and continued use (CU). System quality comprises three dimensions: reliability (SQR), efficiency (SQE), and privacy (SQP). Interaction quality includes cooperation (IQC), confidence (IQCO), and care (IQCA). Information quality encompasses relevance (INQR), accuracy (INQA), and timeliness (INQT). Using a two-stage approach [57], [61], As shown in Figure 2, the first stage evaluated the measurement model by assessing 11 first-order reflective constructs (CU, US, SQR, SQE, SQP, IQC, IQCO, IQCA, INQA, INQR, and INQT).

Reliability was confirmed as all item loadings exceeded 0.708 as shown Table 3 [59]. Internal consistency was established, with Cronbach's alpha (CA) and composite reliability (CR) values above the 0.7 threshold (see Table 3). Convergent validity was supported by average variance extracted (AVE) values exceeding 0.5[59]. Discriminant validity refers to the degree to which each construct is distinct and does not overlap with other constructs in the same structural model [59]. A model with strong discriminant validity is more reliable and interpretable and is more likely to generalizable to other populations and contexts. Discriminant validity, assessed using the Fornell-Larcker criterion, was achieved as each construct's diagonal AVE value was greater than its correlations with other constructs (Appendix 1) [58], [59]. These results confirm reliability, convergent validity, and discriminant validity in the first stage.

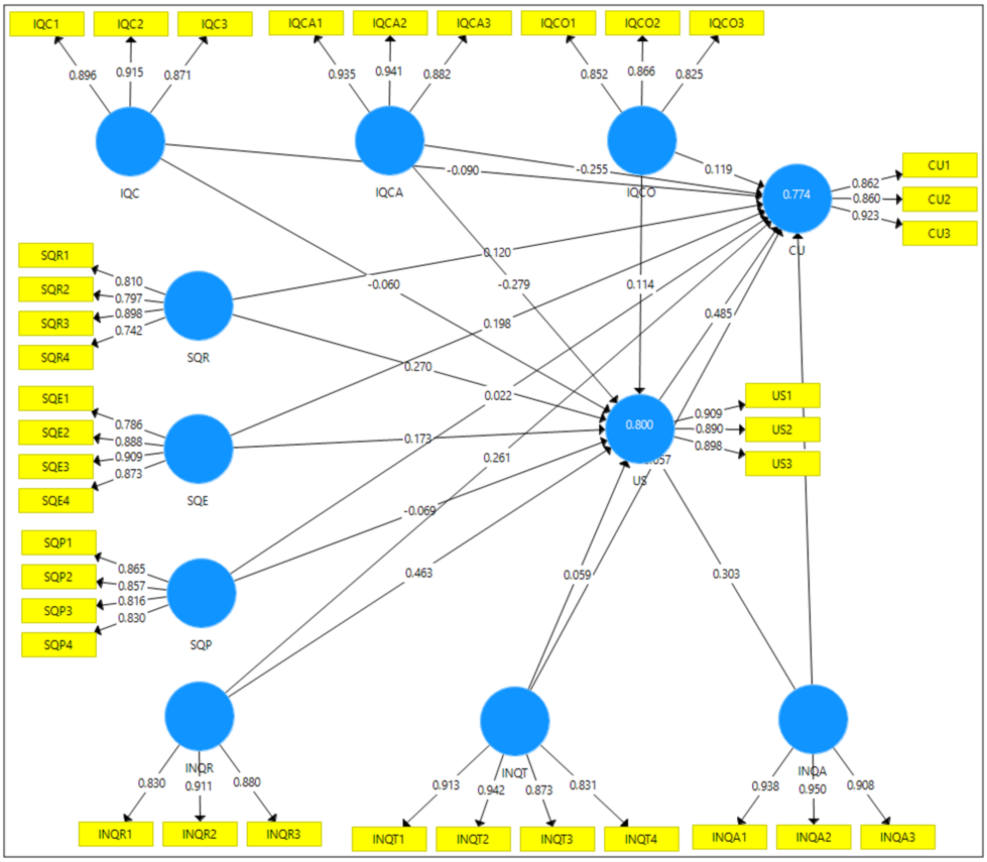

Figure 2. Measurement Model (Stage One)

