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Fostering Continued Use of Mobile Health Apps: An Integrated Socio-Technical and S-O-R Approach

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Abstract. This study applied socio-technical system theory and the stimulus-organism-response framework to examine factors influencing users' intentions to continuously use mobile health(mHealth) apps. An online survey of 288 mHealth app users in China assessed the impacts of technological qualities and social support on building trust and mitigating privacy risks, which shaped continued usage intentions. Partial least squares structural equation modeling was used to test the hypotheses. The results revealed that improved community quality and social support positively influenced trust and alleviated privacy concerns, promoting sustained app usage. This research provides valuable insights into designing mHealth apps to encourage long-term adoption.

Keywords: mHealth app, community quality, social support, trust, perceived privacy risk, continuous use intention.

1. Introduction

Advances in mobile devices provide new opportunities for managing and enhancing individual health. Based on the latest information available, the mobile health (mHealth) app market is experiencing considerable growth. In 2023, the global mHealth apps market size is projected to increase from USD 80.87 billion to USD 861.40 billion by 2030, exhibiting a compound annual growth rate of 40.2% during the forecast period (Fortune Business Insights, 2023). mHealth apps are gaining attention as tools that empower users to proactively manage and monitor their health in this evolving landscape. mHealth services are presented as healthcare services that elevate both the scope and quality of medical care, removing constraints such as location and time to provide healthcare services anywhere and anytime to everyone (Varshney, 2009). According to Estrin and Sim (2010), mHealth encompasses the combination of mobile computing, medical sensors, and medical services communication technology, including chronic disease management and healthcare. mHealth services use information, communication, and big data technologies to offer personalized medical and healthcare services, administer prescriptions, and promote health monitoring (Cha, 2021). mHealth includes smartphones, tablets, sensors for tracking biological signals and health activities, and healthcare apps that can be used in cloud-based computing systems for health data collection. Representative mHealth services such as Samsung Health, Apple Health, and Keep offer apps in this domain.

The swift progression of internet technology has precipitated transformative shifts in mHealth services, with mHealth apps emerging as a pivotal component (Vo et al., 2019). mHealth apps play a crucial role in transforming traditional healthcare services, offering users new avenues for health management through their distinctive features of user-friendliness, utility, and convenience (Liu et al., 2019). Relatively new technologies like mHealth apps have been primarily reviewed in recent literature from perspectives such as usability assessment, novel technology adoption, and healthcare policy support.

Previous research on mHealth apps focused predominantly on acceptance and usage intent. To examine the impacts of mHealth app content presentation on user acceptance, Liu et al. (2022) integrated perceived value and trust. They did this by using the stimulus-organism-response (S-O-R) theory, presenting the effects of mHealth app content presentation on user acceptance by integrating perceived value and trust. Slepchuk et al. (2022) explained how privacy issues and personal information knowledge influence trust and intent regarding health information technology use. While these studies emphasize usage intent, they fail to illustrate the factors influencing continuous use decisions. Some studies have conducted empirical research on the sustainable development of mHealth apps, specifically focusing on individual users' perspectives (Jiang et al., 2023; Zhang et al., 2022). To comprehensively understand people's adoption of new technology, it is essential to investigate the initial adoption and ongoing usage intent.

Despite the value of mHealth apps in healthcare management, their sustained use is limited. Continuous use of mHealth apps is crucial for long-term health management and improved healthcare outcomes. Peng et al. (2016) highlighted nine themes that influence the continued use of mHealth apps, including barriers to adoption, information and personalized guidance, tracking, credibility, goal setting, and sharing personal information. These themes underscore the multifaceted nature of user engagement with mHealth apps. Furthermore, psychological factors such as informational efficacy, instrumental efficacy, playfulness, and responsiveness influence the intention for continuous use of mHealth apps (Lee et al., 2017). This suggests that the psychological disposition of users plays a critical role in their ongoing engagement with these technologies. Issues related to user app attrition are emerging as key challenges. Hence, research on the continuous use of mHealth apps is needed. The objective of this study is to identify the key factors influencing the sustained use of mHealth apps, contributing to practical improvements in user experience and healthcare service quality. This research specifically focuses on understanding how socio-technical system theory and S-O-R theory can be applied to explain the ongoing engagement of users with mHealth apps. By integrating these theoretical frameworks, this study seeks to identify and analyze the social and technical factors that contribute to user trust, perceived privacy risk, and the sustained use of these applications. The ultimate goal is to provide actionable insights for developers and policymakers to enhance the effectiveness and user retention of mHealth apps.

Users may face issues such as perceived privacy risks and mistrust when using mHealth apps. App providers, marketers, and advertisers obtain permissions from mobile app users to access personal information for accurate targeting, customized customer service, and management. Consequently, users' concerns about privacy are growing, which can impact their continued use. Identifying the factors that influence the continuous usage intent of mHealth apps can provide meaningful insights into both consumers and businesses. Therefore, we have formulated the subsequent research questions (RQs):

RQ1: How do community quality and social support in mHealth apps influence the continuous use intention?

RQ2: In this relationship, how do cognitive trust, affective trust, and perceived privacy risk influence the continuous use intention?

