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INVESTIGATING FACTORS AFFECTING THE INTENTION TO USE MOBILE HEALTH FROM A HOLISTIC PERSPECTIVE: THE CASE OF SMALL CITIES IN CHINA

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ABSTRACT

Aim/Purpose	This study aims to develop a comprehensive conceptual framework that incorporates personal characteristics, social context, and technological features as significant factors that influence the intention of small-city users in China to use mobile health.
Background	Mobile health has become an integral part of China's health management system innovation, the transformation of the health service model, and a necessary government measure for promoting health service parity. However, mobile health has not yet been widely adopted in small cities in China.
Methodology	The study utilized a quantitative approach whereby web-based questionnaires were used to collect data from 319 potential users in China using China's health management system. The data was analyzed using the PLS-SEM (the partial least squares-structural equation modeling) approach.
Contribution	This study integrates the protection motivation theory (PMT), which compensates for the limitations of the unified theory of acceptance and use of technology theory (UTAUT) and is a re-examination of PMT and UTAUT in a small city context in China.
Findings	The findings indicate that attitude and perceived vulnerability in the personal characteristic factors, social influence and facilitating conditions in the social

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context factors, and performance expectancy in the technological feature factors influence users' intention to use mobile health in small cities in China.

Recommendations for Practitioners: This study provides feasible recommendations for mobile health service providers, medical institutions, and government agencies based on the empirical results.

Recommendations for Researchers: As for health behavior, researchers should fully explain the intention of mobile health use in terms of holism and health behavior theory.

Impact on Society: This study aims to increase users' intention to use mobile health in small cities in China and to maximize the social value of mobile health.

Future Research: Future research should concentrate on the actual usage behavior of users and simultaneously conduct a series of longitudinal studies, including studies on continued usage behavior, abandonment behavior, and abandoned-and-used behavior.

Keywords: mobile health, small cities, PMT, UTAUT, personal characteristics

INTRODUCTION

The profound aging of Chinese society and the yearly increase in chronic disease patients have intensified the public's demand for healthcare. The contradiction between the rising demand for healthcare and the scarcity and irregular distribution of healthcare resources has become a significant obstacle to China's healthcare system's development (Zhang et al., 2022). China has developed a graded diagnosis and treatment system (GDTS) based on community-first diagnosis, two-way referral, acute and chronic disease treatment, and upward and downward linkage, which has alleviated this contradiction over the past few decades (Xiao et al., 2022). However, China has 22% of the world's population but less than 2% of its medical resources, and 80% of China's medical resources are concentrated in cities, particularly large or developed cities (Tian & Wu, 2022). Consequently, China still confronts a shortage of medical services and a disparity between the supply and demand of medical resources in various provinces and cities (Ye et al., 2019), and rationalizing medical resource allocation and enhancing health equity have risen to the top of China's health sector's agenda (Zhang et al., 2022).

In the rapidly evolving world of innovation and technology, the combination of new technologies and healthcare, such as mobile health (mHealth), is anticipated to overcome the limitations of traditional healthcare, reduce the structural imbalance of healthcare resources, and promote the efficient use of healthcare resources (Karahanna et al., 1999; Tian & Wu, 2022; Zhu et al., 2023). Mobile health provides instant access to medical resources, instant transmission of clinical data, and instant communication between physicians and patients, as compared to conventional medical services. It can also improve the operational efficiency of the medical system, optimize the allocation of medical resources, improve the doctor-patient relationship, increase patient satisfaction, and enable the interaction of medical information at any time and location (Ren et al., 2021).

Despite widespread recognition of the superiority of mobile health as an innovative model for medical services in China, mobile health is not widely used, especially in small cities with limited medical resources (Dai et al., 2020; Nie & Zhang, 2021; Ning, 2020; Z. Zhao et al., 2020). The small cities in this study are defined as the 4th and 5th tier cities in the China City Business Attractiveness Rankings published by the China New First-Tier Cities Institute in 2021 (China Business News, 2021). The China New Tier One Cities Institute utilized the previous year's five indicators of business resource concentration, city hubs, city people activeness, lifestyle diversification, and future possibilities, invited the New Tier One Cities Institute expert committee to assign weights to the five indicators, and scored them by experts. The expert committee of the New Tier 1 City Institute was invited to assign weights to the five indicators, which were scored by experts and included in the scoring system. The data below the second-tier indicators were analyzed using the principal component analysis method and objectively assigned weights to make this list, which re-graded 338 Chinese cities and rated 4 first-tier cities, 15 "new first-tier" cities, 30 second-tier cities, 70 third-tier cities, 90 fourth-tier cities and 129 fifth-tier cities. According to BigData-Research, in the regional distribution of users in China's mobile health market in the first quarter of 2021, first-tier cities accounted for 29.5%; new first-tier cities accounted for the highest percentage at 38.6%, and second-tier cities accounted for 19.7%. However, third-tier cities accounted for 8.4%, and fourth-tier cities and below accounted for only 3.8%. Meanwhile, in the distribution of specific cities, big cities occupy the top 10 cities in the distribution of mobile health users, such as Beijing, Shanghai, Guangzhou, and Chengdu (BigData-Research, 2021). Most medical resources and high-quality providers in China are located in big city centers (Hsu et al., 2016). The development of mobile health applications is also highly skewed toward the centers of large cities and medical interventions for various diseases are conducted in these large cities, resulting in an imbalance between large and small cities in the deployment of medical resources and mobile health interventions (Zhou et al., 2016). In small cities with limited medical resources and a high population density, it is anticipated that mobile health will achieve greater social value by capitalizing on its advantageous characteristics. In contrast, the reality is the opposite. Therefore, it is socially significant to examine the factors that influence the widespread adoption of mobile health in small cities in China.

Furthermore, the utility or social value generated by mobile health is contingent on public acceptance, and user acceptance behavior is a prerequisite for realizing mobile health's numerous benefits (Bhattacherjee & Sanford, 2006). In recent years, researchers have become increasingly interested in mobile health acceptance behavior research. A systematic review of the literature reveals, however, that the discussion of factors influencing the intention of mobile health acceptance behavior is insufficiently comprehensive and lacks a comprehensive research framework (W. Liu et al., 2005). The discipline of mobile health emerged at the intersection of management information systems and health care, multiple sources influence the acceptance behavior of mobile health (Ren et al., 2021). People, technology, and organization are three elements that form a relationship between "people" and "technology," and the impact of mobile health will only become stronger if there is a good match between people, technology, and organization (Yusof et al., 2008). However, the majority of previous research has tended to disregard the interaction and interdependence between human characteristics, technological features, and social contexts, which has frequently resulted in weak implications for the application of medicine in practice (Cimperman et al., 2016). To explain this effect, a holistic approach is required, where "holistic" refers to a focus on the importance of the approach as a whole and the interdependencies between its parts, avoiding distinct analysis of only parts or the absence of a particular part of the approach.

Based on the preceding discussion, this study integrates technology acceptance theory and health behavior theory to develop a comprehensive extended theoretical model that includes mobile health technology features factors, individual characteristics factors, and the social context factors of small cities in China. From the perspective of holistic and health behavior theories, it explains the factors influencing users' intent to use mobile health in small cities in China.

LITERATURE REVIEW

MOBILE HEALTH

The WHO defines mobile health as supporting healthcare and public health via mobile devices such as cell phones, patient monitoring devices, PDAs, and other wireless devices (Kay et al., 2011). The Healthcare Information and Management Systems Society (HIMSS) defines mobile health as applications that deliver healthcare services and medical information using mobile communication technologies such as patient monitoring devices, personal digital devices, cell phones, and satellite communications (Y. Zhao et al., 2018). The National Health Care Commission of China has broadened the definition of mobile health to cover the entire process of utilizing mobile technology to comprehensively monitor, analyze, and evaluate the health status of an individual or group, as well as to provide health counseling, guidance, and intervention on health risk factors. This process consists of essential diagnosis and rehabilitation functions, in addition to health management functions such as psychological counseling, dietary advice, exercise guidance, medication guidance, and self-monitoring. The future of mobile health services may consist of a synergistic and integrated precision medical system established by the interaction of physicians, patients, patient families, and society at all levels (Y. Yang et al., 2015). Accessibility, personalization, timeliness, positioning function, interactivity, and mobility are advantageous features that distinguish mobile health from traditional health services (Varshney, 2005). Due to these advantageous characteristics, mobile health is playing an increasingly essential role in healthcare services.

