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Innovative adoption model for digital health technologies among elderly with chronic diseases: integrating Unified Theory of Acceptance and Use of Technology and Knowledge-Attitude-Practice model in a survey of 1222 patients in Shanghai

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ABSTRACT

Objective To propose and test an innovative model by integrating the Unified Theory of Acceptance and Use of Technology and Knowledge-Attitude-Practice model to explain the mechanisms influencing the adoption of digital health technologies by elderly patients with chronic diseases from the perspective of both internal and external factors, promoting the acceptance and utilisation of digital health technologies among elderly chronically ill patients.

Study design A face-to-face questionnaire survey was conducted from July to September 2023.

Study setting The study was conducted in 12 medical institutions in Shanghai, including 6 tertiary hospitals, 3 secondary hospitals and 3 community hospitals.

Participants 1222 participants aged 60 years or more, diagnosed with one or more of the following chronic diseases: essential hypertension, type 2 diabetes, coronary atherosclerotic heart disease, stroke and chronic obstructive pulmonary disease, were involved in the study using convenience sampling. Critically ill emergency patients and those who were involved in medical disputes were excluded.

Outcome measure The behavioural intention and usage behaviour of older patients with chronic diseases to use digital health technologies.

Results The explanatory power of the proposed model for behavioural intention was 72.9%. There is a significant negative association between technology anxiety and the intention to use digital health technologies among older patients with chronic diseases (β=−0.224, p<0.001); effort expectancy (β=0.530, p<0.001) and performance expectancy (β=0.193, p<0.001) were also significantly associated with intention to use digital health technologies. Men (β=−0.104, p=0.016), relatively younger (β=−0.061, p=0.005), with experience in using digital health technologies (β=−0.452, p<0.001) were more likely to translate behavioural intention into use behaviour.

Conclusions Acceptance of digital health technologies among older patients with chronic diseases was associated with a combination of internal and external factors, with the former playing a dominant role. These valuable findings provided insights and inspiration for improving digital health technologies acceptance and utilisation among older patients with chronic diseases.

STRENGTHS AND LIMITATIONS OF THIS STUDY

- ⇒ This study used a large, multicentre sample of 1222 older adults recruited from 12 medical institutions across different levels of care.
- ⇒ The survey procedure employs illustrated materials, questionnaires with interviewer-assisted data entry, and visualised Likert scale tools to ensure elderly friendly accessibility.
- ⇒ Measurement items were adapted from established Unified Theory of Acceptance and Use of Technology and Knowledge-Attitude-Practice instruments and underwent pretesting to ensure linguistic and cultural suitability.
- ⇒ The cross-sectional design restricts causal inference between behavioural intention and actual digital health technology use behaviour.
- ⇒ The study was conducted within a single metropolitan setting, which may limit the wider generalisability of the findings to older adults in other contexts.

INTRODUCTION

With the rapid revolution of information and communication technologies, a wide variety of digital technologies have been increasingly applied in the health field, especially in healthcare.[1] Digital technologies play a crucial role in improving the accessibility, quality, effectiveness and convenience of healthcare.[2]

According to the definition of Food and Drug Administration, digital health technologies include the use of smart wearable devices, e-health telemedicine, m-health and health information technology. In this study, seven specific scenarios were included, namely mobile health management applications, outpatient appointments, telemedicine services and telesurgery, electronic discharge summaries, electronic health reports, smart wearable devices and electronic health records.[3]

In recent years, increasing evidence of advantages of digital health technologies (DHTs) for older chronic disease patients has been identified in supporting self-monitoring and self-management,[4] enabling immediate contact with health providers on important health issues,[4] maintaining positive health-related outcomes,[5] improving treatment adherence,[6] saving time,[7] among other benefits. Research indicates that chronic disease populations are more likely to benefit from the use of digital health technologies in managing their health conditions; however, they fail to maximise their use of digital health technologies, especially among older patients,[8] where acceptance and utilisation are far from satisfactory.[9] This disparity highlights the significant practical importance of exploring the factors influencing the acceptance and utilisation of digital health among elderly patients with chronic conditions.

With the acceleration of global ageing, the adoption of digital health technologies by elderly groups has drawn academic attention, particularly in developed countries.[10–12] However, as far as we know, there is very little practical evidence on the acceptance and use of digital health technologies for older chronically ill patients in developing countries.

Moreover, it has been pointed out that the implementation of individual health behaviour and the utilisation of health services are influenced by multiple factors. The external environment affects internal attitudes and needs, thus influencing health behaviour.[13] There exist certain research gaps in explaining user acceptance of digital health technologies from the perspective of internal and external factors based on user technology adoption theory.

To fill the knowledge gaps mentioned above, this study proposed and tested an integrated model of Knowledge-Attitude-Practice (KAP) and Unified Theory of Acceptance and Use of Technology (UTAUT) framework, to yield new insights into the behavioural mechanisms of elderly patients with chronic diseases in their acceptance and use of digital health technologies, considering external and internal influencing factors. The moderating role of demographic characteristics is examined to explore the transition from behavioural intention to actual usage behaviour. Our study hopes to provide a theoretical basis for how to improve the acceptance and utilisation of digital health technologies among older patients with chronic diseases, thereby promoting better delivery of the benefits brought by digital health technologies to elderly chronically ill patients.