2. Literature Review

2.1. Socio-Technical System Theory

The socio-technical system theory posits that social and technical elements are interconnected. Social factors pertain to the dynamics of interpersonal relationships among users, while technological factors are associated with technology (Bostrom & Heinen, 1977). This theory introduces the concept of a socio-technical system by combining four factors: structure and people for the social system, and technical and tasks for the technical system. These four variables do not exist independently: they interact with each other to impact the functioning of the entire work system. Technology can influence task execution methods, organizational structure, and communication methods. Therefore, when introducing technology, the interactions between these variables should be considered for a comprehensive assessment of its impact. Technical systems comprise of physical resources, production facilities, and technology, while social systems comprise psychological states of members, relationships between members, the technical system, and relationships between organizational members. Social systems focus more on the human perspective, whereas technical systems emphasize technological capabilities (Leonardi, 2013). Technological changes affect the overall work system, positively or negatively, ultimately influencing individuals and task integration. When technology is well-integrated into tasks, it increases the probability of positive outcomes such as increased usage and acceptance, whereas inadequate integration can lead to negative results (Holdsworth et al., 2022).

Many information system studies have delved into examining user behavior in various situations based on a socio-technical perspective. Research on socio-technical system theory has focused on areas such as social media, e-commerce, and online communities. Min (2013) focused on the four variables of the socio-technical system theory to differentiate the effectiveness of an educational information system based on social media, proposing how each variable would change owing to the adoption of social media technology. Zhang (2022) explored the influence of socio-technical determinants on trust in a live-streaming scenario and investigated how trust influences continuous use intention of users. Kapoor (2021) examined the social and technical dimensions of the platform ecosystem, elucidating the intricate interplay stemming from interactions among actors within the platform context.

Applying the socio-technical system theory to the context of mHealth, Holdsworth and Zaghloul (2022) explored the impact of AI on the healthcare sector in the UK. Zhou (2019) explained that both technological and social factors influence the propensity of users to engage in knowledge dissemination in online health communities. In a study conducted in Peru, Brunette and Curioso (2017) adapted a socio-technical approach to enhance the tuberculosis diagnosis process using mHealth. They highlighted the critical role of socio-cultural factors in strengthening integrated mHealth systems, thereby providing a comprehensive view of socio-technical dynamics in healthcare. From a mHealth perspective, the socio-technical system theory is an efficacious framework for explaining user behavior by applying it as a technological system. It can help analyze how social support and community dynamics impact user engagement with mHealth apps.

We endeavor to distinctly ascertain the crucial factors influencing the sustained use of mHealth apps, contributing to practical improvements in user experience and healthcare service quality. Social factors represent social support, reflecting interpersonal interaction between users. Technological factors derive community quality reflecting the technological characteristics of mHealth.

2.2. Trust–Risk Model

Trust and risk are crucial concepts widely discussed in understanding and explaining user behavior in online environments. These two concepts play key roles in various aspects of information system user behavior, decision-making, and information exchange. Understanding trust and risk contributes to better comprehension of interactions and communication in online environments. Numerous studies have employed the constructs of trust and risk to explain and predict individual attitudes and behavioral intentions. Studies that simultaneously employ both trust and risk concepts are also prevalent (Kim et al., 2005; Kim et al., 2013; Mansour et al., 2019).

Trust develops as a result of a combination of careful and rational thinking (cognition-based) along with emotions, instincts, and intuition (affection-based) (Lewis & Weigert, 1985). McAllister (1995) distinguished between cognitive and affective trust. Cognitive trust is based on competence or attributes, while affective trust is grounded in emotional relationships. Johnson and Grayson (2005) and Morrow (2004) also categorized trust into cognitive trust and affective trust. Cognitive trust originates from the thinking and analysis of consumers, reflecting knowledge-oriented tendencies and their willingness to rely on the subject's competence and reliability. Contrastingly, the perceived intensity of emotional relationships and a sense of security toward a certain subject underpin affective trust (Lee, 2020).

Risk was initially a major topic in economics, and Bauer (1960) initially established the concept of perceived risk in the realm of consumer behavior. Despite differing opinions among scholars regarding the definition of perceived risk, it can be summarized as the expectation of uncertainty about the outcomes of a choice and the anticipation of losses resulting from the consequences of the choice (Jang, 2005).

From a psychological standpoint, trust is described as a trustor's readiness to accept risks in uncertain conditions. (Mayer et al., 1995). This psychological perspective of trust, closely related to risk and risk-taking, is commonly addressed in many studies that explain user behavior.

Recent research in the domain of technology and health applications has increasingly focused on the application of trust-risk models. Khosrowjerdi (2016) provided a comprehensive review of theory-driven models of trust in online health contexts, discussing frameworks such as the technology acceptance model and the health belief model, which are pivotal in understanding user trust in health technologies. In the context of eHealth, Arfi et al. (2021) explore the trust-risk relationship in IoT adoption, demonstrating the critical role of trust in users' intention to use Internet of Things (IoT) for eHealth, while noting that performance expectancy does not impact this intention. These studies collectively contribute to a nuanced understanding of the dynamics of trust and risk in the context of health technology, highlighting the need for further exploration in this area.

