pISSN: 1906 - 6406 The Scholar: Human Sciences
eISSN: 2586 - 9388 The Scholar: Human Sciences
https://assumptionjournal.au.edu/index.php/Scholar

Exploring Factors Shaping Patients' Intentions to Adopt Cancer Management Apps: An Extended UTAUT Approach

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Received: August 31, 2024. Revised: November 19, 2024. Accepted: February 18, 2025.

Abstract

Purpose: This study aimed to identify the determinants of cancer patients' behavioral intention to use cancer management applications based on the Extended Unified Theory of Acceptance and Use of Technology Model and other expanded variables. **Research Design, Data, and Methodology:** 500 adult cancer patients treated at Sichuan Cancer Hospital were surveyed using the Web-based survey tool. They were familiar with mobile applications but had no experience in using them for cancer management. The index of the-item-objector congruence (IOC) method was used for the pretest, and the Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) were finally used to analyze the data. **Results:** The results showed that perceived disease threat (β=0.235, t=4.685), social influence (β=0.231, t=4.316), and performance expectancy (β=0.231, t=4.154) had a positive direct effect on patients' behavioral intention to use mobile health applications for cancer management. What is more, perceived disease threat and social influence indirectly affected behavior intention mediated by performance expectancy. However, effort expectancy, facilitating condition, trust, and privacy showed no causal relationship with behavioral intention toward mobile health applications for cancer management. **Conclusions:** Further research is needed to investigate additional mobile health acceptance factors. Additionally, system developers of mobile health applications for cancer management should focus on improving performance expectancy.

Keywords: Performance Expectancy, Behavior Intention, Mobile Health Applications, UTAUT, Cancer

JEL Classification Code: E44, F31, F37, G15

1. Introduction

With the rise of mobile phones and the internet, mobile applications (apps) have rapidly developed. One specific type of app, mobile health (mHealth) app, which relates to people's health, has also steadily increased in recent years (Yang et al., 2023). Mobile health applications for cancer management are one of the specific types of mHealth apps used for education, pharmacotherapeutic monitoring, chemotherapy management, symptoms management, pain and fatigue management, self-management, and so on.

With about 19.3 million new cancer cases diagnosed worldwide in 2020 (Sung et al., 2021), and higher incidence and death rates in developing countries, the need for a sustainable infrastructure for global cancer control is paramount. The proliferation of health-related mobile phone applications, coupled with a theory-based framework of mobile health applications, offers a ray of hope. These applications, when used for cancer prevention and treatment, can significantly enhance patient education, patient reported outcome, self-management, and importantly, reduce the costs of healthcare services.

With the global shortage of medical staff and medical resources, mHealth apps can reduce the burden of medical staff and improve the health literacy and self-management of oncology patients. Descriptive studies of app usage willingness found that 60% of patients were willing to use apps, which they found to be helpful, but the real usage rate was still low at present. Empirical studies in the areas of diabetes (Zhang et al., 2019), hypertension (Dou et al., 2017),

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and other chronic diseases (Portz et al., 2019) found those factors influencing mHealth app usage, but there was a lack of literature reports in oncology in China. Therefore, this study would like to investigate the influential factors towards cancer patients' behavior intentions to use cancer management apps based on UTAUT model. This study can benefit the cancer patients, physicians, nurses, or mobile health apps developers.

2. Literature Review

2.1 Perceived Disease Threat

Perceived disease threat refers to patients' awareness or consciousness of cancer and measures the extent to which daily activities integrate medical issues, according to previous research (Baek et al., 2024). Perceived disease threat has been shown to directly and indirectly influence consumers' intention to use health information technology through perceived usefulness in several studies (Dou et al., 2017; Schretzlmaier et al., 2022; Zhang et al., 2019). Cancer can induce serious physical and psychological hurt in patients. More and more studies have indicated that mobile health applications effectively manage cancer. The more serious the cancer was, the more patients would have behavioral intentions toward mobile health applications for cancer management. Hence, the researcher proposed the following hypothesis:
H1: Perceived disease threat has a significant impact on performance expectancy.
H5: Perceived disease threat has a significant impact on behavior intention.