Theoretical background and research hypotheses

Theoretical framework

The KAP model, also known as Knowledge-Attitude-Behaviour theory, is a classical framework in health education that explains how knowledge and attitudes influence health behaviour.[14] It conceptualises behaviour change as a three-stage process involving knowledge acquisition, attitude formation and behaviour adoption.[15]

UTAUT, one of the most impactful theories in the field of user technology adoption behaviour,[16] is composed of eight important models, namely Theory of Reasoned Action (TRA),[17] Technology Acceptance Model (TAM),[18] Model of Personal Computer Utilisation (MPCU),[19] Combined Technology Acceptance Model and Theory of Planned Behaviour (C-TAM-TPB),[20] Social Cognitive Theory (SCT),[21] Motivational Model (MM),[22] Theory of Planned Behaviour(TPB)[23] and Innovation Diffusion Theory (IDT).[24] UTAUT has demonstrated up to 70% explanatory power for technology use intention,[25] surpassing many foundational models. In recent years, UTAUT has been widely used as a theoretical basis to study the issue of acceptance in the fields of mHealth,[16] eHealth,[26] telemedicine[27] and digital health.[3]

Although UTAUT is widely used to predict technology acceptance and use, findings in medical and health contexts are inconsistent.[28] Ward pointed out that, in many cases, the original UTAUT shows limited predictive power for health technology acceptance.[29] In recent years, there have been more and more attempts to develop the UTAUT model by adding new variables,[16 30] changing the original framework[31 32] and integrating UTAUT with other theoretical models,[33] so that it can be suitable for explaining the acceptance and use of different populations in various domains.

This study examines the acceptance and use of digital health technologies among elderly patients with chronic illnesses by integrating the KAP and UTAUT frameworks to capture internal and external factors.

Research hypotheses

Figure 1 presented an integrated model, combining KAP theory and UTAUT.

According to Almathami *et al*,[34] in the context of digital health technologies, external factors relate to the usage environment and system characteristics, whereas internal factors encompass use behaviour, motivation during system interaction and patients' attitudes towards digital health relative to traditional care.

Analysis of the UTAUT framework indicates that social influence primarily involves key figures—family, relatives, teachers or healthcare workers—who are likely to transmit their knowledge and attitudes about digital health technologies to elderly chronic patients. Furthermore, facilitating conditions refer to the support obtainable from the external world. These factors can be comprehensively regarded as the external factor dimension, which together forms the element 'Knowledge' in KAP.

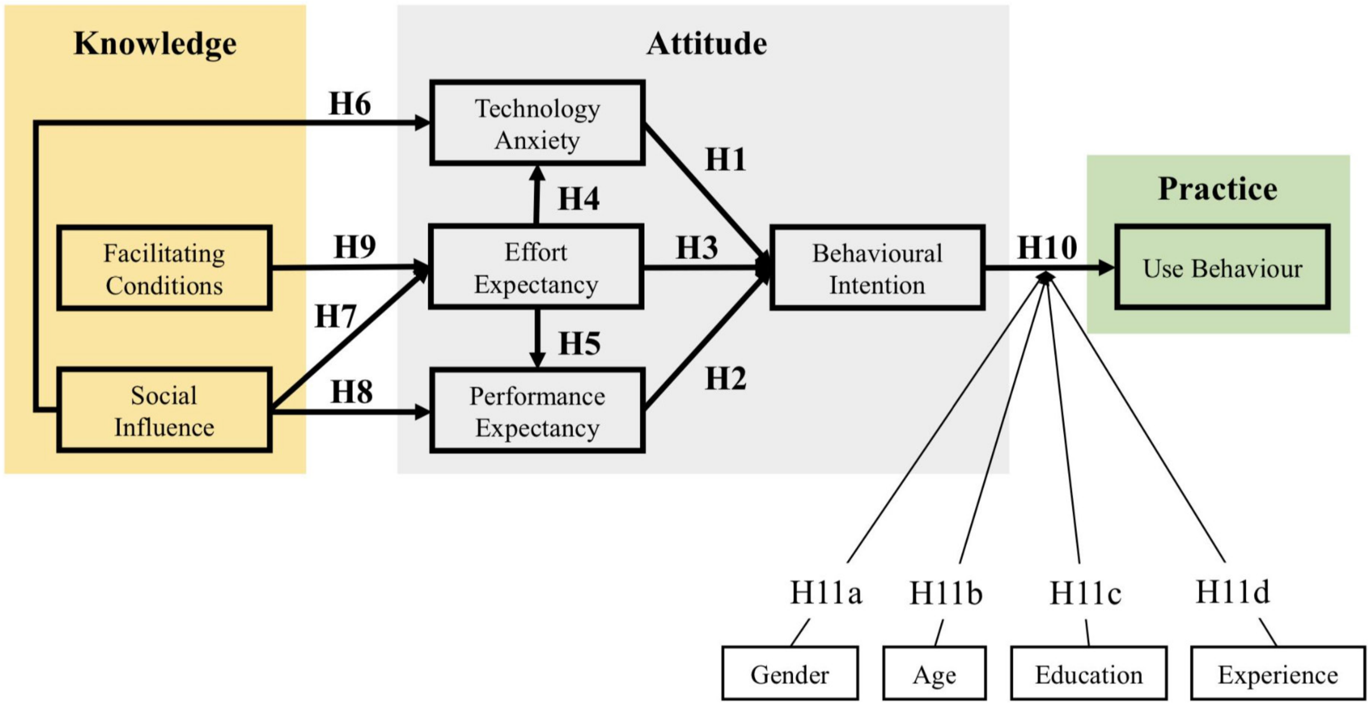

Figure 1 The conceptual model (KAP-UTAUT model). Note: H1–H10 stand for 10 main pathway hypotheses, while H11a, H11b, H11c and H11d represent four moderating pathway hypotheses. KAP-UTAUT, Knowledge-Attitude-Practice and Unified Theory of Acceptance and Use of Technology.