2.3. S-O-R Theory

S-O-R theory is a classical paradigm that explains how external stimuli interact with the internal state of an individual, leading to subsequent behavioral responses. This theory emphasizes that the external environment triggers individual stimuli. In accordance with S-O-R theory, human responses in a physical environment are generated through a three-stage process (Mehrabian & Russell, 1974): through various external factors (stimuli), individuals undergo changes in their internal psychological activities (organism) based on their judgments, resulting in corresponding behavioral changes (response).

S-O-R theory is an environmental psychology theory. It explains how the environment influences human behavior. Currently, research within this paradigm explores the association between technology and behavioral intention. It is commonly used in information system research to investigate user behavior. Hewei and Youngsook (2022) investigated the elements that influence the intention to continue purchasing fashion products through e-commerce. Kamboj et al. (2018) examined user motivations to participate in social networks and brand communities, trust, and brand loyalty. Song et al. (2021) probed into the responses of information avoidance exhibited by Chinese consumers during the COVID-19 pandemic. Liu et al. (2022), grounded in S-O-R theory, delved into the influence of content presentation within mHealth apps on users' adoption intentions. They presented practical strategies to improve mHealth app adoption and furnished invaluable insights for researchers, developers, service providers, and users striving to optimize the utilization of modern mobile medical services.

Drawing from existing research, S-O-R theory is applicable to explaining the internal psychological perceptions and behavioral responses of individuals to environmental stimuli in information systems. Based on previous studies, this study differentiates three stages: stimulus (community quality, social support), organism (trust, perceived privacy risk), and response (continuous use intention). Users can be influenced by environmental stimuli (e.g., community quality, social support) that affect their emotional and cognitive states. Additionally, two types of trust (cognitive and affective trust) and perceived privacy risk are integrated into the model as part of the organism. The aim is to investigate users' continuance intention.

3. Research Model and Hypotheses

3.1. Research Model and Second-Order Factors Setting

We aimed to explain the factors that influence the intention to continue using mHealth apps through the lenses of the socio-technical system and S-O-R theories. Figure 1 depicts the research model employed for analyzing the intention to continue using mHealth apps. The model incorporates the derived conceptual elements from the socio-technical system and S-O-R theories.

Community quality reflects users' perceptions of the community platform. It has three principal dimensions: system quality, information quality, and service quality, which are derived from the information system success model (DeLone & McLean, 2003).

Social support, as proposed by Cohen and Syme (1985), is categorized into emotional, informational, tangible, and evaluative support. Social support encompasses psychological stability leading users to feel cared for, loved, respected, and valued through information and actions (Yang et al., 2012). In mobile apps, engagement with fellow users to obtain social support encompasses both informational and emotional assistance (Zhang et al., 2018).

Trust decisions encompass both inferential and emotional dimensions, distinguishable as cognitive and emotional trust (McAllister, 1995). From a consumer service perspective, cognitive trust pertains to confidence and willingness regarding the capability and expertise of the service provider, while emotional trust refers to willingness and confidence bestowed upon the service provider based on emotional connections (Johnson, 2005). In the context of mHealth, cognitive trust can be conceptualized as trust derived from the capability and reliability of the mHealth app, while emotional trust can be conceptualized as users' willingness to use the app founded upon emotional connections (Johnson, 2005; Meng et al., 2021).

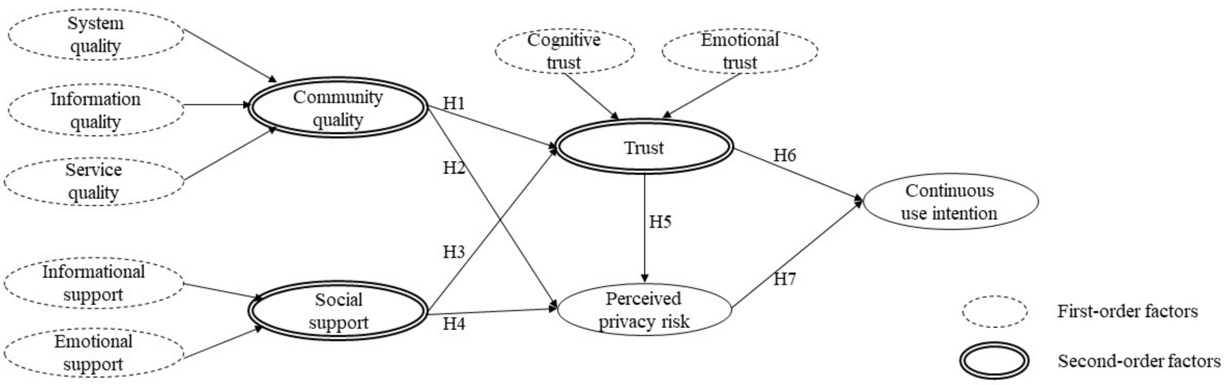

Fig. 1: Research Model

3.2. Hypothesis Development

3.2.1 Relationship between Community Quality and Trust, Perceived Privacy Risk

System quality reflects the evaluation of an information system from a performance perspective, considering factors such as usability, responsiveness, user interface, and system stability (DeLone & McLean, 1992). Users perceive system quality based on the functional performance of the environment offered by a system. In the absence of these functionalities, users may experience inconvenience, leading to a reduction in mobile app usage and raising suspicions about the system quality of the mobile app (Sharma et al., 2019). Conversely, a mobile app with high system quality can enhance user reliability.