3.3. *The measurement model of the second-order construct (Second Stage)*

In the second stage, second-order reflective constructs SQ, IQ, and INQ were developed based on their first-order dimensions. Specifically, SQR, SQE, and SQP formed SQ; IQC, IQCO, and IQCA formed IQ; and INQR, INQA, and INQT formed INQ. The finalized framework includes five constructs: CU, US, IQ, INQ, and SQ. The structural model was evaluated using several indices: coefficient of determination (R^2), path coefficients, redundancy index (Q^2), effect size (f^2), and Standardized Root Mean Square Residual (SRMR). As shown Figure 3, the R^2 values for CU (0.756) and US (0.762) exceeded the behavioral research standard of 0.2, indicating strong predictive power [59].

Table 4 and Figure 4 present the hypothesis testing results. AI-powered SQ positively and significantly affected US (β = 0.462, t = 4.037,$p < 0.05$) and CU(β = 0.344, t = 2.927, $p < 0.05$), supporting H1 and H2. This suggests that enhancing SQ in terms of reliability, efficiency, and privacy is vital for improving user satisfaction and sustaining engagement with mHealth technologies, aligning with prior studies [54].However, Some users may prefer traditional, human-centric support that prioritizes personal interaction over automated systems [17]. This could lead to a segment of users feeling dissatisfied, thereby questioning the overall effectiveness of AI in enhancing SQ.

AI-powered IQ demonstrated a significant positive effect on US (β= 0.753, t = 5.419, $p < 0.05$), supporting H3. However, its effect on CU was insignificant (β = 0.165, t = 0.900, $p > 0.05$), failing to support H4. These findings suggests that while high-quality interactions with AI features like chatbots and virtual assistants create a satisfying and positive immediate user experience, this satisfaction does not automatically translate into long-term engagement. This finding can be interpreted through two theoretical lenses. First is the concept of feature

Table 3. Convergent Validity Outputs of the First-Order Constructs

Construct	Item	Loading	CA	CR	AVE
CU	CU1	0.862	0.857	0.913	0.778
	CU2	0.86			
	CU3	0.923			
INQA	INQA1	0.938	0.924	0.952	0.869
	INQA2	0.95			
	INQA3	0.908			
INQR	INQR1	0.83	0.845	0.907	0.764
	INQR2	0.911			
	INQR3	0.88			
INQT	INQT1	0.913	0.912	0.939	0.793
	INQT2	0.942			
	INQT3	0.873			
	INQT4	0.831			
IQC	IQC1	0.896	0.876	0.923	0.799
	IQC2	0.915			
	IQC3	0.871			
IQCA	IQCA1	0.935	0.908	0.943	0.846
	IQCA2	0.941			
	IQCA3	0.882			
IQCO	IQCO1	0.852	0.806	0.885	0.719
	IQCO2	0.866			
	IQCO3	0.825			
SQE	SQE1	0.786	0.887	0.922	0.748
	SQE2	0.888			
	SQE3	0.909			
	SQE4	0.873			
SQP	SQP1	0.865	0.863	0.907	0.71
	SQP2	0.857			
	SQP3	0.816			
	SQP4	0.83			
SQR	SQR1	0.81	0.828	0.886	0.662
	SQR2	0.797			
	SQR3	0.898			
	SQR4	0.742			
US	US1	0.909	0.882	0.927	0.809
	US2	0.89			
	US3	0.898			

habituation, wherein the novelty and initial enjoyment of interactive AI features diminish over time as users become accustomed to them. While a responsive chatbot is satisfying initially, its appeal may wane if the app fails to deliver substantive health value. Second, and more fundamentally, this result aligns with Task-Technology Fit (TTF) theory, which argues that technology adoption is driven by the alignment between the technology's capabilities and the user's specific tasks. High interaction quality may provide a good fit for simple, transient tasks (e.g., checking a symptom), but continued usage is contingent on the technology fitting more complex, evolving health management needs. For sustained use, the technology must effectively support core health goals, a function more closely tied to system quality and tangible outcomes than to the pleasantness of the interaction alone. This