Moreover, having a closer look into UTAUT, two core variables effort expectancy and performance expectancy were derived from the concept 'perceived ease of use' and 'perceived usefulness'.[25] The former implicates the attitude towards whether DHTs can bring benefits, and the latter points to the attitude towards whether individuals can master this technology. In addition, behavioural intention, similar to the concept of attitude in KAP, serves as an important link in transforming willingness into final practice. We also observe that the age-related variable technology anxiety focuses on individual psychological and emotional factors. Based on the characteristics of the four variables mentioned above, in this study, we categorise effort expectancy, performance expectancy, behavioural intention and technology anxiety into the element 'Attitude' in KAP, as well as internal factors that influence digital health technology.

Finally, UTAUT concentrates on the transition from the behavioural intention to the use behaviour, which is equivalent to putting behaviour into practice, aligning with 'Practice' in KAP.

The following sections explain the hypotheses between the constructs.

Technology anxiety

Technology anxiety is considered a negative emotion related to the use of digital health technology.[35] Older adults facing new technology may experience higher levels of anxiety due to declines in physical and cognitive abilities, thereby reducing their willingness to use innovative technology further.[36] In previous research, technology anxiety has been identified as a significant factor influencing the intention of older adults to adopt mobile healthcare services[16] and digital health technologies.[3] Therefore, we proposed the following hypothesis:

H1. Technology anxiety is negatively associated with behavioural intention to accept and use digital health technologies.

Performance expectancy

In the context of digital healthcare, performance expectancy refers to perceptions of the utility of digital health technology. Previous research indicated that performance expectancy significantly influences the intention to use mobile healthcare services.[16 31] Therefore, we proposed the following hypothesis:

H2. Performance expectancy is positively associated with behavioural intention to accept and use digital health technologies.

Effort expectancy

In this study, effort expectancy represents the ease with which people use digital health technologies to manage health. Prior research has confirmed that effort expectancy directly affects the intention to use.[16] It has been pointed out that the easier it is for older users to use a new technology, the less anxious they may feel.[37] Cimperman *et al* have found that effort expectancy positively influences performance expectancy when it comes to the usage of home telehealth services of older adults.[38] Therefore, we proposed the following hypotheses:

H3. Effort expectancy is positively associated with behavioural intention to accept and use digital health technologies.

H4. Effort expectancy is negatively associated with technology anxiety of accepting and using digital health technologies.

H5. Effort expectancy is positively associated with performance expectancy to accept and use digital health technologies.

Social influence

Social influence is defined as the degree to which an individual believes that other people think they should use the new system.[25] Previous studies indicated that technology anxiety stems from social cognitive theory, where individuals who perceive themselves as inefficient under the influence of others may experience stress.[36] Moreover, researchers found that social influence significantly affects effort expectancy in the field of mobile learning services.[39] It has been confirmed in prior research that social influence indirectly affects behavioural intention through performance expectancy.[31] Therefore, we proposed the following hypotheses:

H6. Social influence is negatively associated with technology anxiety of accepting and using digital health technologies.

H7. Social influence is positively associated with effort expectancy to accept and use digital health technologies.

H8. Social influence is positively associated with performance expectancy to accept and use digital health technologies.

Facilitating conditions

In digital healthcare, facilitating conditions reflect the extent to which existing digital health infrastructure and conditions support digital health services. A Japanese study reported that facilitating conditions indirectly affect behavioural intentions through effort expectancy.[31] Therefore, we proposed the following hypothesis:

H9. Facilitating conditions are positively associated with effort expectancy to accept and use digital health technologies.

Behavioural intention

Behavioural intention is widely confirmed as a crucial predictive factor for usage behaviour in the digital healthcare field. Gu *et al*[40] found that users' behavioural intention in developing countries has a significant positive influence on the actual usage behaviour of electronic health technology. Therefore, we proposed that:

H10. Behavioural intention is positively associated with actual use behaviour to accept and use digital health technologies.

Moderating variables

Demographic factors have long been considered as important predictors in the field of technology acceptance and use.[41] The previous literature mainly focuses on the effects of these moderating variables on the formation of behavioural intention.[42] However, it is pointed out that the transition from behavioural intention to use behaviour is influenced by different factors,[43] which need to be further discussed through empirical studies.

A study investigating Chinese people's use of mobile social networking services paid attention to whether gender moderated the impact of behavioural intention on use behaviour,[44] finding no difference in intention-to-behaviour transition between men and women. There is a lack of evidence regarding the moderating influence of gender on behavioural intention on use behaviour in the field of digital health, which needs to be further explored.

Research in the education sector shows that users with prior experience of new technologies are more likely to translate intention into actual use.[45] This finding aroused the interest of the role experience plays of experience in converting behavioural intention into use behaviour in the context of digital health technologies.

In the area of digital health, Gu *et al*[40] explored how age and education moderate the translation of behavioural intention into use among Pakistani adults. Although their results were not statistically significant, examining these moderators in a Chinese population may enhance the model's explanatory power. Therefore, we proposed the following hypotheses:

H11a. Gender moderates the association between behavioural intention and use behaviour.

H11b. Age moderates the association between behavioural intention and use behaviour.

H11c. Education moderates the association between behavioural intention and use behaviour.

H11d. Experience with digital health technologies moderates the association between behavioural intention and use behaviour.

METHODS AND MATERIALS

Study design and setting

From July 2023, a 2-month cross-sectional patient survey was conducted on-site in 12 medical institutions across six administrative districts in Shanghai, including 6 tertiary hospitals, 3 secondary hospitals and 3 community hospitals, as illustrated in online supplemental figure S1. The healthcare institutions enrolled in the study exhibit good diversity in terms of service levels, organisational characteristics and geographical regions, meeting the representativeness requirements of this research. Data were collected using convenience sampling.