Information quality is a crucial component in measuring the success of a system (DeLone & McLean, 2003). The platform's information should be personalized, complete, easy to understand, and well-formatted to individual users. Information quality encompasses community-specific characteristics, including relevance, sufficiency, accuracy, and timeliness (Urbach et al., 2010). If users discover that community information is outdated and inaccurate, or that it may jeopardize their health, trust is eroded.

Service quality has five key sub-dimensions: appearance of tangibility, responsiveness, empathy, assurance, and the ability of a service provider to consistently deliver dependable and promised services (Yang et al., 2017). Users commonly anticipate quick and dependable services from the community. Fulfilling these anticipations can build trust in the capabilities of the community. Conversely, delays in responses may erode trust in the mHealth application.

Prior studies posited that community quality positively influences trust, emphasizing the significance of system, information, and service quality within mHealth apps. High system quality contributes to user reliability, accurate and relevant information fosters trust, and dependable services enhance community capabilities. Therefore, the following hypothesis was formulated:

H1. Community quality positively influences trust.

Edward et al. (2017) examined how consumer perceptions of quality influence trust in location-based services and whether this affects users' perceived risk and their willingness to continue using the services. Ali (2020) explained the relationship between the stability of mobile apps and users' perceived privacy risk. Nonetheless, empirical research on the direct causal link between the quality of online communities and perceived privacy risk is still somewhat limited.

Maintaining high-quality information in datasets is crucial in protecting individual privacy (Fletcher et al., 2015). Andreas (2006) confirmed that perceived information quality influences perceived risk. Kim (2021) found that high-quality information in mobile apps exerts a positive influence on the awareness of privacy protection. Many scholars have researched the relationship between service quality and perceived privacy risk (Edward et al., 2017; Kim et al., 2021). Lee (2013) explored the relationship between e-service quality and privacy risk. Outdated or inaccurate community information may erode user trust, resulting in increased perceived privacy risks, therefore, we hypothesize the following:

H2. Community quality negatively influences perceived privacy risk.

3.2.2 Relationship between Social Support and Trust, Perceived Privacy Risk

Liang (2011) defined informational support as advice, suggestions, and recommendations that aid in problem-solving. When mHealth users face health issues, health apps remotely provide information through which users can check their health status, and gain insights into health risk assessment, illness prevention, diagnosis, and recommended treatments (Xiao et al., 2014). Users can also obtain past treatment histories and medical experiences from other patients with analogous health concerns (Zhang et al., 2018). As users gain more health-related information, their capacity to comprehend and ameliorate their health status is enhanced. Recognizing the value and utility of this information builds informational and emotional trust.

Emotional support refers to expressions of encouragement, empathy, and interest from other community members (Liang et al., 2011). In mHealth apps without geographical limitations, more people can partake in online social interactions and secure emotional support. This can reduce loneliness and depression, enhance stress-coping abilities, and provide encouragement to continue treatment (Zhang et al., 2018). Emotional support may not directly resolve individual health issues but can provide warmth to an individual's emotions (Deng et al., 2017). Wang (2019) found that emotional support had a significant impact on consumer trust in the case of WeChat users who were consuming health products. Informational support aids in problem-solving, and emotional support contributes to reduced loneliness and stress, fostering user trust; therefore, we propose the following hypothesis:

H3. Social support has a positive impact on trust.

In mobile communities, the interaction between users can provide not only effective information support from experts but also social support, including emotional support from other users. Nevertheless, owing to the dissemination of information and unlimited data access, concerns about personal privacy of users may increase (Zhu et al., 2021). According to existing research, perceived privacy risk can negatively impact the intentions of individuals to explore and share information (Dinev & Hart, 2005; Krasnova et al., 2010). Tseng et al. (2022) researched the negative impact of perceived privacy risk on social support. However, few studies focused on the impact of social support on perceived privacy risk, particularly in the context of mHealth communities. The potential escalation of privacy concerns arising from information dissemination in such communities prompted the formulation of the following hypothesis:

H4. Social support has a negative impact on perceived privacy risk.

3.2.3 Relationship among Trust, Perceived Privacy Risk, and Continuous Use Intention

When users interact within the mHealth community, concerns arise about the community inappropriately collecting and using information, encompassing both personal and health-related data, potentially escalating risk-related concerns and risk perceptions (Lin et al., 2017). To alleviate such risks and facilitate knowledge sharing within the community, trust in other members must be established (Zhou, 2019). Trust–risk models have been used in various studies to explain user behavior (Kim et al., 2005; Kim et al., 2013; Mansour et al., 2019). Therefore, this study hypothesizes that a higher level of trust, indicating a belief that privacy will be appropriately handled in the mHealth app community, will reduce the perceived risk of potential losses.

H5. Trust has a negative impact on perceived privacy risk.

User trust has a positive impact on behavioral intentions, such as continued use (Jiang et al., 2023; Zhang et al., 2022; Meng et al., 2021). Jiang (2023) investigated the unique roles of cognitive trust and emotional trust in mHealth apps, suggesting that each type of trust influences user behavioral intentions at different levels. Zhang et al. (2022) explained that informational trust in an application positively influences continuous use by recognizing the stability and quality of services provided by the platform.