2.2 Effort Expectancy

Effort expectancy was defined as the degree to which a person believes using a particular system would be free of effort (Venkatesh et al., 2003). In this research, Effort expectancy in the context of mobile health apps for cancer management refers to the degree to which a patient believes that using apps will be effortless. In another study, EE was defined by the perceived ease of use with chronic disease about mHealth (Quaosar et al., 2018). Extensive empirical evidence has shown that EE was often the most critical influencing factor on behavioral intention for technology adoption mediated by performance expectancy (AlBar & Hoque, 2019). People's willingness to adopt mHealth technology increases when it is easy to use (Palos-Sanchez et al., 2021). However, when patients do not find a particular app easy to use, helpful in completing tasks, comfortable, and convenient, they will usually reject using the app, which fails. Accordingly, adopting mHealth apps depends on whether the apps are easy to use and effort-free. Hence, the researcher proposed the following hypothesis:
H2: Effort expectancy has a significant impact on performance expectancy.
H6: Effort expectancy has a significant impact on behavior intention.

2.3 Facilitating Condition

Facilitating condition is the degree to which a patient believes that an organizational or technical infrastructure exists to support mobile health services (Venkatesh et al., 2003). It was reported that FC was positively associated with the behavioral intention of using smartphones for health services (Rahimi et al., 2018; Schretzlmaier et al., 2022; Zhang et al., 2019). Patients must have the ability, knowledge, and resources to use mHealth. Today, despite the popularity of mobile devices, the availability of a wide range of free apps, and the fact that apps like WeChat and TikTok are used almost every day, new apps can be difficult for a few older people. Hence, the researcher proposed the following hypothesis:
H3: Facilitating condition has a significant impact on performance expectancy.
H8: Facilitating condition has a significant impact on behavior intention.

2.4 Social Influence

Social influence is a common feature of everyday life: We either try to influence others or are influenced by them many times daily. According to the researchers, social influence was defined as the extent to which a patient perceived that significant other (physicians, peers, family members, and relatives) supported him/her in using the new system (Venkatesh et al., 2003, 2012). It underlies the aspects of subjective norms, social factors, and image. Uncovska et al. (2023) studied the acceptance of reimbursed mHealth apps in Germany. The SI construct referred to how far individuals believed physicians, people important to the individual, and the public perceived they should use mHealth apps. In other words, physicians, relatives, and peers of the same disease in society might influence patients' decisions to use mHealth (Hoque, 2016; Hoque et al., 2017; Quaosar et al., 2018). Social influence indirectly affected behavioral intention through performance expectancy mediation has also been identified (Zhang et al., 2019). Hence, the researcher proposed the following hypothesis:
H4: Social influence has a significant impact on performance expectancy.
H9: Social influence has a significant impact on behavior intention.

2.5 Performance Expectancy

Performance expectancy was defined as the extent to which people believed that using a specific technology or system would help them improve their performance in accomplishing a particular action (Venkatesh et al., 2003). In this research, Performance expectancy can be defined as the degree to which cancer patients perceive that using mobile health applications will enable them to achieve improved performance in their health conditions. PE, as one of the primary factors predicting the behavior intention to use information technology, has been identified by several studies (Hoque, 2016; Hoque et al., 2017; Quaosar et al., 2018). Performance expectancy strongly impacted behavioral intention towards mobile health in developed and developing countries (Semiz & Semiz, 2021; Uncovska et al., 2023). PE in mHealth services correlates with patients perceiving advantageous aspects of these services, such as lower medication and transport expenses, improved communication with healthcare professionals, and enhanced monitoring and detection of chronic ailments. This indicates that patients evaluate mHealth services based on the efficiency they confer against their cost and utility. Performance expectancy represents the usefulness of a system or technology and is the most important construct. Hence, the researcher proposed the following hypothesis:
H7: Performance expectancy has a significant impact on behavior intention.