Study population

Patients met the following inclusion criteria were recruited: (1) aged 60 years or above; (2) capable of independent judgement and understanding and (3) according to the International Classification of Diseases-10, diagnosed with one or more of the following chronic diseases: essential (primary) hypertension (I10.x00), type 2 diabetes (E11.900), coronary atherosclerotic heart disease (I25.103), stroke (I64.x00) or chronic obstructive pulmonary disease (J44.900). Critically ill emergency patients and those who were involved in medical disputes were excluded. All participants volunteered to take part in the study and signed informed consent with no remuneration paid. The survey ensured respondents' anonymity, and all information collected was used solely for research purposes. Data were stored in a password-protected electronic system to prevent unauthorised access.

Sample size determination

A widely used method for minimum sample size estimation in partial least squares structural equation modelling (PLS-SEM) is the '10-times rule',[46] which states that the sample size should be at least ten times the number of inner model constructs.[47] In this study, the questionnaire comprised 28 questions, and the sample size of 1222 satisfied the statistical requirements.

Data collection tools, data quality control and procedures

The questionnaire consisted of two sections, demographic information collection and a survey on the use and acceptance of digital health technologies, as shown in online supplemental tables S1 and S2. In the second section, the question items in the scale were adapted from a number of published global studies grounded in the UTAUT framework and were sinicised by two native Chinese speakers according to the topic and subject of the study. To assure that the meaning of the questionnaire remained the same before and after the translation, a translator who did not know the content of the questionnaire translated the Chinese questionnaire into English and cross-referenced the two questionnaires. This forward–backward translation process was used to minimise translation bias and ensure conceptual consistency.[3] A five-point Likert scale was used to measure all the constructs, ranging from 1 (strongly disagree) to 5 (strongly agree). To enhance the accuracy of subjective data collection among older adults, a visual five-point response scale was used as an assisting tool during field surveys. Participants were asked to indicate the point on the scale that best reflected their personal perception, after which responses were recorded by the surveyors. In addition, the questionnaire adopted in this study covers both positive and negative questions, which eliminates acquiescence bias to some extent. In order to avoid common method bias, the questionnaire in this study was worded in plain language. Before formally asking questions, examples were provided to the respondents with the help of an illustrative instruction to introduce scenarios of digital health technology and applications, clarifying the research theme and key concepts. Due to visual impairment and less nimble finger movements in the elderly population, surveyors read each question to the participants and assisted them in selecting the corresponding options on the electronic questionnaire according to their responses. In the setting of electronic questionnaires, all items were required to be completed before submission, and questionnaires with missing responses could not be submitted. This procedure ensured that the final analytical dataset contained no missing data. The phone number of the participants was collected to avoid multiple participation. All surveyors received standardised training to ensure consistency in administration across study sites. A pilot study was conducted through field testing prior to the large-scale survey, making sure whether each question could be understood by older chronic disease patients correctly. In accordance with the predefined inclusion and exclusion criteria, the pilot was carried out among older patients with chronic diseases at a tertiary hospital in Shanghai. The demographic characteristics of participants in the pilot study were broadly comparable with those of the final study sample. Feedback from the pilot survey was used to refine item wording. During the pilot survey, any items that older participants found difficult to understand or interpret were systematically recorded by the surveyors, discussed within the research team and revised to improve clarity and age-appropriateness of the final questionnaire.

Patient and public involvement

Patients and public were not involved.

Data processing and analysis

Our study attempted to develop the classical UTAUT, and given the high applicability of PLS-SEM in terms of theory development,[48] PLS-SEM was adopted in this study. Further considering the complexity of the conceptual model and the truth that algorithmic performance of PLS-SEM is better than CB-SEM in complex models,[49 50] PLS-SEM becomes an optimal approach for our study. SmartPLS (V.4.0.9.5), a commonly used software for conducting PLS-SEM, was used to perform validation analyses on theoretical hypotheses, reliability and validity within the structural equation model.[49]

Internal reliability was measured by composite reliability (CR) and Cronbach alpha, with a threshold exceeding 0.7, indicating satisfactory internal consistency.[51] To ensure convergent validity, an evaluation was performed on average variance extracted (AVE) and item loadings. If AVE is larger than 0.5 and loadings exceed 0.7, structural validity meets the required standards.[52] If the square root of AVE for each construct is greater than the correlation coefficient between constructs, it suggests ideal discriminant validity.[49] Specifically, the square root of AVE for each construct should be greater than the correlation coefficient between constructs on the diagonal and off-diagonal elements.[53] The bootstrap method was used to calculate path coefficients and their significance. To ensure maximum reproducibility of results, this study employed 5000 random subsamples in bootstrapping.[31] The issue of multicollinearity and common method bias in the model is checked by examining the variance inflation factor (VIF) values, which should be below a threshold of 5 and preferably approach 3 or below.[54]

Table 1 Demographics of sample (n=1222)

Item	Category	n	Per cent
Ethnicity	Han	1222	100
Gender	Male	611	50
	Female	611	50
Age (years)	60–64	277	23
	65–69	326	27
	70–74	280	23
	75–79	173	14
	≥80	166	13
Chronic disease*	Hypertension	663	54
	Cardiovascular disease	387	32
	Diabetes	453	37
	Stroke	100	8
	COPD	151	12
	Other	53	4
Education	Elementary School or below	107	9
	Junior High School	456	37
	High School	527	43
	University or beyond	132	11
Experience in digital health	Yes	1121	92
	No	101	8

*Note: The table displays the conditions listed in participants' medical histories, with many individuals having multiple chronic illnesses.
COPD, chronic obstructive pulmonary disease.