Zhang et al. (2022) further argued that if patients trust a doctor in a remote healthcare service app, they may provide personal information for accurate diagnosis, and this emotional trust makes patients believe in the doctor's advice. Once a relationship is built between patients and doctors, patients' intention to continue using the application for future medical consultations with particular doctors increases (Yang et al., 2021). We propose the following:

H6. Trust has a positive impact on continuous use intention.

Perceived privacy risk refers to increased uncertainty due to loss of control over one's data (Milne et al., 2017). Health information privacy—control of acquisition, use, or disclosure of identifiable health data—is considered an individual's right (Cohn, 2006). Accurate health information and medical service provision are crucial functions of mHealth apps. When users register with the app, sensitive personal information such as sex, age, personal medical history, current health status, and family medical history should be adequately disclosed (Hsu, 2016). Users may worry about the handling of their sensitive information since mHealth technologies and services involve collecting and disclosing massive amounts of personal health information to platforms and medical professionals (Haley et al., 2021).

Ali (2020) explained that perceived privacy risk in mHealth apps can influence user behavior and attitudes. Other studies have also suggested that perceived privacy risk can have a negative impact on behavioral intentions in the continued use of technology, such as location-based services or mobile-payment apps (Edward et al., 2017; Mombeuil et al., 2021). Therefore, we hypothesize the following:

H7. Perceived privacy risk has a negative impact on continuous use intention.

4. Research Methods

4.1. Design and Procedure

This study derived social factors, represented by social support through socio-technical system theory, and technological factors, reflected in community quality as a representation of the technical characteristics of mHealth. Stimulus factors, including community quality, social support, organism factors like trust, perceived privacy risk, health consciousness, and response factors like continuous usage intention, were identified using S-O-R theory. The operational definitions and measurement items for the variables are provided in the Appendix. Each construct was measured using established scales from previous research, ensuring the robustness of our measurements. A pre-test was conducted to assess and validate the proposed research model, ensuring that the conceptualizations of this study are well reflected. Given the need for a large sample size and the desire to capture a broad spectrum of user experiences, an online survey targeting adult male and female users of mHealth apps in China was conducted and used to perform empirical analysis.

The survey was distributed to users with experience in using mHealth app platforms in China through WENJUANWANG (問卷網) —a widely used online survey platform—from July 19, 2023, to August 8, 2023. The questionnaire began with an explanation of the meaning of mHealth apps, accompanied by a screening question to filter participants without prior experience using such applications. Furthermore, each respondent's IP address was recorded, and the submission of two responses from the same address would result in the rejection of both. Of the 300 respondents, 12 were excluded owing to unreliable responses. The responses of 288 respondents were used as the final analysis sample. All responses were measured on a five-point Likert scale, based on previous studies. SPSS 26.0 was used for exploratory factor and basic data analyses. The validation of the research model and hypotheses was conducted through structural equation modeling (SEM), which facilitates accurate parameter estimation to assess the validity of hypotheses. Two primary calculation methods—maximum likelihood estimation method and partial least squares (PLS)—are commonly utilized in SEM. Given the ability of PLS to maximize the prediction of weights and factor loadings in hypothesized relationships, we opted for the PLS method for hypothesis testing in the SEM. SmartPLS 3.0 was employed as the analytical tool, allowing for a comprehensive analysis of the relationships between variables. The PLS-SEM approach was chosen owing to its suitability for handling complex models and small sample sizes.

Table 1 summarizes the demographic characteristics of the sample. Examination of the main characteristics of the sample reveals that 53.47% were male, and 46.53% were female. Respondents aged 21 to 40 constituted more than half of the sample. In terms of occupation, office workers were the highest at 37.5%, and the monthly average income of 6001 yuan to 10000 yuan was the most prevalent at 47.92%. In the questionnaire, respondents were specifically asked about their usage frequency of mHealth app platforms. The highest percentage was for once a week at 31.94%, while less than once a month was the lowest at 3.13%.

Table 1. Demographic characteristics

Demographic variable		Frequency	Percent
Gender	Male	154	53.47%
	Female	134	46.53%
Age	Under 20	30	10.42%
	21~30	102	35.42%
	31~40	115	39.93%
	Over 41	41	14.24%
Occupation	Student	30	10.42%
	Employee	108	37.50%
	Government official	100	34.72%
	Freelancer	37	12.85%
	Other	13	4.51%
Salary	Less than RMB 3000	30	10.42%
	RMB 3001~RMB 6000	88	30.56%
	RMB 6001~RMB 10000	138	47.92%
	More than RMB10001	32	11.11%
Frequency	Daily or more	65	22.57%
	1-3 times a week	76	26.39%
	Once a week	92	31.94%
	Once a month	46	15.97%
	Once every month or more	9	3.13%
Total		288	100%

4.2. Analysis

An empirical analysis was conducted following the two-step analysis method commonly used in SEM. Initially, a confirmatory factor analysis was performed to evaluate the basic reliability and validity of the measurement variables for the first-order measurement model. The results of the reliability analysis, presented in Table 2, indicate that the Cronbach's α values for the overall factors exceeded 0.7, confirming the internal consistency of the measurement variables constituting the conceptual constructs. The average variance extracted (AVE), which represents the proportion of variance explained by the measurement variables forming a single conceptual construct, all exceeded 0.5. Furthermore, the composite reliability (CR), representing the shared variance among latent factors, met the criterion of 0.7 or higher for all constructs, indicating satisfactory reliability (Nunnally et al., 1994).