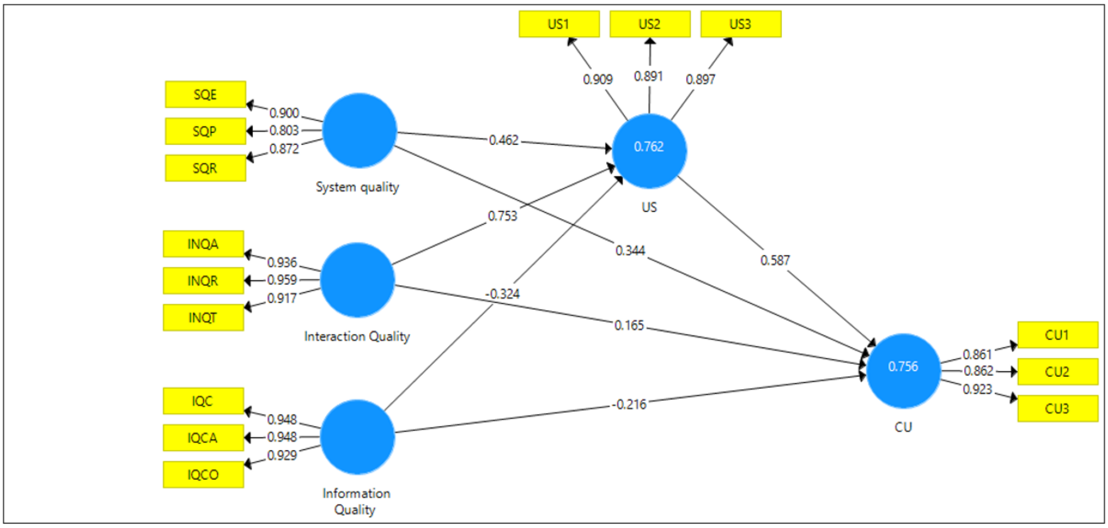

Figure 3. The measurement model of the second-order construct

Table 4. Results of PLS analysis

Path	Std. Bata	SE	t-value	P Values	f2	Supported
H1	System Quality – > US	0.462	0.113	4.073*	0	0.332
H2	System Quality – > CU	0.344	0.118	2.927*	0.002	0.135
H3	Interaction Quality – > US	0.753	0.139	5.419*	0	0.348
H4	Interaction Quality – > CU	0.165	0.184	0.9	0.184	0.012
H5	Information Quality – > US	-0.324	0.132	2.466*	0.007	0.073
H6	Information Quality – > CU	-0.216	0.194	1.109	0.134	0.029
H7	US – > CU	0.587	0.131	4.465*	0	0.336

results partially aligns with Akter et al. [49] and Oppong et al. [23], who reported varied impacts of interaction quality on satisfaction and usage.

Conversely, and counterintuitively, AI-powered INQ had a significant negative effect on US (β = -0.324, t = 2.466, $p < 0.05$), supporting H5, while its effect on CU was non-significant (β = -0.216, t = 1.109, $p > 0.05$). The negative impact on satisfaction moves beyond simple issues of inaccuracy and points to challenges unique to AI-generated health information. This information, while plentiful, may be perceived by users as overly technical, impersonal, and lacking the empathetic nuance of advice from a human healthcare provider, leading to frustration and dissatisfaction [19], [23]. This issue is compounded by the“AI Black-Box” problem, the inherent lack of transparency in how many AI models arrive at their conclusions. Without clear Explainable AI (XAI), users cannot scrutinize the AI's reasoning, which can erode trust and confidence in the information provided, regardless of its technical accuracy. This effect may have been amplified by our sample, which consists of a highly-educated population. Such users are likely to be more critical of information sources and may be less willing to trust algorithmic health advice without clear justification, thus leading to greater dissatisfaction when transparency is lacking.