RESULTS

Demographics of sample

1291 questionnaires were distributed, of which 1222 were retrieved, with a response rate of 94.7% of giving consent. The demographic results (table 1) showed that the sample was evenly distributed between male and female participants. It should be pointed out that although the final sample contains an equal number of male and female respondents, this distribution arose coincidentally (participants number of each surveyed institution is shown in online supplemental table S3). Each of the twelve participating institutions collected data independently, without gender-based quotas. Gender proportions varied across institutions, and the overall balance emerged only after pooling the datasets. All participants were elderly individuals aged 60 and above with at least one chronic disease. The average age of the participants was 70 years, with the majority (26.68%) falling in the range of 65–69 years. Almost half of the respondents (42.96%) had a high school education. Additionally, most of the participants (91.74%) had prior experience using digital health applications.

Measurement model

Before delving into the results of the structural equation analysis, a comprehensive assessment of the questionnaire survey's quality was conducted by systematically evaluating convergent validity and internal reliability. The data suggested that the AVE of the construct Facilitating Conditions was lower than the recommended threshold of 0.5, while the loadings of *FC2*, *FC3* and *FC4* were lower than 0.7.

It should be noted that although the loading value of *FC1* performs better, there existed a paradoxical conflict between *FC1* and the other three question items of this construct. The analysis of the frequency distribution of scores for the four question items revealed the underlying issue: the characteristics of the *FC1* curve differed from those of *FC2*, *FC3* and *FC4*, with about half of the older adults having little or no knowledge of digital health. However, as reflected in the other three question items, the vast majority of the elderly individuals with chronic diseases have already received adequate support, including getting help from others, having access to various resources and encountering no ambivalence when it comes to the use of digital health technologies.

According to the reasons mentioned above, we ultimately removed the *FC1* item from the structural equation.[55 56] After the exclusion of non-conforming items, the reliability and validity of the conceptual model perform well (table 2). CR ranged from 0.791 to 0.969, Cronbach alpha ranged from 0.755 to 0.969, higher than the recommended value of 0.7, meaning the internal reliability is at a desirable level. Furthermore, AVE ranged from 0.665 to 0.942, greater than the standardised value of 0.5. Meanwhile, the loadings of all the items were higher than 0.7, showing satisfactory construct validity. The results (table 3) showed excellent discriminant validity as well.

In this study, as shown in table 4, the values of VIF of each path ranged from 1.011 to 2.797, indicating that the model does not suffer from multicollinearity nor common method bias. With no problem of multicollinearity, the explained variance of the endogenous structure was examined through the coefficient of determination (R^2). According to the criteria of academia, R^2 should be >0.1.[57] For this study, R^2 values ranged from 0.145 to 0.729 as shown in figure 2, which demonstrates good explanatory power.

With regard to model fit, standardised root mean square residual in the model is 0.021, less than the threshold value of 0.08.[58] D_ULS valued 0.153, which was below 95% bootstrap quantile (HI95 of d_ULS), meanwhile, d_G valued 0.240, which was below 95% bootstrap quantile (HI95 of d_G).[59] Normed fit index valued 0.860, highly close to the perfect fit metric of 0.9.[60] This indicated that the model fit in this study was at a satisfactory level.

Table 2 The measurement model before and after removing non-conforming items (n=1222)

	Before				After			
Items	Loadings	AVE	CR	Cronbach alpha	Loadings	AVE	CR	Cronbach alpha
BI1	0.952	0.833	0.937	0.898	0.952	0.833	0.937	0.898
BI2	0.836				0.836			
BI4	0.945				0.945			
EE1	0.892	0.840	0.955	0.936	0.892	0.840	0.955	0.936
EE2	0.946				0.945			
EE3	0.950				0.949			
EE4	0.878				0.879			
FC1	0.872	0.487	0.787	0.727	–	0.665	0.856	0.755
FC2	0.584				0.794			
FC3	0.604				0.804			
FC4	0.695				0.848			
PE1	0.965	0.942	0.980	0.969	0.965	0.942	0.980	0.969
PE2	0.971				0.971			
PE3	0.976				0.976			
SI1	0.769	0.789	0.937	0.909	0.770	0.789	0.937	0.909
SI2	0.924				0.924			
SI3	0.936				0.936			
SI4	0.914				0.914			
TA1	0.931	0.878	0.956	0.931	0.931	0.878	0.956	0.931
TA2	0.959				0.959			
TA3	0.921				0.921			
UB1	0.878	0.846	0.956	0.939	0.878	0.846	0.956	0.939
UB2	0.942				0.942			
UB3	0.925				0.925			
UB4	0.933				0.933			

Note: Item refinement was applied only for the facilitating conditions construct, which did not initially meet the predefined thresholds. The remaining constructs met the criteria in the initial assessment and were therefore unadjusted.
AVE, average variance extracted; BI, behavioural intention; CR, composite reliability; EE, effort expectancy; FC, facilitating conditions; PE, performance expectancy; SI, social influence; TA, technology anxiety; UB, use behaviour.

Table 3 Correlation matrix and square root of the AVE after removing non-conforming items (n=1222)

	BI	EE	FC	PE	SI	TA	UB
BI	0.913						
EE	0.824	0.917					
FC	0.357	0.350	0.815				
PE	0.666	0.654	0.374	0.971			
SI	0.166	0.225	0.222	0.304	0.888		
TA	0.731	0.752	0.350	0.566	0.152	0.937	
UB	0.758	0.725	0.478	0.816	0.369	0.606	0.920

AVE, average variance extracted; BI, behavioural intention; EE, effort expectancy; FC, facilitating conditions; PE, performance expectancy; SI, social influence; TA, technology anxiety; UB, use behaviour.