Table 2. Reliability and convergent validity testing results

Variable		Item	Loading	t-value	α	AVE	CR
Community quality	System quality	SQ1	0.849	27.533	0.845	0.682	0.896
		SQ2	0.822	28.547			
		SQ3	0.809	26.926			
		SQ4	0.824	25.285			
	Information quality	IQ1	0.830	31.086	0.836	0.670	0.890
		IQ2	0.827	33.153			
		IQ3	0.792	24.263			
		IQ4	0.824	29.867			
	Service quality	SEQ1	0.818	31.491	0.835	0.669	0.890
		SEQ2	0.823	34.374			
		SEQ3	0.789	31.390			
		SEQ4	0.841	37.905			
Social support	Informational support	IS1	0.881	57.262	0.846	0.684	0.896
		IS2	0.824	30.393			
		IS3	0.818	30.615			
		IS4	0.783	21.566			
	Emotional support	ES1	0.821	23.376	0.823	0.653	0.882
		ES2	0.822	31.297			
		ES3	0.749	16.796			
		ES4	0.837	30.510			
Trust	Cognitive trust	CT1	0.824	34.089	0.841	0.678	0.894
		CT2	0.818	35.421			
		CT3	0.798	29.769			
		CT4	0.851	46.643			
	Emotional trust	AT1	0.840	28.426	0.895	0.705	0.923
		AT2	0.810	29.204			
		AT3	0.822	36.275			
		AT4	0.863	44.860			
		AT5	0.861	37.437			
Perceived privacy risk		PR1	0.839	35.087	0.841	0.676	0.893
		PR2	0.800	28.225			
		PR3	0.801	30.420			
		PR4	0.848	39.789			
Continuous use intention		CI1	0.845	39.587	0.873	0.724	0.913
		CI2	0.841	39.754			
		CI3	0.856	52.661			
		CI4	0.862	43.425			

Validity analysis distinguishes between convergent validity, which indicates how well the variables measuring each conceptual construct are concentrated on that construct; and discriminant validity, which indicates how different a specific construct is from other constructs. The standardized estimates of the measurement variables for each conceptual construct exceeded the criterion of 0.5, confirming convergent validity (Table 2).

Discriminant validity analysis compares the square root of the AVE with the correlation coefficients between different conceptual constructs (Fornell & Larcker, 1981). Discriminant validity is considered established when the square root of the AVE is greater than the correlation coefficients. The results are shown in Table 3.

Table 3. Discriminant validity testing results

	SQ	IQ	SEQ	IS	ES	CT	ET	PR	CU
SQ	**0.826**								
IQ	0.303	**0.818**							
SEQ	0.167	0.301	**0.818**						

IS	0.300	0.260	0.255	**0.827**					
ES	0.373	0.340	0.272	0.255	**0.808**				
CT	0.274	0.192	0.294	0.280	0.272	**0.823**			
ET	0.275	0.286	0.326	0.219	0.294	0.263	**0.839**		
PR	-0.218	-0.283	-0.288	-0.373	-0.241	-0.382	-0.196	**0.822**	
CU	0.486	0.426	0.383	0.413	0.432	0.450	0.514	-0.413	**0.851**

Following the analysis of the first-order measurement model, a validity analysis of the second-order measurement model, based on the latent variable scores obtained from the analysis of the first-order measurement model, was conducted. In this study, the second-order constructs were community quality (system, information, and service quality), social support (informational and emotional support), and trust (cognitive and emotional trust). Measurement variables were set as formative indicators.

To assess the validity of constructs with formative indicators, a multicollinearity analysis was conducted between the measurement variables. The results revealed the variance inflation factor values for community quality (system quality: 1.109, information quality: 1.185, service quality: 1.107), social support (informational support: 1.07, emotional support: 1.07), and trust (cognitive trust: 1.075, emotional trust: 1.075) were all below 5, meeting the acceptance criteria and suggesting the absence of multicollinearity between the measurement variables of the constructs (Hair et al., 2011). Hence, the validity of the second-order constructs with formative indicators was deemed satisfactory.

5. Results

A fit assessment of the structural model was conducted to test the research hypotheses. Fit assessment involves evaluating the fit of each conceptual construct and the overall fit of the model. The fit of each conceptual construct is evaluated based on the R^2 values indicating the explained variance of endogenous variables and the redundancy values, a statistical estimate of the structural model. A positive redundancy value and an R^2 value exceeding 0.26 are considered a “high” fit, between 0.13 and 0.26 a “moderate” fit, and below 0.13 a “low” fit (Cohen, 1988; Chin, 1998). In this study, the redundancy values for each conceptual construct were positive, and R^2 values for trust (0.277) and perceived privacy risk (0.41) were at a “high” level, while the intention to continue using had a “moderate” level with a value of 0.219.