Mobile health has been demonstrated to provide adequate services for numerous diseases and health interventions, including mental illness (Becker, 2016), psychiatric disorders (Li et al., 2020), prenatal care (Haddad et al., 2019), eye diseases (T. Chen et al., 2018), HIV (Han et al., 2021), various chronic diseases (Breil et al., 2019; Y. Guo et al., 2020; Mao et al., 2020; Yan et al., 2021), health monitoring (Haddad et al., 2019), and promoting positive changes in patient health behaviors (Free et al., 2013). Its value in responding to significant public health emergencies, such as novel coronaviruses, has also been progressively demonstrated (Singh et al., 2020; Torous & Keshavan, 2020). Mobile health has been recognized by the WHO as an effective way to manage health (Vital Wave Consulting, 2009). It has become an important factor in the innovation of health management systems and the transformation of medical service models, as well as a necessary measure for the government to promote the equalization of medical services (X. Yang & Feng, 2016). China's mobile health infrastructure was initiated in 2000, after the emergence, cold period, and accelerated development period, more than a thousand companies in China are involved in the mobile health industry, with more than 13,000 patents and more than 2,000 mobile health APPs (BigData-Research, 2021). Its service varieties can be divided into four main categories: (1) online diagnosis and treatment, which involves establishing an interactive platform between users and physicians for remote online medical consultation services for users; (2) health management, which is the provision of health consultation, daily health management, health exams, and chronic disease management services to users; (3) pharmaceutical services, including B2C or B2B pharmaceutical sales and purchase services and pharmaceutical purchasing guide services for end-users; and (4) medical information services, primarily for doctors or other medical professionals, to provide various categories of medical information or to aid in the management of patient information and other services to increase efficiency (McCurdie et al., 2012; Wilhide et al., 2016; Zhu et al., 2023).

A Review of Research on the Intention to Use Mobile Health

The study of mobile health adoption and acceptance behavior focuses on mobile health as an innovative technology, uses the technology acceptance model as a theoretical framework, and employs incentive models to evaluate individuals' propensity to adopt. According to existing research, the UTAUT model has greater explanatory power in predicting user adoption of the technology (Wang et al., 2021). The UTAUT model is the most popular technology acceptance theory due to its comprehensiveness, explanatory capacity, and predictive ability (Ben Arfi, Ben Nasr, Kondrateva & Hikkerova, 2021). The model is simple in structure, provides a clear link between building factors and customer-driven behavior intention (BI), and models tested in healthcare settings can explain up to 70% of the variance in intent (Duarte & Pinho, 2019; Venkatesh et al., 2003) and approximately 50% of the actual usage variance (Alam, Hu, et al., 2020; Cimperman et al., 2016; Venkatesh et al., 2012). The UTAUT model is extensively utilized to predict and explain the adoption intentions of various technologies, including healthcare. Previous researchers have demonstrated its applicability in health care (Hsieh et al., 2016; Kijsanayotin et al., 2009). Based on the benefits of the UTAUT model, this study considers employing this model to investigate mobile health adoption intent.

Four core independent variables comprise the UTAUT model: effort expectancy, performance expectancy, social influence, and facilitation conditions. The first three variables influence user behavior indirectly through behavior intention, while the facilitation conditions directly influence user behavior (Venkatesh et al., 2012). In previous studies on the acceptance and use of IT in the medical and health fields, these four fundamental independent variables were identified as indispensable and crucial (Alam et al., 2018; Dwivedi et al., 2016; Gao et al., 2015; Patil et al., 2020; Semiz & Semiz, 2021). Nonetheless, the significant effects of the four core variables varied between countries and the study's target population. Table 1 demonstrates the impact of the four core variables on the intention to use mobile health in prior studies.

Table 1. Effects of four core variables from prior studies on intention to use mobile health

Variables	Significant effect	Non-significant effect
Performance Expectancy	Ben Arfi, Ben Nasr, Khvatova, and Ben Zaied (2021); Chang et al. (2021); Cimperman et al. (2016); Dwivedi et al. (2019); Dwivedi et al. (2016); Ramdani et al. (2020); Semiz and Semiz (2021)	Boontarig et al. (2012); Gu et al. (2021)
Effort Expectancy	Ben Arfi, Ben Nasr, Khvatova, and Ben Zaied (2021); Bawack and Jean (2018); Cimperman et al. (2016); Dwivedi et al. (2016); Gu et al. (2021); Semiz and Semiz (2021); Wang et al. (2021)	Chang et al. (2021); Ramdani et al. (2020)
Social Influences	Ben Arfi, Ben Nasr, Khvatova and Ben Zaied (2021); Bawack and Jean (2018); Dwivedi et al. (2016); Gu et al. (2021); Hoque and Sorwar (2017); Ramdani et al. (2020); Semiz and Semiz (2021)	Chang et al. (2021); Cimperman et al. (2016); Wang et al. (2021)
Facilitating Conditions	Bawack and Jean (2018); Chang et al. (2021); Cimperman et al. (2016); Dwivedi et al. (2016); Gu et al. (2021); Semiz and Semiz (2021)	Ben Arfi, Ben Nasr, Khvatova and Ben Zaied (2021); Hoque and Sorwar (2017)

Venkatesh et al. (2012) suggested that, in order to increase the applicability and comprehensive explanatory power of the original UTAUT model, it is frequently necessary to expand other relevant factors to meet the specific requirements of various applications, technologies, and countries. Additionally, they concluded that later scholars' expansion and incorporation of the UTAUT model could be categorized into three groups: (1) to test the UTAUT model in a new context, researchers select a new IT background, a new specific user background, and a new cultural background; (2) add new constructs to expand the theoretical mechanism of the UTAUT model; and (3) adding exogenous predictors for the original UTAUT variables. Additionally, after reviewing the literature, this study determined that the majority of expansion's influencing factors were the expansion of group (2), adding new constructs.

These new constructions can be divided into two groups. (1) The three constructs dropped from the original technology acceptance model: attitude, anxiety, and self-efficacy. Previous empirical studies have demonstrated that these three constructs have a significant impact on the adoption and use of medical and health IT (Cimperman et al., 2016; Deng et al., 2014; Kim et al., 2015; Shiferaw & Mehari, 2019). (2) From the research of other academics, a summary of new constructs that influence the acceptance and use of IT is obtained. Griebel et al. (2013) summarized ten UTAUT model extension factors after a systematic review of 75 health IT articles, excluding the three previously mentioned structures. The remaining seven structures are trust, user condition, perceived system quality, satisfaction with medical care, search strategy, internet dependency, and health-specific knowledge. This study compares the expanded constructs found in related literature and concludes that they can still be included in these seven construct types. Several of the external variables introduced as independent variables have a direct effect on the use intention (Alam, Hoque, et al., 2020; Alam, Hu, et al., 2020; Bawack & Jean, 2018; Ben Arfi, Ben Nasr, Kondrateva, & Hikkerova, 2021; Dwivedi et al., 2016; Gao et al., 2015; Gu et al., 2021; Hoque & Sorwar, 2017; Semiz & Semiz, 2021; Sun et al., 2013). The other portion influences usage intentions indirectly via other UTAUT model variables (Ben Arfi, Ben Nasr, Kondrateva, & Hikkerova, 2021; Cimperman et al., 2016; Sari et al., 2019; Shiferaw & Mehari, 2019; Wang et al., 2021).