Hypothesis testing

Our model explained 0.729 of the general total variances in behavioural intention and 0.610 of the variances in use behaviour (figure 2).

The hypotheses testing outcomes (table 5) show that technology anxiety was significantly negatively associated with behavioural intention, effort expectancy was significantly negatively associated with technology anxiety; facilitating conditions were significantly positively associated with effort expectancy, social influence and effort expectancy were significantly positively associated with performance expectancy; effort expectancy and performance expectancy were significantly positively associated with behavioural intention, and behavioural intention was significantly positively associated with use behaviour. No statistically significant association was observed between social influence and technology anxiety, indicating Hypothesis 6 was invalid.

Table 4 Variance inflation factor of each path in the model (n=1222)

Path	VIF
BI→UB	2.491
EE→BI	2.797
EE→PE	1.053
EE→TA	1.053
FC→EE	1.052
PE→BI	1.788
SI→EE	1.052
SI→PE	1.053
SI→TA	1.053
TA→BI	2.353
BI→UB (gender)*	1.989
BI→UB (age)*	1.038
BI→UB (education)*	1.109
BI→UB (experience)*	2.128

*Points to the moderating effects of gender, age, education and experience on the relationship between BI and UB, respectively BI, behavioural intention; EE, effort expectancy; FC, facilitating conditions; PE, performance expectancy; SI, social influence; TA, technology anxiety; UB, use behaviour; VIF, variance inflation factor.

Regarding moderating factors, gender, age and experience moderated the association between behavioural intention and use behaviour concerning the acceptance and use of digital health applications, these moderating associations were statistically significant, supporting Hypothesis 11a, Hypothesis 11b and Hypothesis 11d. The educational level of the participants was not significantly associated with moderation of the relationship between behavioural intention to use behaviour in the acceptance and use of digital health applications, rejecting Hypothesis 11c.

DISCUSSION

Principal findings

Model influencing pathway

Our study confirms that effort expectancy and performance expectancy are significantly positively associated with behavioural intention respectively, as reported in prior studies.[16 30] Interestingly, it is noted that social influence is a stronger determinant of the adoption of DHTs for an all-age adult study population.[61 62] However, among older people, effort expectancy plays a more important role in their DHTs acceptance and usage. compared with other age groups, older adults are less effective at using digital health technologies, implying that more effort is needed to accomplish the same task.[63] Elderly individuals are willing to learn or sustain the use of new technologies

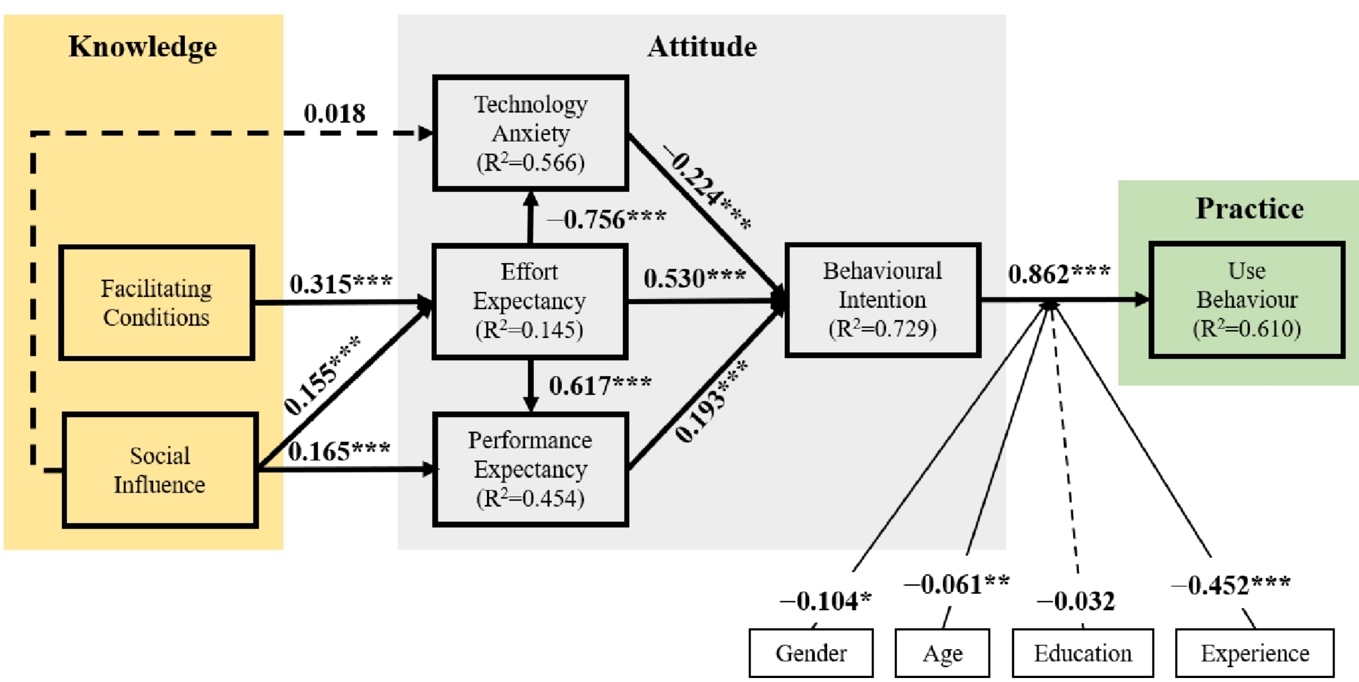

Figure 2 The validated conceptual model. Notes: (1) *, **, *** refers to significance level at p<0.05, p<0.01, p<0.001, respectively. (2) Gender is a dichotomous variable, where 1 represents men and 2 represents women. Age is set as a tri-categorical variable, where 1 represented 60–69 years, 2 represented 70–79 years and 3 represented 80 years or older. Education is set as a four-categorical variable, where 1 represents primary school, 2 represents junior high school, 3 presents high school and 4 represents the university or beyond. Experience is a dichotomous categorical variable, where 1 represents having experience with digital health applications and 2 represents no experience. (3) The adjusted R^2 value is annotated in the figure.