US positively influenced CU (β = 0.587, t = 4.465, $p < 0.05$), supporting H7. This reinforces the critical role of user satisfaction in fostering long-term engagement with digital health services. The results not only corroborate previous studies [23], [30], [49], but also highlight the necessity for developers and providers of digital health services to prioritize user experience and satisfaction in order to foster long-term relationships with their users. Predictive relevance was confirmed (Q^2 = 0.591 for US; Q^2 = 0.571 for CU). Effect size analysis indicated that IQ (f^2 = 0.348) and SQ (f^2 = 0.332) had large effects on US, while US (f^2 = 0.336) significantly influenced CU

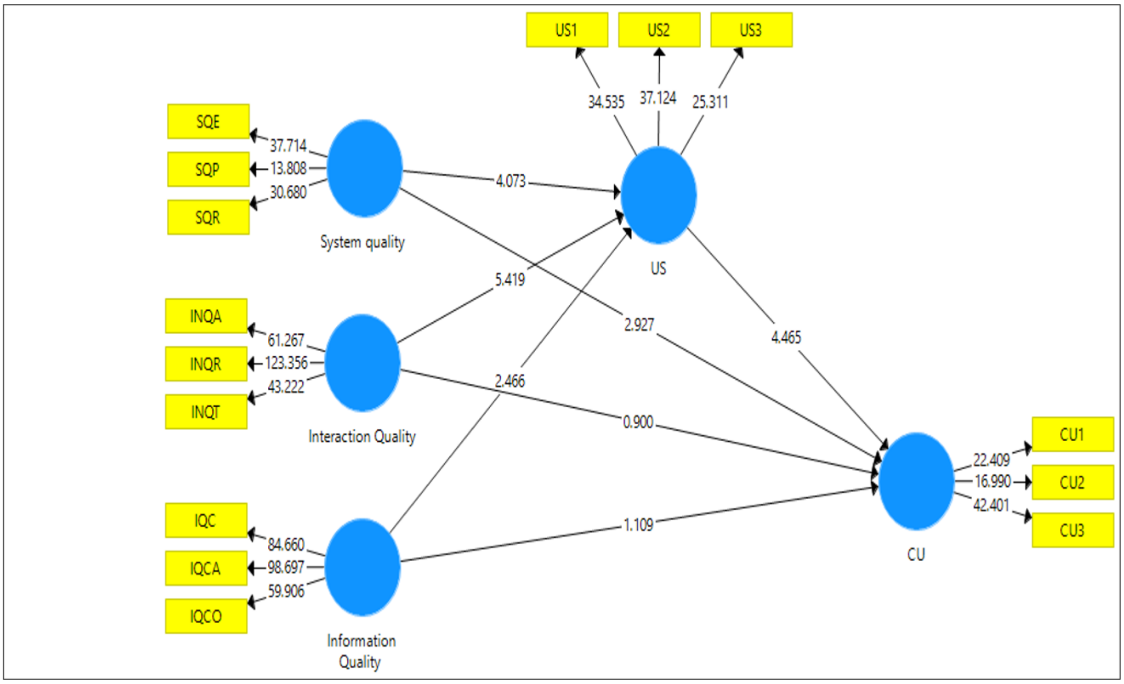

Figure 4. Structure Model for Hypothesis Testing Results

[62]. The SRMR value of 0.064, below the 0.08 threshold, validated the model's fit [63]. Second-order constructs demonstrated reliability and validity. As shown in Table 5, factor loadings exceeded the 0.7 minimum, while AVE values confirmed convergent validity for SQ (0.738), IQ (0.887), and INQ (0.879). CA and CR values above 0.7 further validated internal consistency. Discriminant validity, confirmed using the Fornell-Larcker criterion (see in table 7), indicated distinctiveness among constructs. These results provide robust evidence for the reliability and validity of second-order constructs