In addition, Ramdani et al. (2020) constructed a technology-organization-environment (TOE) framework to investigate the determinants of mHealth adoption in Chinese hospitals. The results of the study showed that perceived ease of use, system security, IT infrastructure, and system reliability among the technical factors; top management support, and hospital size among the organizational factors; and external pressure, and government policy among the environmental factors were significant predictors of mHealth adoption in hospitals. Cao et al. (2022) developed an extended UTAUT model containing four items – personal characteristics, environmental characteristics, usage conditions, and subjective perceptions – to investigate Japanese adolescents' mobile health usage intentions. The research results show that performance expectancy, effort expectancy, and trust have a positive and significant impact on usage intention and health consciousness, and social influence and facilitation conditions have an indirect impact on mobile health usage intention.

Chrisdianti et al. (2023) divided the influencing factors into internal and external factors in their study of intention to use personal health tracking mobile health applications. The results of the study indicated that among the internal factors hedonic motivation, habit, performance risk, perceived usefulness, and among the external factors social influence, facilitating conditions have a significant effect on the intention to use. The results of the meta-analysis by Y. Zhao et al. (2018) showed that perceived usefulness, perceived ease of use, perceived vulnerability, and perceived severity had a significant effect on attitudes while perceived usefulness, perceived ease of use, subjective norms, trust, perceived risk, and attitudes had a significant effect on mobile health adoption intentions.

However, previous studies have neglected the holistic perspective of the research framework, failing to achieve an integrated analysis of personal, technological, and contextual factors within a single framework, while previous studies have tended to focus only on a particular population, such as the elderly (Y. Chen & Xu, 2022; Hoque & Sorwar, 2017; J.-Y. W. Liu et al., 2023; Palas et al., 2022), patients (Balapour et al., 2019; Gu et al., 2021; Uncovska et al., 2023), and health professionals such as doctors or nurses (Bawack & Jean, 2018; Kim et al., 2015; Nezamdoust et al., 2022; Wu et al., 2022). This study is based on previous research; however, it is different from previous studies. First, this study innovatively integrates the health behavior theory PMT into the UTAUT model and acts as the factor used to explain individual characteristics in the model, which compensates for the limitations of UTAUT and builds a holistic extended model. Second, the target population of this study is not limited and has a certain degree of generalizability. Meanwhile, this study focuses on small cities in China and fills the gap by adding variables for the characteristics of small cities and constructing a framework that comprehensively explains the mHealth usage intention of users in small cities in China.

RESEARCH MODEL AND HYPOTHESES

Previous researchers have explained users' intent to use mobile health as an innovative technology primarily in terms of technology acceptance, ignoring the impact of the technology on users' intent to use it as a new healthcare model for healthcare. Nutbeam (1998) defines health behavior as any activity an individual engages in to promote, protect, or maintain health, irrespective of his or her actual or perceived health status and regardless of whether such behavior is objectively valid. Mobile health use behavior is identified as a response to a potential threat to health (Laugesen & Hassanein, 2011) or may be triggered by the intent to avoid health threats and maintain health safety (Milne et al., 2000). Thus, the adoption of mobile health is also a health behavior. In order to distinguish the behavioral intentions of health services technologies from those of other technologies, researchers should combine the technology perspective and the health behavior perspective when analyzing the behavioral intentions of users who adopt health services technologies (Holden & Karsh, 2010). Previous research has neglected that adopting mobile health is an innovative technology acceptance and health behavior (Scammon et al., 2011).

PMT is one of the most influential explanatory theories for studying individuals' behavioral intentions to adopt protective behaviors (Anderson & Agarwal, 2010). In addition, studies have demonstrated that the PMT is as effective as the UTAUT in predicting mobile health adoption intent (Hsieh et al., 2016). Studies even suggest that technology acceptance theories like TAM and TPB are more concerned with general technology acceptance issues. However, the predictive power of the PMT, which emphasizes health behavior adoption intentions, is greater than the previous two (Sun et al., 2013). For these reasons, this study integrates PMT theory with UTAUT theory to jointly construct a unified extended UTAUT model to achieve the unified model's total explanatory power and predictive power. However, in constructing a holistic explanatory model, different variables in both models have similar explanatory validity, and to strike a balance between simplicity and comprehensiveness in the unified model (Walton & DeRenzi, 2009), this study merged different variables with similar explanatory validity. In the mobile health context, performance expectancy in the UTAUT model refers to the extent to which users believe that mobile health will help improve their health (Venkatesh et al., 2003). The response efficacy in PMT is the extent to which users perceive that the use of mobile health services can reduce the risk to their health (Rogers, 1975). The measurement dimensions of these two variables are essentially similar, leading to integrating the above two variables in a unified model to explain the performance expectations of mobile health. The facilitating conditions in UTAUT indicate the individual's perception of the ability of the relevant technology and equipment to support the use of the system when using a specific system (Venkatesh et al., 2003). From the TPB perspective, perceived behavioral control refers to the ability that individuals have to control the resources and opportunities needed to perform a specific behavior which can be divided into internal self-efficacy and external resources (Ajzen, 1991). Self-efficacy refers to the individual's perception of whether they can accomplish a particular behavior, which has the same validity as the self-efficacy variable in PMT, and external resources refer to the availability and hindrance of resources available to the individual, which is similar to response cost in PMT (Ajzen, 2002), as shown in Table 2.

Table 2. A comparison of theories

The Unified Model	Similar Explanatory Variables	TPB/UTAUT	PMT
Performance Expectancy	Perceived Usefulness/Response Efficacy	✓	✓
Effort Expectancy	Perceived Ease of Use	✓	
Social Influence	Subjective Norm	✓	
Facilitating Conditions	Self-efficacy (Internal)	✓	✓
	Response Cost (External)	✓	✓
Perceived Vulnerability	Threat Appraisals		✓
Perceived Severity			✓

The UTAUT Core Variables

Reviewing the literature, it was discovered that the four core variables of the UTAUT model yielded different significant results in different research contexts; thus, to verify the significant relationship between the four core variables and mobile health adoption intention in the context of average users in small cities in China, this study combines all four core variables into a unified framework.

Performance expectancy

Performance expectancy (PE) is the degree to which users believe the system will improve performance (Venkatesh et al., 2003). In the context of mobile health, since mobile health adoption is a voluntary and personal act of the user, PE is expressed as the extent to which users believe that the mobile health system will improve their overall performance by helping to understand their physical condition, saving medical time, facilitating doctor-patient communication, and enabling users to receive more accurate, appropriate, and rapid services. Users are more motivated to embrace and adopt mobile health if they believe it will be more beneficial in managing their health. Previous studies have demonstrated the positive impact of PE on users' behavioral intentions (Alam, Hoque, et al., 2020; Ben Arfi, Ben Nasr, Kondrateva & Hikkerova, 2021). Therefore, this study hypothesized that:

> H1: The performance expectancy of users positively influences the intention to use mobile health.

Effort expectancy

Effort expectancy (EE) is the degree to which users find the system easy to use (Venkatesh et al., 2003). In mobile health, effort expectancy is expressed as the ease with which users learn how to use the mobile health system. Hence, before adopting new technology, users frequently evaluate the required effort (Venkatesh et al., 2012). Personalization of services characterizes mobile health systems (X. Guo et al., 2016). End users may be more likely to increase their intention to use mobile health if the system's user-interface design makes it easier for them to develop personalized services to manage their health and less effort and energy are required to use the mobile health system (Ben Arfi, Ben Nasr, Kondrateva & Hikkerova, 2021; Cimperman et al., 2016; Wang et al., 2021). Therefore, this study proposes that:

> H2: The effort expectancy of users positively influences the intention to use mobile health.

Social influence

Social influence (SI) refers to the extent to which individuals believe others recognize their use of emerging technologies (Venkatesh et al., 2003). In the context of mobile health, social influence refers to the perceived approval of the system by those who significantly impact the system. According to the findings of Shiferaw and Mehari's (2019) study on the factors influencing users' intention to use electronic medical cases in Ethiopia, social influence was the most influential factor. The study by Bawack and Jean (2018) revealed that social influence was the most influential factor influencing physicians' adoption of health information systems in the context of Cameroon in developing countries. In this study, however, mobile health is unfamiliar to users in small cities in China; therefore, recommendations or suggestions from family members, friends, or coworkers can influence users' intent to adopt mobile health. Therefore, this study proposed the following hypothesis:

> H3: Users' social influence positively influences the intention to use mobile health.