Table 5 Results of the hypothesis test (n=1222)

Hypothesis	Path	β	P value	Hypotheses
H1	TA→BI	−0.224	0.000	Supported
H2	PE→BI	0.193	0.000	Supported
H3	EE→BI	0.530	0.000	Supported
H4	EE→TA	−0.756	0.000	Supported
H5	EE→PE	0.617	0.000	Supported
H6	SI→TA	0.018	0.404	Not supported
H7	SI→EE	0.155	0.000	Supported
H8	SI→PE	0.165	0.000	Supported
H9	FC→EE	0.315	0.000	Supported
H10	BI→UB	0.862	0.000	Supported
H11a	BI→UB (gender)*	−0.104	0.016	Supported
H11b	BI→UB (age)*	−0.061	0.005	Supported
H11c	BI→UB (education)*	−0.032	0.086	Not supported
H11d	BI→UB (experience)*	−0.452	0.000	Supported

*Points to the moderating effects of gender, age, education and experience on the relationship between behavioural intention and use behaviour, respectively.
BI, behavioural intention; EE, effort expectancy; FC, facilitating conditions; PE, performance expectancy; SI, social influence; TA, technology anxiety; UB, use behaviour.

only when they perceive digital health technologies as easy to use.[64] When elderly patients perceive the benefits and support of digital health technology for self-health management, they are more likely to continue using this technological application in the future.[65]

We found that technology anxiety is negatively associated with behavioural intention. Our finding is aligned with previous studies concerning older population.[3 16] Additionally, some elderly patients harbour scepticism towards new technologies, especially when these technologies are related to the medical and health field, which intensifies their negative emotions.[66]

Effort expectancy shows a significant positive association with performance expectancy of elderly patients with chronic diseases in using digital health technology. According to Venkatesh *et al*, both effort expectancy and performance expectancy were evolved from the technology acceptance model. Effort expectancy originated from the variable 'perceived ease of use', while performance expectancy originated from the variable 'perceived usefulness'.[25] Li *et al* stated that perceived usefulness depends on perceived ease of use when Chinese elderly individuals adopt remote health management services. In other words, making digital health technologies simpler for elderly patients will help to increase their willingness to adopt them, thereby enhancing their perception of the benefits of DHTs.[30]

Moreover, our finding suggested that effort expectancy negatively affects technology anxiety. The lack of confidence among the elderly population in their ability to independently operate digital health devices frequently leads to anxiety, hindering the acceptance and use of digital health technologies.[11] Therefore, the easier the digital health technology is to operate, the higher the construct effort expectancy score, and the lower the likelihood that elderly patients with chronic diseases will experience technology anxiety.

Results also indicate that social influence is significantly positively associated with performance expectancy of elderly patients with chronic diseases regarding digital health technologies. Previous studies have also identified interpersonal support as a promoting factor in the acceptance and usage of digital health technology[31] among young adult populations. Whereas fewer scholars have investigated the effects of social influence on effort expectancy in their studies, our results confirm that social influence has a significant positive effect on effort expectancy, which is consistent with the prior finding.[39] This finding suggests that older people with chronic illnesses perceive increased usability of digital health technology with the intervention and help of significant others, suggesting that family members, patients, healthcare professionals and others play an important role in promoting the adoption of DHTs in the older population.

In previous studies, there has been limited focus on the influence of facilitating conditions on effort expectancy in the field of healthcare. Our findings showed that facilitating conditions were significantly positively associated with when elderly patients with chronic diseases accept and use digital health technology. This has been corroborated by recent research findings.[31] The elderly population generally lacks confidence in their knowledge of the digital health domain, believing that these technological applications surpass their cognitive and skill capabilities.[11]

Therefore, one measure to be considered is providing the elderly with more knowledge and resources needed to use digital health technology, enhancing their effort expectancy and stimulating their behavioural intention to accept and use digital health technologies.

In contrast with previous findings, no statistically significant correlation was discovered between social influence and technology anxiety. Despite that, Cao *et al* stated that social influence could alleviate anxiety regarding mobile health among Japanese young adults.[31] The situation may vary in older populations and in other countries, which requires further exploration in the future.

Regarding the moderating variables between behavioural intention and use behaviour, men, relatively younger elderly individuals and participants with experience in digital health usage are more likely to translate the intention to use digital health technologies into actual usage behaviour. As age increases, problems such as decline in memory, vision and finger flexibility emerge, preventing older people with chronic illnesses from turning their intention to use the Internet into action. Goswami and Dutta demonstrated that women are more prone than men to have anxiety regarding the use of information technology (IT), leading to lower self-efficacy,[67] which partially discourages women from using digital health technologies. A Swedish research study also stated that lack of experience hinders the adoption of older patients in adopting e-health in primary healthcare.[11] Contrary to contemporary young people who are familiar with the Internet, the older age group belongs to the age of telephone and radio,[68] which may account for the fact that the level of education did not play a moderating role between behavioural intention and use behaviour in this study.

External and internal factors

This study examines the core variables in the UTAUT theory in terms of both external and internal factors, which contribute to a more nuanced understanding of the mechanisms influencing digital health technology adoption behaviours among older chronic disease populations, and consequently to a more targeted proposal of strategies for the acceptance and use of digital health technologies.