Table 5. Convergent Validity of the Second-Order Constructs

Variable	First-order constructs	Factor loadings	CA	CR	AVE
Continue use	CU1	0.861	0.857	0.913	0.778
	CU2	0.862			
	CU3	0.923			
Information quality	INQA	0.936	0.931	0.956	0.879
	INQR	0.959			
	INQT	0.917			
Interaction Quality	IQC	0.948	0.936	0.959	0.887
	IQCA	0.948			
	IQCO	0.929			
System quality	SQE	0.9	0.823	0.894	0.738
	SQP	0.803			
	SQR	0.872			
users satisfaction	US1	0.909	0.882	0.927	0.808
	US2	0.891			
	US3	0.897			

Table 6. Discriminant Validity (Fornell Larcker criterion) for First Order Constructs

Construct	CU	INQA	INQR	INQT	IQC	IQCA	IQCO	SQE	SQP	SQR	US
CU	0.882										
INQA	0.680	0.932									
INQR	0.742	0.857	0.870								
INQT	0.599	0.770	0.830	0.890							
IQC	0.606	0.796	0.860	0.879	0.890						
IQCA	0.524	0.825	0.830	0.810	0.870	0.920					
IQCO	0.596	0.782	0.730	0.750	0.800	0.820	0.848				
SQE	0.743	0.591	0.710	0.590	0.660	0.530	0.583	0.870			
SQP	0.560	0.702	0.660	0.640	0.700	0.670	0.720	0.610	0.842		
SQR	0.707	0.592	0.650	0.610	0.590	0.540	0.575	0.680	0.533	0.810	
US	0.848	0.77	0.830	0.710	0.700	0.640	0.664	0.740	0.589	0.750	0.899

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Table 7. Discriminant Validity (Fornell Larcker criterion) for Second-Order Constructs

	CU	INQ	IQ	SQ	US
Continue use	0.882				
Information Quality	0.613	0.942			
Interaction Quality	0.722	0.912	0.937		
System quality	0.787	0.757	0.788	0.859	
User satisfaction	0.848	0.712	0.821	0.810	0.899

4. Conclusion and Future Direction

This study examined the influence of AI-powered mHealth service quality on user satisfaction and continued usage, using Saudi Arabia's Sehhaty app as a case study. The findings offer several key implications for theory, practice, and policy, providing actionable insights for stakeholders in understanding of user behavior in AI-powered healthcare apps. Theoretically, this research contributes to and refines existing technology acceptance models by highlighting the unique complexities introduced by AI, suggesting that traditional service quality frameworks require adaptation for the AI era. The strong positive impact of System Quality on both satisfaction and continued usage (H1, H2) reinforces its foundational role in technology acceptance. However, the more nuanced findings for other dimensions suggest that user behavior in AI-driven contexts follows a more complex relationship. This result supports the integration of concepts such as feature habituation and theories like Task-Technology Fit (TTF), which posit that long-term use is driven by the technology's alignment with core user tasks rather than merely satisfying interactions. Furthermore, the negative influence of Information Quality on user satisfaction (H5) is a critical finding that underscores the need to incorporate constructs like trust and transparency into service quality models. This outcome can be explained by phenomena such as algorithmic aversion and the ”black box” problem, where users may distrust or feel overwhelmed by AI-generated information that lacks a clear explanation, thereby leading to dissatisfaction. To mitigate this, developers must prioritize Explainable AI (XAI) mechanisms that clarify the rationale behind AI-generated health recommendations to foster user confidence and mitigate cognitive overload.

From a practical perspectives, these findings offer a clear, prioritized roadmap for the developers and designers of AI-powered mHealth applications. The results show that a reliable, efficient, and secure system is the bedrock of both user satisfaction and retention; therefore, developers must prioritize a robust technical infrastructure, seamless performance, and transparent data privacy protocols. While AI-driven features such as chatbots and personalized assistants can significantly enhance the immediate user experience, they should be regarded as complementary enhancements rather than as the primary determinants of long-term use.