Facilitating conditions

Facilitation conditions refers to the extent to which an individual believes that the necessary organizational and technical infrastructure exists to support the system's use (Venkatesh et al., 2003). The foundation of mobile health is networked communication technologies. The proper use and success of mobile health relies heavily on continuous communication between different locations, and the ability of service providers to continuously monitor and respond reliably anywhere and at any time is a common requirement that motivates users to adopt any innovative technology (Dwivedi et al., 2016). In the context of mobile health, facilitation conditions are the extent to which users perceive the presence of organizational and technological infrastructure and a continuous and reliable support system. According to a study conducted by Ben Arfi, Ben Nasr, Kondrateva and Hikkerova (2021), facilitation conditions are the most significant factor influencing users' adoption of mobile health applications in Turku. Gu et al. (2021) studied and validated that facilitation conditions significantly positively impacted users' intention to use eHealth technology. Semiz and Semiz (2021) argued that infrastructure and organizational support play an essential role in user acceptance and adoption of mobile health. Users are more likely to accept mobile health systems with adequate technical and organizational infrastructure and continuous and dependable support. Therefore, this study hypothesized that:

H4: Users' facilitating conditions positively influence the intention to use mobile health.

Adding personal characteristic variables

Although the UTAUT model has greater explanatory and predictive power than other models, the UTAUT theory has limitations (Tamilmani et al., 2021). Dwivedi et al. (2019) reviewed the UTAUT model in detail by combining structural equation modeling and meta-analytic techniques. They classified the four variables of the UTAUT model as representing technical characteristics (performance expectancy and effort expectancy) and contextual factors (social influence and facilitating conditions). They considered them as explanations of individuals' behavioral intentions for the technical and contextual factors of the target under study. Although previous studies have demonstrated that these four variables explain a large part of the variance differences in acceptance and adoption behaviors, the UTAUT model lacks a description of the subjects involved in the behaviors. This means that the model lacks variables that explain the influence of users' personal characteristics on the intention to accept and adopt behavior (Tamilmani et al., 2021). To develop a comprehensive theoretical framework, it is necessary to address the limitations of UTAUT by adding variables describing personal characteristics.

Attitude

Attitude is derived from the TAM and TPB models and refers to an individual's positive or negative feelings about engaging in the target behavior; numerous studies have confirmed the significant effect of attitude on intention to use (X. Guo et al., 2015; Patil et al., 2020; Shiferaw & Mehari, 2019). Dwivedi et al. (2019) conducted a meta-analysis of 1,600 observations of 21 relationships encoded by 162 prior studies on the acceptance and use of IS/IT, developed an alternative theory, and then empirically tested the modified alternative model with the structural equation modeling technique. The results indicate that attitude is the central determinant of behavioral intention and use behavior, partially moderates the effect of exogenous variables on behavioral intention, and directly influences user behavior. The predictive power of surrogate models incorporating attitudes increased from 38% to 45% for behavioral intentions. Moreover, attitudes played a more significant role in the underlying behavioral intentions of individuals in the early stages of technology adoption (Patil et al., 2020). Studies have shown that attitude is the most fundamental predictor of the successful deployment of new technology in resource-constrained environments (Shiferaw & Mehari, 2019). The public's adoption of mobile health is also at an early stage in small cities in China, consistent with resource-constrained environments' characteristics. Therefore, attitude should be a crucial variable when investigating the intention to use mobile health among China's small city users. Holden and Karsh (2010) defined attitudes in the context of mobile health as the tendency of consumers to evaluate mobile health positively or negatively. Based on the external information and their e-health literacy, the more positive the attitudinal evaluation of mobile health, the more favorable it is for users to actively adopt them. Conversely, the more negative the attitudinal evaluation formed by users, the lower their intention to use. Therefore, this study proposed the hypothesis that:

H5: Users' attitude positively influences the intention to use mobile health.

Threat appraisal factors in PMT theory

The cognitive process in PMT theory is divided into response appraisal and threat appraisal (Rogers, 1975). Response cost, response efficacy, and self-efficacy in response appraisal are already present in the extended model of this study through convergence between theories. Therefore, only the perceived severity and perceived vulnerability in the threat appraisal can be validated separately. Perceived severity refers to an individual's judgment of the degree of harm to his or her physical and mental health; and perceived vulnerability refers to an individual's subjective evaluation of his or her likelihood of developing a particular disease and the core beliefs that result from that evaluation (Rogers, 1975). When users perceive the serious impact of threats on their health and perceive themselves as more vulnerable to health threats, they may have a higher expectation to reduce the impact of threats by adopting mobile health (Prentice-Dunn & Rogers, 1986). Previous studies have shown that threat appraisal significantly impacts the intention to use mobile health. Gao et al.'s (2015) study showed that perceived vulnerability significantly influenced users' intention to use fitness wearables and that medical wearables users' intention to use was significantly influenced by perceived severity. Sun et al. (2013), through a survey study of 212 elderly users, empirically showed that threat appraisal significantly influenced the intention of elderly users to use mobile health. Therefore, this study proposes the relevant hypothesis:

H6: Users' perceived vulnerability positively influences the intention to use mobile health.
H7: Users' perceived severity positively influences the intention to use mobile health.

Ultimately, this study constructs a holistic conceptual framework that includes technical features factors, personal characteristics factors, and contextual factors, as shown in Figure 1.

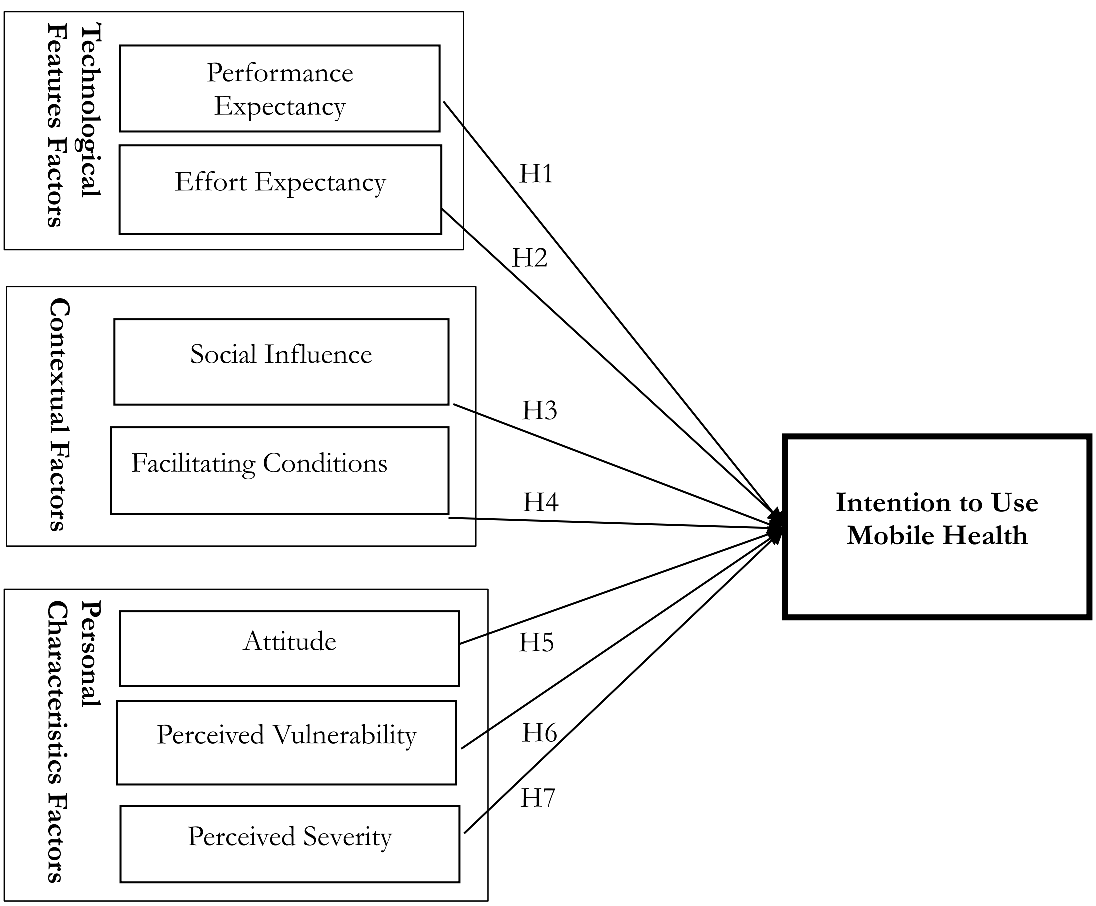

Figure 1. Research model

RESEARCH METHODOLOGY

This cross-sectional empirical study collected quantitative data from respondents using a structured questionnaire in order to test the proposed research framework. The collection of data for this study occurred between September and November 2022 in two small cities in China.