The standardized root mean square residual (SRMR) and normed fit index (NFI) values were used to assess the overall fit of the research model. SRMR values less than 0.08 (Hu & Bentler, 1998) or NFI values above 0.9 (Bentler & Bonett, 1980) indicate good fit. With an SRMR value of 0.048 and an NFI value of 0.81, the findings suggest that the overall fit of the research model was generally acceptable. Having no issues in causal relationship analysis, significance testing for the causal relationships was conducted.

Bootstrapping with 500 iterations was performed to test the significance of the paths in the research model, providing t-values through repeated sampling. Table 4 illustrates the analytical results.

First, community quality had a positive impact on trust (t=6.962, p<.01), and community quality had a negative impact on perceived privacy risk (t=2.210, p<.05), supporting both Hypotheses 1 and 2. This finding aligns with prior research suggesting that positive user experiences within a community contribute to trust in technology (Lee & Hong, 2020), and emphasizing the role of community trust in mitigating privacy concerns in online environments (Kim & Kim, 2013). Second, social support positively influenced trust (t=3.567, p<.01), and social support negatively influenced perceived privacy risk (t=3.603, p<.01), supporting Hypotheses 3 and 4. This finding corroborates existing literature emphasizing the positive relationship between social support and user trust (Wang et al., 2019), and the role of social support in building user confidence in online platforms (Zhang et al., 2018). Third, trust negatively affected perceived privacy risk (t=2.926, p<.01), and trust positively influenced the intention to continue using (t=9.775, p<.01), while perceived privacy risk had a negative impact on the intention to continue using (t=4.482, p<.01), supporting Hypotheses 5, 6, and 7. The negative impact of trust on perceived privacy risk implies that as users' trust in the mHealth app increases, their concerns about privacy decrease. Furthermore, the positive influence of trust on the intention to continue using, alongside the negative impact of perceived privacy risk, emphasizes the pivotal role of trust in fostering sustained app usage, which aligns with prior research on technology adoption (Jiang et al., 2023).

Table 4. Analysis results of research model

Hypothesis	Path	Path coefficient	S.E.	t-value	p	Result
H1	Community quality -> Trust	0.371	0.053	6.962	0.000	Supported
H2	Community quality -> Perceived privacy risk	-0.159	0.072	2.210	0.014	Supported
H3	Social support -> Trust	0.226	0.063	3.567	0.000	Supported
H4	Social support -> Perceived privacy risk	-0.229	0.064	3.603	0.000	Supported
H5	Trust -> Perceived privacy risk	-0.191	0.065	2.926	0.002	Supported
H6	Trust -> Continuous use intention	0.525	0.054	9.775	0.000	Supported
H7	Perceived privacy risk -> Continuous use intention	-0.221	0.049	4.482	0.000	Supported

6. Discussion and Conclusion

Through a review of prior research on mHealth, this study identified community quality of mHealth apps—including system, information, service quality, and informational and emotional support—as determinants of mHealth user behavior. While prior research has pinpointed several factors of mHealth user behavior, including trust and perceived privacy risk, it has rarely delved into the internal decision-making processes related to users' continuous use intention. The examination of how external factors influence the internal decisions of users is still underexplored. Therefore, we empirically analyzed the impact of mHealth app community quality and social support on the continuous use intention among Chinese users based on the social-technical systems and S-O-R theories.

The implications of this study are as follows: First, both technological factors represented by community quality and social factors represented by social support influence users' trust and perceived privacy risk, ultimately determining users' continuous use intention. This contributes to a comprehensive understanding of users' sustained intention to use mHealth apps. Second, by applying a socio-technical perspective, we further examined the impact of social and technological factors on users' sustained intention to use mHealth apps, extending previous research that primarily focused on a single perspective. Finally, cognitive trust and affective trust both had a negative impact on perceived privacy risk, aligning with prior results (Jang, 2005; Kim et al., 2013). Additionally, cognitive trust and affective trust influenced users' continuous use intention, emphasizing the key role of cognitive and affective trust in promoting users' sustained usage within a broader context.

In summary, our study contributes considerably to the theoretical understanding of users' sustained intention to use mHealth apps. Specifically, our study aligns with socio-technical system theory by demonstrating the combined influence of technological factors (community quality) and social factors (social support) on users' trust and perceived privacy risk, which ultimately shapes their continuous use intention. Moreover, the application of the S-O-R framework provides a structured lens to interpret our results. The technological factors represented by community quality and the social factors (stimuli) represented by social support collectively influence users' trust and perceived privacy risk (organism). These factors contribute to users' continuous use intention (response). Our study thus extends the application of the S-O-R framework to the domain of mHealth, demonstrating its utility in understanding the intricate relationships between stimuli, organism, and response. This nuanced perspective adds depth to existing theories that predominantly focused on isolated factors.