External factors include social influence and facilitating conditions, and internal factors include effort expectancy, performance expectancy, behavioural intention and technology anxiety. Our study confirms that adoption of digital health technologies by older patients is influenced by a combination of both internal personal and external environmental factors. In the field of digital health, Conway *et al*[69] drew similar conclusions from their literature review, that personal and contextual factors together have a positive influence on the adoption of digital health apps by dementia patients.

The results of the coefficient of influence pathway further reflect that internal personal factors of older patients with chronic diseases have a dominant role in digital health technology adoption behaviours, which implies that internal factors play a more crucial role than external factors. Effort expectancy, as a core variable among the internal factors, was significantly associated with various variables including performance expectancy, behavioural intention, and technology anxiety, and needs to be given particular attention. In response to the three aspects of the 'effort expectancy', the following measures should be taken: to publicise the advantages of digital health technologies, so as to stimulate intrinsic motivation and alleviate the discomfort of older patients with chronic diseases in accepting digital health technologies; to increase accessibility and lower the threshold of learning digital health technologies for older patients with chronic diseases through more training; and to improve the ease of use of digital health technologies for older patients with chronic diseases through more age-friendly operation design and timely provision of assistance and guidance in the utilisation of digital health technologies.

In addition, external environmental factors exert a significant influence on the internal personal factors. External factors are prerequisite factors for older individuals with chronic diseases to be exposed to digital health technologies. The perceptions of important individuals in the context, the accessibility of help and the conditions under which the technologies are used all contribute to the older individual's perceptions of and attitudes towards digital health technologies. This suggests the urgent need for children to shoulder the responsibility of 'digital parenting' and to create a favourable family environment for the acceptance and use of digital health technologies by older persons with chronic diseases. Policy makers need to design a top-level support system for the adoption of digital health technologies by older people with chronic diseases. Family members, volunteers and healthcare professionals are required to work together to ensure the accessibility of help in different digital health application scenarios, such as at home, in hospitals and in the community. In the meantime, product designers ought to optimise the product performance and operation smoothness to reduce the possibility of equipment failure. In this way, the positive influence of external environmental factors on internal personal factors will be enhanced, boosting the acceptance and use of digital health technologies by elderly patients with chronic diseases.

Theoretical and practical implications

By combining the foundation of the KAP theory and reconstructing the UTAUT extended model, our study examines the factors influencing the adoption of digital health technologies, contributing to a better understanding of the mechanisms behind the formation of older chronic patients' behaviour regarding digital health technologies. Whereas previous studies have generally been limited to adding new variables within the framework of existing classical models of acceptance and use of domains, this study makes a theoretical contribution by reconstructing the UTAUT model in an innovative way. In addition, to our knowledge, there are currently only a few studies that focus on older people's use behaviours from both an individual and an environmental perspective. To examine the acceptance and use of digital health technologies, it is not sufficient to observe the effects of individual variables on behavioural intentions or use behaviours in a simple and isolated manner. Therefore, this study identifies multiple associations between internal and external factors on the acceptance and use of digital health technologies.

In practical terms, the empirical results from this study's large-sample, multi-centre survey provide valuable guidance for product designers, policy makers and healthcare practitioners. Specifically, stakeholders are encouraged to work towards reducing the difficulty of operating digital health technologies, enhancing age-friendly design, minimising the effort involved in accepting and using digital health technologies for older patients with chronic diseases. Additionally, accessibility of knowledge, resources and assistance for older patients with chronic conditions should be implemented to fully capitalise on the positive effects of external environmental conditions.

Limitations and suggestions for future research

We may consider some limitations to be explored in the near future. first, we conducted on-site convenience-sampling surveys by distributing questionnaires in Shanghai, which is a mega city with certain unique characteristics. So, concerns may arise regarding the generalisation of the results. Moreover, the study relied on self-reported questionnaires, which may introduce recall and social desirability biases and affect measurement precision. Future research should further expand the scope of the present investigation, including samples from different populations and geographical factors, providing more valuable evidence for the popularisation and development of digital health technology and various applications in the elderly population. In addition, as a study of health-related behaviours and intentions, body mass index (BMI) and lifestyle factors (eg, smoking, alcohol use, physical activity) warrant further consideration to explore how these factors shape older adults' acceptance and use of digital health technologies. Also, we mainly focused on the five major chronic diseases with higher prevalence rates in the elderly population: hypertension, diabetes, coronary heart disease, stroke and chronic obstructive pulmonary disease, without including cancer patients. Given that many recent studies have confirmed the enormous potential of digital health technology to improve health behaviours in cancer patients,[70 71] the adoption behaviour of cancer patients for digital health applications should not be ignored in future research. Lastly, we only considered elderly patients with the ability for self-care. As age advances and physical function declines, some older adults may gradually experience reduced capacity for independent self-care. Considering the fact that different health conditions of elderly individuals may affect their intentions to use mobile health technology to varying extents,[32] future research also needs to focus on the use of digital health technologies by older adult populations with personality traits, self-efficacy or the presence of older patients with reduced self-care skills.

CONCLUSIONS

By proposing, testing and validating an acceptance model for digital health technologies by integrating the UTAUT and the KAP model, our study explains the acceptance of digital health technologies by elderly patients with chronic conditions, considering external environmental factors and internal personal factors. Our innovative model accounts for 72.8% of the behavioural intention to use digital health technologies among elderly patients with chronic conditions. Furthermore, external factors exert a significant influence on internal factors, while internal factors play a more crucial and dominant role.

Our study provides valuable insights for developers of digital health technology products and policymakers, not only highlighting some reference points for an optimisation of digital health technology, but also, particularly, facilitating the acceptance and use of digital health technologies, particularly among elderly people.

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