TARGET POPULATION AND SAMPLING

The primary objective of this study is to predict and explain the factors and their interrelationships that influence the intention of small-city Chinese users to use mobile health. To ensure the generalizability of the study, the target population of this study is the average mobile terminal user in small cities in China. Since Hong and Zhou (2018) demonstrated that socioeconomic status significantly influences e-health behavior in China, the selection of target cities for this study was based more on business indices rather than the number of city residents population. Therefore, this study defines small cities as Tier 4 and Tier 5 in the China City Business Attractiveness Ranking published by the China New Tier One Cities Institute in 2021 (YiCai, 2021). However, among them are 90 cities of the fourth tier and 129 cities of the fifth tier. Due to the large number of cities, it is impossible to collect all relevant data for this study; therefore, it is necessary to select representative cities as samples from among these cities. Some studies have demonstrated a clear digital divide at the prefecture level in China, with ICT development index values decreasing from eastern coastal cities to western cities and from core cities in each province to peripheral cities (Song et al., 2019). Nonetheless, this substantial digital divide at the terrestrial level leads directly to disparities in eHealth literacy (Bol et al., 2018). Previous research has found that the most common determinants studied across all digital divides are socio-demographic and socio-economic (Scheerder et al., 2017). Because the eastern coastal cities of China have faster economic development compared to the western cities (Song et al., 2019), basically all the small cities in the eastern coastal cities of China are fourth-tier cities, while most of the small cities in western China are fifth-tier cities. To realize the authenticity and universality of the sample data, this study selects the eastern Chinese city of Zaozhuang (a fourth-tier city), which ranked at the end of the GDP among the cities in Shandong Province in 2022 (Public Network, 2023). Meanwhile, the city of Tianshui (a fifth-tier city) in western China is selected as the second largest city in Gansu Province, and its GDP in 2022 ranks fourth among the cities in Gansu Province (Tian Ming Sheng Shang, 2023). At the same time, both cities have a population of around 3 million permanent residents as of 2022. This is to avoid excessive differences between the economic and demographic characteristics of the two cities selected. By combining sample data from the east and west of China, fourth-tier cities, and fifth-tier cities, this study sample is made to reflect the characteristics of small cities more accurately in China.

DATA COLLECTION

This study used the Credamo platform (www.credamo.world) to collect the required data online and restricted the required sample characteristics on the platform to obtain an accurate distribution of participants, with the age range of participants restricted to 18-70 years old and a quota criterion for gender. The sample size determination was chosen for this study using G*Power software (Erdfelder et al., 1996). The sample size required for this study was calculated using G*Power version 3.1 and was 153. To ensure sufficient accuracy of estimates, the sample size for this study was determined to be 300. According to the resident populations of the two cities, 153 samples were acquired in Zaozhuang, and 147 samples were acquired in Tianshui. Combining the eastern and western, fourth-tier and fifth-tier cities makes the sample characteristics more representative of the overall characteristics.

MEASUREMENTS SCALE

This study was based on variable-specific measurement items from the existing literature, which were tested by previous researchers and found to be sufficiently reliable and valid (see the Appendix for items used). The four core variables of the UTAUT model and the measurement of "intention to use" were adapted from Alam, Hoque, et al. (2020). The measurement items of "perceived severity" and "perceived vulnerability" in PMT theory were adapted from Hsieh et al. (2016). The measurement items for the "attitude" variable were adapted from X. Guo et al. (2015). (For more detailed information, please refer to the appendix).

In this study, the measurement items were translated into Chinese using the back-to-back method, and ten undergraduate and five graduate students were recruited to conduct a pre-test. Students were chosen as subjects for the pre-test because they are young, have some level of education, may be more familiar with mobile health and information technology, and may have more perspectives and insights on the survey items. Once each respondent completed the questionnaire, the researcher asked for their opinion and evaluation, which were recorded in the section "Your comments and suggestions on the questionnaire" at the end of the questionnaire. Revisions on the semantic and ambiguous statements were done and alterations on the questionnaire's measurement items format were based on the 15 pre-test questionnaires and the feedback received.

DATA ANALYSIS METHODS

This study used the SPSS 26 software for descriptive statistical analysis, missing values, outliers, and other routine data testing and processing. The empirical model was tested using the Partial Least Square Structural Equation Modelling (PLS-SEM) method, which is recommended for predictive research models rather than theoretical validation models (Hew & Kadir, 2017). While this method can overcome the underestimation of standard errors and inflation of fit due to non-normally distributed data (Lei & Lomax, 2005), it can also ensure greater precision in the analysis results.

DATA ANALYSIS AND RESULTS

A distribution of 350 questionnaires was sent out garnering 331 responses in total and obtained 319 valid responses after excluding 12 invalid ones, including 162 from Zaozhuang City and 157 from Tianshui City. Table 3 displays the specific demographic information of the subjects.

Table 3. Respondents' profile

Demographic Data	Items	Frequency	Percent (%)
Gender	Male	167	52.4
	Female	152	47.6
Age	20 years old and below	22	6.9
	21-30 years old	129	40.4
	31-40 years old	120	37.6
	41-50 years old	37	11.6
	51 years old and above	11	3.4
Education Qualification	Secondary school and below	23	7.2
	College	28	8.8
	Undergraduate	222	69.6
	Master's degree	45	14.1
	PhD	1	0.3

Demographic Data	Items	Frequency	Percent (%)
Respondent's Income	Less than ¥3000	58	18.2
	¥3000 to ¥5000	58	18.2
	¥5000 to ¥8000	93	29.2
	Above ¥8000	110	34.5
Physical Condition	Never felt uncomfortable	35	11
	Occasional discomfort	275	86.2
	Frequent discomfort	9	2.8
How many times did you visit the clinic in the past six months	0 times	58	18.2
	1-3 times	234	73.4
	4-6 times	27	8.5

Missing Data Values, Normal Distribution, and Common Method Variance Tests

As this study used the Credamo platform to collect data online, each section and all questions in the questionnaire were mandatory for respondents to fill in. They could not proceed to the next step to complete the questionnaire, so no missing values were found in the data. Nonetheless, one of the advantages of the PLS-SEM method is the reliability of the obtained results supported by non-normal data (Reinartz et al., 2009; Wetzels et al., 2009). Furthermore, it has been argued that it is essential to ensure the normalization of data before performing any type of inferential statistics (Hair et al., 2012). As explained by George and Mallery (2010), the skewness and kurtosis values of the data were between 2 and -2 to test the normalized distribution of the data in this study, demonstrating the normality of the data distribution. In this study the skewness and kurtosis of the data are within the accepted range, indicating that the data distribution is normal.

Since this study collected the necessary data through a questionnaire, the dependent and independent variables were derived from cross-sectional data collected from the same target respondents at the same time and location, which could lead to common method variance. To avoid common method variance, this study considered the effect of CMV on the questionnaire's structural design and the model's construction. To detect and control for common method variance in this study, we used the PLS marker variable method (Rönkkö & Ylitalo, 2011), and three irrelevant marker variables from Lin et al. (2015) were employed. The addition of marker variables did not result in a statistically significant change in the value of Beta(β) value (difference of 0.000-0.020) and the value of R^2 (difference of 0.004), indicating that there is no common method variance issue in this study.