For policymakers, particularly the Saudi Ministry of Health and the Saudi Data and AI Authority (SDAIA), these findings provide evidence to support the development of targeted governance frameworks for AI in healthcare, aligning with the goals of Saudi Vision 2030 and the National Strategy for Data and AI (NSDAI). The results suggest a need to establish clear standards for AI transparency in mHealth, mandating that patient-facing applications explain the basis for their outputs in accessible language. To counter algorithmic aversion and build public confidence, policymakers could launch public awareness campaigns and develop a certification program for mHealth apps that meet national standards for AI safety and reliability. Finally, in line with Vision 2030's goal of improving healthcare value, policies should incentivize the development of AI applications that demonstrably improve patient outcomes, not just engagement metrics, ensuring that innovation remains focused on creating a healthier society.

In summary, this study confirms that while AI holds immense potential to transform mHealth, its success depends on a user-centric approach that balances technical performance with human factors like trust and the need for understanding. By optimizing system, interaction, and information quality in a holistic and transparent manner, developers and policymakers can unlock the full potential of AI to enhance health outcomes, user satisfaction, and long-term engagement.

4.1. Limitations of the Study and Future Research Directions

While this study provides important insights into the role of AI in mHealth service quality, several limitations should be considered when interpreting the findings. These limitations, in turn, highlight critical directions for future research.

Measurement Instrument: A key limitation, and a significant opportunity for future research, lies in the use of an adapted measurement scale. Although the instrument's psychometric properties were established for the present study, scales developed prior to the widespread integration of AI may not fully capture the range of user perceptions unique to AI-driven services. These services introduce novel dimensions of user experience, particularly in areas such as trust in algorithmic decision-making and concerns about data privacy associated with predictive analytics. Accordingly, future research should focus on developing and validating a dedicated AI-Perceived Service Quality (AI-PSQ) scale specifically for mHealth contexts. This instrument should extend beyond traditional dimensions to incorporate new constructs, such as:

- Algorithmic Transparency and Explainability: The extent to which users understand how AI systems generate recommendations or decisions. - Personalization Accuracy: The perceived precision and relevance of AI-driven health content and recommendations. - Interaction Naturalness: The intuitiveness and human-likeness of interactions with AI agents such as chatbots or virtual assistants. - Proactive Support: User perceptions of AI's ability to anticipate user needs and provide timely interventions. The development of a validated AI-PSQ scale would represent a major contribution to the health informatics field, enabling more nuanced and accurate measurement of AI's impact on user experience and service quality.

Sample Size and Generalizability: Another limitation concerns the relatively small and demographically narrow sample, which was drawn primarily from an urban, university-educated population in Riyadh. Consequently, the generalizability of the findings may be limited. User perceptions of AI in mHealth are likely to vary across levels of digital literacy, cultural backgrounds, and access to technology, particularly between rural and urban populations. Therefore, future research should employ larger, more diverse samples spanning different regions and socio-demographic groups to enhance external validity.

Focus on a Single mHealth Application: This study examined only the Sehhaty app, which constrains the scope of the findings. Relationships between service quality dimensions, user satisfaction, and continued usage may differ across various types of AI-powered mHealth applications, such as diagnostic tools, mental health chatbots, or fitness trackers. Thus, comparative studies encompassing multiple mHealth platforms are essential to develop a more comprehensive theoretical model of AI-powered service quality.

Potential Bias in Data Collection: Finally, the cross-sectional design and reliance on self-reported online survey data introduce the potential for common method bias. To mitigate this in future work, longitudinal designs could be employed to examine how user perceptions of AI-powered service quality evolve over time as technologies mature and user familiarity increases. Moreover, integrating mixed-method approaches, such as qualitative interviews or observational studies, would offer deeper contextual understanding of the user experience that quantitative measures alone cannot fully capture.

Addressing these limitations will allow future research to build upon the present study's findings and advance a more sophisticated understanding of how to design, evaluate, and optimize AI-driven mHealth services. Such efforts will ultimately contribute to more effective, user-centered, and equitable digital health interventions.

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