From a practical perspective, community quality and social support are crucial for mHealth companies aiming to promote users' sustained usage. It is necessary to allocate resources to enhance community features, prioritize a user-friendly interface, provide reliable information, and promote seamless communication channels within mHealth apps. A well-designed and functional community is instrumental in fostering cognitive trust and creating a positive and trustworthy environment for users. Integrating features that enable social interactions among users, such as discussion forums, support groups, or live chats, is necessary to enhance social support within the mHealth community. Establishing a supportive atmosphere encourages users to share experiences, promoting affective trust and a sense of belonging. Providing personalized health information based on the health status and search history of users can enhance the relevance and usefulness of the provided information, as users perceive the information as more relevant and aligned with their specific needs. Furthermore, creating a supportive atmosphere in the community using incentive systems such as points can contribute to the development of affective trust by creating a positive emotional connection between users and the app. Additionally, mHealth companies should enforce robust security measures, including encryption protocols and strict privacy policies. Users should be provided with customizable privacy settings to empower them with control over their personal information.

This study has limitations that offer avenues for future research. First, this study was conducted in China, and generalizing the results to diverse cultures may not be appropriate. Future research should verify users' sustained intention to use mHealth apps in various countries and cultural contexts. Second, while the measurement items for the constructs used in this study primarily drew upon research outside China, there may be errors introduced during translation. Although some items were modified to align with the emotional characteristics of Chinese individuals, and a refinement stage for measurement items was conducted, the accuracy of the measurement items may still be compromised. Third, the age range of the respondents was 18 to 40. The findings may not comprehensively capture user behaviors across other age groups. Future research endeavors should involve expanding the participant pool and implementing a stratified sampling approach to ensure representation from diverse age cohorts. Additionally, employing experimental or mixed research methods could elucidate the impact of mHealth app content presentation on the continuous use intention of different user groups.

The findings suggest that fostering positive user perceptions of mHealth apps' community quality and social support systems helps build trust and mitigate privacy risks, which are key factors driving sustained usage intentions. The study makes important theoretical contributions through integration of socio-technical system theory and S-O-R models in understanding continuance intentions. From a practical standpoint, mHealth providers should focus efforts on improving app information quality, system stability, service responsiveness, and enabling user social connections that enhance emotional support. Ensuring robust privacy protections is also essential. This research provides a framework to guide strategies for supporting long-term mHealth app adoption.

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Appendix: Definitions and Measurement items

Construct	Definition	Measurement Item	Reference
System quality(SQ)	The degree of system quality that allows consumers to use the mHealth app without inconvenience.	The community is easy to use.	DeLone and McLean, 2011;Zhou et al., 2013
		The mHealth app responds quickly.	
		The community is easy to navigate.	
		The community is visually attractive.	
Information quality(IQ)	The usefulness of the information provided in the mHealth app.	The community provides me with information relevant to my needs.	DeLone and McLean, 2011;Zhou et al., 2013
		The community provides me with accurate information.	
		The community provides me with sufficient information.	
		The community provides me with up-to-date information.	
Service quality(SEQ)	The usefulness of the services provided in the mHealth app.	The community provides on-time services.	DeLone and McLean, 2011;Zhou et al., 2013
		The community provides prompt responses.	
		The community provides professional services.	
		The community provides personalized services.	
Informational support(IS)	Advice, suggestions, and recommendations that help solve problems.	It gives me advice when I really need it.	Cohen and Syme, 1985; Liang et al., 2011; Leung & Lee, 2005
		It provides helpful advice when I face health issues.	
		It offers information to help me understand the situation.	
		It suggests solutions to resolve the problem.	
Emotional support(ES)	Encouragement, empathy, and interest expressed by other members.	When facing health issues, others make me feel comfortable.	Cohen and Syme, 1985; Liang et al., 2011; Leun & Lee, 2005
		When faced with health difficulties, some people in the community expressed interest and concern in my well-being.	
		When faced with health difficulties, some people in the community comforted and encouraged me.	
		When faced with health difficulties, some people in the community listened to me talk about my private feelings.	
Cognitive trust(CT)	User trust based on the capabilities and reliability of the mHealth app.	I can trust the mHealth app.	Mayer et al., 1995; McAllister,1995
		I follow what the mHealth app claims to be right.	
		The mHealth app I use approaches users with professionalism and dedication.	
		There is no reason to doubt the performance of the mHealth app I use.	
Emotional trust(ET)	User willingness to use the app based on emotional connection.	I have positive feelings towards the mHealth app.	Mayer et al., 1995; McAllister,1995; Johnson & Grayson(2005)
		The mHealth app I use is eager to hear about users' issues.	
		Sharing problems with the mHealth app results in sufficient responsiveness.	
		The mHealth app treats users diligently.	
		The mHealth app responds attentively to my issues.	
Perceived privacy risk(PR)	Perceived risk due to loss of control over the personal information	Providing personal information to a mHealth app involves many uncertainties.	Javenpaa et al., 2000; Pavlou & Gefen, 2004
		Providing personal information to a mHealth app can result in potential losses for me.	
		Sharing personal information with a mHealth app comes with inherent risks.	

	provided by internet users.	Providing personal information to a mHealth app may lead to unforeseen issues.	
Continuous use intention(CU)	Intentions to continue using the mHealth app.	I will continue to use mHealth apps.	Bhattacherje e, 2001; Roca et al., 2006
		I will continue to obtain health information through mHealth apps.	
		I will use the collected health information positively.	
		I will tell others about the good aspects of the mHealth apps.	