Assessment of Reflective Measurement Model

Hair et al. (2019) proposed that reflective model evaluation should begin by determining the indicator extrinsic load value. A value of indicator extrinsic load greater than 0.7 denotes that the structure explains at least 50% of the indicator variance and that the indicator is reliable. To ensure the accuracy of CR and AVE, the indicator should be removed if its extrinsic load value is less than 0.5 (Hair et al., 2012). Settling the PLS calculation, the external load value of the PS3 measurement item in the PS variable was 0.405, which was then deleted with the continuation of the calculation for other measurements. As shown in Table 5, the load values of all the measurement items satisfied the minimum threshold, indicating that the reliability of the indicators was satisfactory.

The composite reliability (CR) method was utilized to evaluate internal consistency reliability (Jöreskog, 1971). In general, the composite reliability method is regarded as superior to Cronbach's alpha assessment method, with higher composite reliability indicating greater reliability. Generally, acceptance for composite reliability values ranges between 0.6 and 0.7, and results between 0.7 and 0.95 indicate good reliability. However, when the value exceeds 0.95, the items are nearly identical and redundant (Hair & Alamer, 2022).

After PLS operation, the composite reliability of all measures fell within the standard thresholds, and the composite reliabilities ranged from 0.823 to 0.885, indicating that all measures in the study had high levels of reliability. Typically, the average variance extraction (AVE) method is used to evaluate the convergent validity of the model for all items related to reflexive measure constructs. Convergent validity is accepted when the AVE value is greater than 0.50, indicating that the construct can explain at least 50% of the variance of its items (Hair, Sarstedt et al., 2017). As shown in Table 4, the AVE of all constructs in this study was greater than 0.50, ranging from 0.538 to 0.741. This study's results indicate that all constructs' convergence was satisfactory.

This study used the Fornell-Larcker standard method to validate the convergent validity of the model (Fornell & Larcker, 1981). Fornell and Larcker (1981) suggested that it is possible to detect convergent validity by comparing the square root of the AVE of all model constructs to the correlation between potential constructs. In addition, the square root of AVE is greater than the correlation value between potential constructs for all constructs. As shown in Table 5, the square root of AVE is greater than the correlation between potential constructs for all constructs in this study. The results of this study indicate that the model has discriminant validity.

Table 4. Reflective measurement model evaluation metrics

Constructs	Indicators	Outer Loadings	Composite Reliability	Average Variance Extracted (AVE)
ATTD	ATTD1	0.751	0.849	0.584
	ATTD2	0.789		
	ATTD3	0.765		
	ATTD4	0.750		
EE	EE1	0.697	0.844	0.644
	EE2	0.727		
	EE3	0.764		
	EE4	0.796		
FC	FC1	0.801	0.823	0.538
	FC2	0.716		
	FC3	0.726		
	FC4	0.687		
PE	PE1	0.782	0.843	0.575
	PE2	0.741		
	PE3	0.701		
	PE4	0.804		
PS	PS1	0.869	0.851	0.741
	PS2	0.852		
PV	PV1	0.647	0.845	0.648
	PV2	0.892		
	PV3	0.856		

Constructs	Indicators	Outer Loadings	Composite Reliability	Average Variance Extracted (AVE)
SI	SI1	0.828	0.867	0.621
	SI2	0.801		
	SI3	0.821		
	SI4	0.693		
UI	UI1	0.826	0.885	0.719
	UI2	0.842		
	UI3	0.876		

Table 5. Fornell-Larcker criterion analysis for checking discriminant validity

	ATTD	EE	FC	PE	PS	PV	SI	UI
ATTD	**0.764**							
EE	0.615	**0.803**						
FC	0.633	0.600	**0.734**					
PE	0.666	0.595	0.662	**0.758**				
PS	0.288	0.292	0.217	0.234	**0.861**			
PV	0.137	0.086	0.134	0.103	0.201	**0.805**		
SI	0.555	0.432	0.620	0.602	0.098	0.116	**0.788**	
UI	0.701	0.570	0.678	0.671	0.286	0.215	0.586	**0.848**

Assessment of Structural Model

Given that the coefficients of the internal structural model are derived from a series of regression equation analyses, the researchers first examine the internal structural model for collinearity issues to ensure that the analysis results are not biased. The variance inflation factor (VIF) of each item in the structural internal model determines if the model has a collinearity problem, with a higher VIF value indicating a greater degree of item collinearity. According to Diamantopoulos and Siguaw (2006), the VIF should not be higher than 3.3. As shown in Table 6, the VIF of all constructs in this study's internal model is less than 3.3, and the range of VIF values is between 1.057 and 2.424. Results indicate that this model's degree of covariance falls within an acceptable range.

Table 6. Values of the variation inflation factor for collinearity

	ATTD	EE	FC	PE	PS	PV	SI	UI
ATTD								2.317
EE								1.946
FC								2.397
PE								2.424
PS								1.169
PV								1.057
SI								1.895

To test the hypothesized relationships, this study used bootstrap procedures to perform operations for each inter-constructive path relationship in the model. In the preceding sections, seven hypotheses were proposed. The bootstrap procedure was configured with a significance level of 0.05, a one-tailed test, and 5000 subsamples (Hair, Hollingsworth, et al., 2017). For the one-tailed test, the critical values for 1% (α=0.01), 5% (α=0.05), and 10% (α=0.1) significance levels were 2.33, 1.645, and 1.28 (Ramayah et al., 2018). As shown in Table 7, in this study, intention to use mobile health was influenced by Attitude (β=0.287, t-value=4.350, p<0.01), Facilitating Conditions (β=0.218, t-value=3.095, p<0.01), Performance Expectancy (β=0.180, t-value=2.790, p<0.01), and Perceived vulnerability (β=0.094, t-value=2.756, p<0.01), and Social Influence (β=0.121, t-value=2.090, p<0.05) of significant positive effects. The results indicate that the hypotheses of H1, H3, H4, H5, and H6 are supported by the hypotheses previously proposed in this study.

Table 7. Path coefficient

Hypothesis	Relationship	Std. Beta	Std. Error	t-value	P Values	Results
H1	PE -> UI	0.180	0.064	2.790	0.003**	Supported
H2	EE -> UI	0.088	0.064	0.064	1.376	Not Supported
H3	SI -> UI	0.121	0.058	2.090	0.018*	Supported
H4	FC -> UI	0.218	0.070	3.095	0.001**	Supported
H5	ATTD -> UI	0.287	0.066	4.350	0.000**	Supported
H6	PV -> UI	0.094	0.034	2.756	0.003**	Supported
H7	PS -> UI	0.057	0.040	1.441	0.075	Not Supported

Note: *p<0.05, **p<0.01

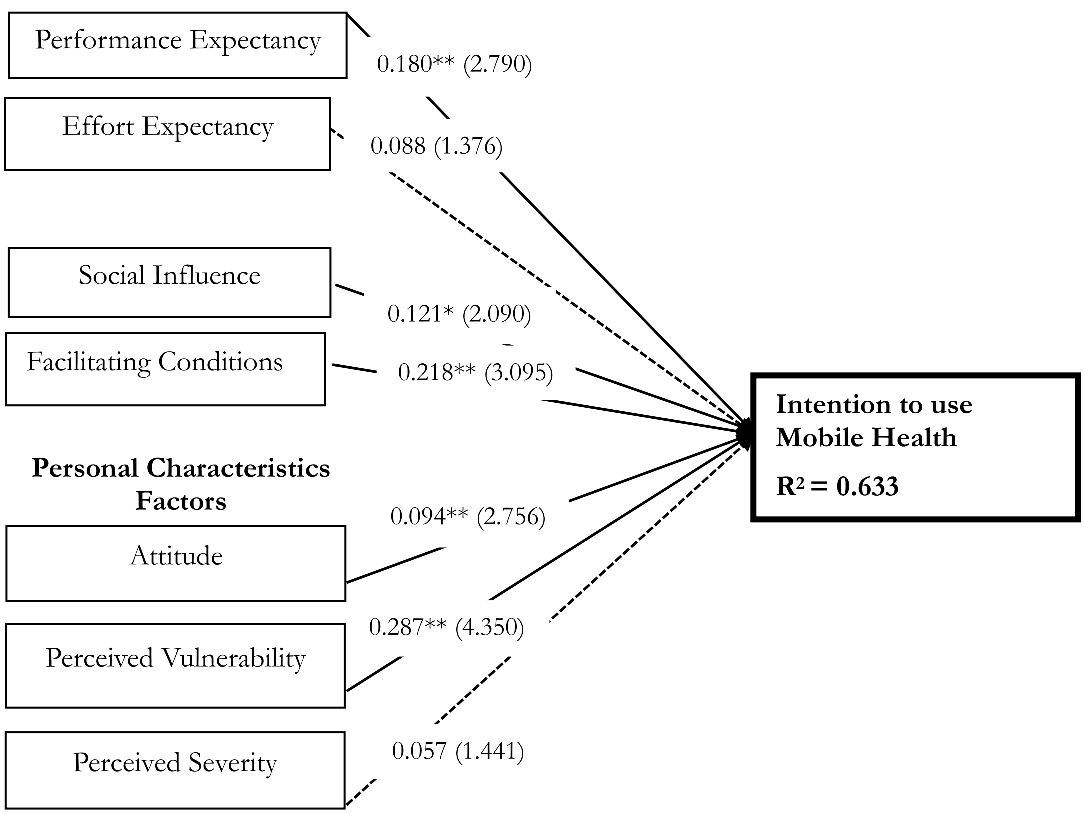

Figure 2. Structural model

Note: *p<0.05, **p<0.01

DISCUSSION

This study aims to investigate the factors that influence the intention of mobile health use among small-city users in China. Thus, we proposed an extended UTAUT model that incorporates personal characteristics, technological features, and contextual factors. Based on the model, seven hypotheses were proposed, and five were confirmed. The theoretical model of this study explained 63% of the variance in usage intention and had good predictive power for identifying the factors that influence the usage intention of mobile health among small city users in China.

This study provides evidence that perceived expectancy (PE) significantly positively affects users' intentions to use mobile health in China's small cities. The findings of this study are consistent with the majority of previous research (e.g., Bawack & Jean, 2018; Ben Arfi, Ben Nasr, Kondrateva & Hikkerova, 2021; Chang et al., 2021; Dwivedi et al., 2019; Ramdani et al., 2020; Semiz & Semiz, 2021; Wang et al., 2021). The findings of this study suggest that users in China's small cities have initial knowledge or impressions of mobile health and are familiar with its benefits. The greater its performance capability, the greater the user's intent to utilize mobile health.

The results of this study indicated that there was no significant relationship between effort expectancy (EE) and the intention of users to adopt mobile health. The findings of Chang et al. (2021) for 650 hospital patients in China regarding their intention to use the mobile health app revealed no significant correlation between EE and intention to use. After surveying 400 Bangladeshi university students, Alam, Hu, et al. (2020) concluded that EE did not influence the intention of Bangladeshi university students to use mobile health. This result differs from the relationship between EE and UI in the original UTAUT model, which can be explained by the fact that, as a result of the significant improvement in the interactivity of the mobile software interface and the optimization of the navigation function in the software for mobile health, it is easier than ever for users to become proficient with mobile health. In recent years, mobile applications have become ubiquitous in all aspects of daily life and work, and people are familiar with and proficient with their operations. Thus, the effect of EE on UI is negligible.

Social influence (SI) is positively and significantly related to the intention to use mobile health among Chinese users in small cities. The results of this study are consistent with prior research findings (Ben Arfi, Ben Nasr, Khvatova & Ben Zaied, 2021; Ramdani et al., 2020; Semiz & Semiz, 2021). In this study, the disparity in eHealth literacy caused by the digital divide among users in China's small cities renders mobile health novel. Users are at a disadvantage when confronted with novelty due to information asymmetry. Due to the sensitivity of healthcare information and the lack of necessary health information, they may rely more on the advice of trusted individuals (family, friends, and coworkers) to reduce decision costs. Additionally, when a significant influencer recommends a product or service, the user's psychological defenses are more easily breached, and the user's intention to accept or use the product or service is increased. In addition, 78% of the survey participants in this study fell within the age range of 21 to 40. Younger users will be more inclined toward technology and social media than older users, meaning they will be more susceptible to being influenced by the opinions, thoughts, and recommendations of fellow industry authorities regarding technology use. End-users can modify their behavioral intentions based on information knowledgeable authorities share (Alam, Hoque, et al., 2020). Therefore, SI was identified as a strong predictor of mobile health usage intentions among users in small cities in China.

The mobile health application is a network-based wireless mobile application. Effective use and deployment of mobile health depend heavily on constant communication between locations (Dwivedi et al., 2016). A common condition that motivates users to adopt innovative technology is the service provider's ability to continuously monitor and respond reliably and promptly at all times (Dwivedi et al., 2016). This theory is supported by the findings of this study, which demonstrate a positive and statistically significant correlation between facilitating conditions (FC) and users' intention to use mobile health in China's small cities. The results of this study are consistent with those of previous research (Bawack & Jean, 2018; Gu et al., 2021; Semiz & Semiz, 2021). This study concludes that the greater the application foundation provided by the mobile health infrastructure communication facilities and application platforms for mobile health, the greater the people's confidence in using them. Consequently, their intent to utilize them. In contrast, the intention to use mobile health decreases as users lose confidence in the hardware infrastructure of mobile health.

"Attitude" is an extension factor of the UTAUT model, and previous studies have confirmed that adding attitude variables to the UTAUT model increases the explanatory power of the model (Dwivedi et al., 2019). The results of this study indicated that attitude was the strongest positive direct factor for mobile health usage intention among Chinese users in small cities. The findings are consistent with prior research in various fields (Deng et al., 2014; Kim et al., 2015; Patil et al., 2020; Shiferaw & Mehari, 2019; Y. Zhao et al., 2018). This research confirms that attitude is the most important predictor of the successful deployment of novel technologies in resource-constrained contexts (Shiferaw & Mehari, 2019; Yehualashet et al., 2015). The more positive attitudes people have towards mobile health, the more favorable it is for users to adopt them actively. On the contrary, the more negative the attitudinal evaluations formed by users, the lower the adoption intention.

Perceived vulnerability and perceived severity, as components of threat appraisal in PMT theory, also serve as measurement variables for personal characteristics in the holistic framework of this study from the perspective of health behavior theory. The study's findings indicated that perceived vulnerability significantly influenced users' intent to adopt mobile health, thus supporting Hypothesis 6. The findings of this study are consistent with those of previous studies (X. Guo et al., 2015; Sun et al., 2013). Perceived severity did not significantly affect the intention to use in this study, and H7 was not supported, which is consistent with previous research findings (Hsieh et al., 2016; Y. Zhao et al., 2018). The findings of the meta-analysis conducted by Milne et al. (2000) revealed that perceived vulnerability had a greater influence on intention to use than perceived severity. This study explains that with the improvement in living conditions, people have begun to pay more attention to their health, shifting from passive medical consultation in the past to proactive self-examination, such as regular medical checkups, which makes people more aware of their health conditions and makes it easier for them to determine which diseases are prevalent based on their health conditions and lifestyles; in other words, their perception of vulnerability to certain diseases. Users view mobile health as a potent tool for staying healthy and mitigating the risk of certain diseases. However, perceived severity investigates changes in people's lifestyles after a serious illness, and this outlook and philosophy of life are not changed easily by improved economic conditions and knowledge of one's health status.

CONCLUSION

In this study, a holistic model was developed based on the UTAUT model and the health behavior theory PMT to examine the significant factors influencing the intention to use mobile health among small city users in China. The findings suggested that mobile health usage intention among small city users in China is directly and positively influenced by attitude and perceived vulnerability in the personal characteristics factor, social influence and facilitating conditions in the social context factor, and performance expectancy in the technology factors. Attitude was the most significant positive influencing factor in the overall model. Effort expectancy and perceived severity had no significant effect on the intention to use mobile health among small-city users in China in this study. The theoretical contributions made by this study's findings provide a foundation for future research. This study's findings also included recommendations for stakeholders involved with mobile health. Through any luck, stakeholders will consider the recommendations and take the necessary steps to increase the adoption rate of mobile health in China's small cities and maximize the social value of mobile health in China's small cities.

Theoretical Implications and Practical Implications

First, this study constructed a holistic theoretical framework that includes technological features, personal characteristics, and social contextual factors in a small city context in China. This framework compensated for the limitations of the UTAUT theory which lacks the description of users' personal characteristics factors and integrates the health behavior theory PMT to empirically test that the UTAUT model had good explanatory power for the intention to use mobile health in a small city context in China. It also verified that attitude as the most fundamental predictor variable in resource-constrained contexts is crucial to improve the overall explanatory power of the model. This study is a revisiting of the health behavior theory PMT in a specific Chinese small city context, and it served as a theoretical reference for subsequent researchers.

Based on the results of this empirical study, mobile health service providers should first consider improving the functional usefulness of mobile health to improve users' performance expectations and maintain their brand image to establish a positive reputation and enhance the social impact of mobile health. Concurrently, mobile health service providers need to strengthen cooperation with government and medical institutions. Multi-party cooperation can reduce the duplication of resources for mobile health development, and can also consider various needs of patients before, during, and after medical treatment to improve the medical treatment experience, thus improving users' perception of the facilitating conditions and ultimately improving users' intention to use. For medical institutions, it is important to focus on the special role of medical professionals, such as doctors and nurses, in promoting mobile health, while regularly providing medical knowledge and health knowledge training to patients and their families to improve users' perceived vulnerability. The interconnectedness of the medical system will help improve users' perception of health threats and the usefulness of mobile health, as well as increase the social impact of mobile health, forming a positive cycle for the development of mobile health. In the early stages of mobile health development, government departments should pay more attention to the dissemination of the basic concepts and key advantages of mobile health, increase the channels of reach, strengthen the publicity and guidance of mobile health from multiple angles and directions, and increase the exposure rate of mobile health to increase the social influence of mobile health. Government departments can use community clinics and village clinics to conduct regular training and health knowledge lectures on mobile health, which can both expand the social influence of mobile health and encourage the development of positive public attitudes toward mobile health, thereby increasing the intention to use mobile health.

Limitations and Future Research Suggestions

This study has some theoretical contributions and practical implications but also some limitations. First, this cross-sectional study focuses solely on intention to use and does not investigate actual or sustained use. Since mobile health as a new e-health tool is not widely adopted in China's smaller cities, it is challenging to examine actual behavior. At this stage, the importance of studying usage intention is relatively greater. Through the rapid development of mobile health, however, future research should concentrate on the actual usage behavior of users and simultaneously conduct a series of longitudinal studies, including studies on continued usage behavior, abandonment behavior, and abandoned-and-used behavior.

Second, the sample data collected for this study are limited to small cities in China. However, the adoption rate of mobile health in rural areas of China is even less optimistic. Looking at the rapid development of mobile health, the gap between urban and rural areas may gradually close, but it will not simply disappear. Future research should continue to concentrate on the user behavior of mobile health in China's rural areas.

Finally, this study did not employ moderating variables from the classical model, such as age and gender, even though previous research has confirmed the moderating effect of age and gender on users' intention to use. Future research should combine existing studies' findings to investigate in depth the moderating effects of age and gender on the intention to use in China's small cities.

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APPENDIX: MEASUREMENT ITEMS

Items	Original measurement items	Current measurement items	Sources
Performance Expectancy (PE)	PE1. I find mHealth useful in my life.	PE1. I find the mobile health services are useful in my daily life.	Alam, Hoque, et al. (2020)
	PE2. Using mHealth increases my chances of meeting my needs.	PE2. Using the mobile health services can satisfy my medical healthcare needs.	
	PE3. Using mHealth helps me in managing my daily healthcare more quickly.	PE3. Using the mobile health services help me in managing my daily healthcare more quickly.	
	PE4. Using mHealth service increases my capability to manage my health.	PE4. Using the mobile health services increase my capability to manage my health.	
Effort Expectancy (EE)	EE1. Learning how to use mHealth is easy for me.	EE1. Learning how to use mobile health is easy for me.	Alam, Hoque, et al. (2020)
	EE2. My interaction with mHealth is clear and understandable.	EE2. My interaction with mobile health is clear and understandable.	
	EE3. I find mHealth easy to use.	EE3. I find mobile health easy to use.	
	EE4. It is easy for me to become skillful at using mHealth services.	EE4. It is easy for me to become skillful at using mobile health services.	
Social Influence (SI)	SI1. People who are important to me think that I should use mHealth services.	SI1. People who are important to me believe that I should use the mobile health services.	Alam, Hoque, et al. (2020)
	SI2. People who influence my behavior think that I should use mHealth.	SI2. People who influence my behavior believe that I should use the mobile health services.	
	SI3. People whose opinions that I value prefer that I use mHealth.	SI3. People whose opinions I value prefer using the mobile health services.	
	SI4. People in my society who use mHealth service have more prestigious than those who do not.	SI4. People in my society who use the mobile health services have more prestigious than those who do not.	
Facilitating Conditions (FC)	FC1. I have the resources necessary to use mHealth services.	FC1. I have the resources necessary to us mobile health services.	Alam, Hoque, et al. (2020)
	FC2. I have the knowledge necessary to use mHealth.	FC2. I have the knowledge necessary to use mobile health services.	
	FC3. mHealth is compatible with other technologies I use.	FC3. The mobile health services are compatible with other technologies I use.	

Items	Original measurement items	Current measurement items	Sources
	FC4. I can get help from others when I have difficulties using mHealth services.	FC4. I can get help from others when I have difficulties using mHealth services.	
	FC5. Guidance will be available to me in the use of mHealth services.	None	
Attitude (ATTD)	ATTD1. Using the mobile health services is a bad/good idea.	ATTD1. Using the mobile health services is a good idea.	Guo et al. (2015)
	ATTD2. Using the mobile health services is a foolish/wise idea.	ATTD2. Using the mobile health services is a wise idea.	
	ATTD3. I dislike/like the idea of using the mobile health services.	ATTD3. I like the idea of using the mobile health services.	
	ATTD4. Using the mobile health services is unpleasant/pleasant	ATTD4. Using the mobile health services is pleasant.	
Perceived Severity (PS)	PS1. If too slow to find a serious disease, it will delay the timing of treatment.	PS1. If too slow to find a serious disease, it will delay the timing of treatment.	Hsieh et al. (2016)
	PS2. If I get a serious disease, it will change my whole life.	PS2. If I get a serious disease, it will change my whole life.	
	PS3. I would be afraid to get serious illness.	PS3. I would be afraid to get serious illness.	
Perceived Vulnerability (PV)	PV1. I think I have a high risk to get serious disease.	PV1. I think I have a high risk to get serious disease.	Hsieh et al. (2016)
	PV2. I will worry about my own serious illness.	PV2. I will worry about my own serious illness.	
	PV3. I feel more vulnerable than others.	PV3. I feel more vulnerable than others.	
Intention to Use (UI)	BI1. I intend to continue using mHealth in the future	BI1. I intend to use mobile health services in the future.	Alam, Hoque, et al. (2020)
	BI2. I will always try to use mHealth in my daily life	BI2. I will always try to use mobile health services in my daily life.	
	BI3. I plan to continue to use mHealth services frequently	BI3. I plan to use mobile health services frequently.	
General Questions (Maker Variable)	MV1. Once I've come to a conclusion, I'm not likely to change my mind.	MV1. Once I've come to a conclusion, I'm not likely to change my mind.	Lin et al. (2015)
	MV2. I don't change my mind easily.	MV2. I don't change my mind easily.	
	MV3. My views are very consistent over time.	MV3. My views are very consistent over time.	

AUTHORS

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