2.6 Privacy

Warren and Brandeis (1890) defined privacy as the right to "being let alone". According to this conception, privacy is something that you have if people, organizations, or institutions are denied access to you. Privacy has different meanings and implications in different contexts and cultures and is complex. This research defines privacy as the right to keep one's personal matters and relationships secret. Previous research has revealed that privacy concerns hinder the adoption of healthcare technologies among older adults (Deng et al., 2018; Fischer et al., 2014; Rasche et al., 2018). Therefore, it was hypothesized that privacy concerns were negatively associated with patients' behavioral intention to use mHealth.
H10: Privacy has a significant impact on behavior intention.

2.7 Trust

Trust was a relational notion between people, people and organizations, and people and events. Trust's definitions differed according to different research fields and perspectives. In healthcare, a patient's trust in the physician can be defined as a collection of expectations or a feeling of reassurance or confidence from providers (Anderson & Dedrick, 1990; Rasiah et al., 2020). In this research, trust refers to the patient's positive expectations for mobile health applications for cancer management, which he trusts in uncertain situations, and based on this commitment to behavioral intention. By providing competitive advantages in the services industry, the positive impact of trust in the digital age has gained support from previous researchers, practitioners, and scholars (Guo, 2022). Trust has also been reported as one of the most important variables in adopting eHealth and mHealth (Zhao et al., 2018). Hence, the researcher proposed the following hypothesis:
H11: Trust has a significant impact on behavior intention.

2.7 Behavioral Intention

Behavioral intention is implementing a particular behavior action (Davis, 1989). It can be predicted by three determinants: attitude, subjective norm, and perceived behavioral control based on the theory of consumer behavior. In this research, behavioral intention refers to an individual's intention to use mobile health applications. Behavioral intention was widely used in most of the classic theory model and as the core construct of the technology acceptance model. Many researchers have confirmed that behavioral intention has been influenced by performance expectancy, effort expectancy, social influence, and facilitating conditions in the UTAUT model (Schomakers & Ziefle, 2022; Zhang et al., 2019).

3. Research Methods and Materials

3.1 Research Framework

There were three theoretical frameworks based on the previous research, and the correlations of factors and the research path were clearly described. The first theoretical framework was conducted by Zhang et al. (2019). This study aimed to identify the determinants of patients' intention to use diabetes management apps applied to the extended UTAUT model. The second theoretical framework was conducted by Alam et al. (2020). This study aimed to examine the factors influencing behavioral intention and actual usage behavior of mHealth apps among the technology-prone young generation. The third theoretical framework was conducted by Schomakers et al. (2022). This research study aimed to compare the factors influencing the acceptance of lifestyle and therapy apps to understand what drives and hinders the better use of mHealth apps. The research framework is illustrated in Figure 1.

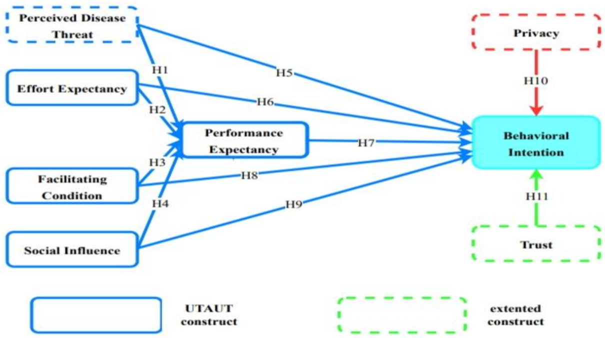

Figure 1: Research Conceptual Framework

H1: Perceived disease threat has a significant impact on performance expectancy.
H2: Effort expectancy has a significant impact on performance expectancy.
H3: Facilitating condition has a significant impact on performance expectancy.
H4: Social influence has a significant impact on performance expectancy.
H5: Perceived disease threat has a significant impact on behavior intention.
H6: Effort expectancy has a significant impact on behavior intention.
H7: Performance expectancy has a significant impact on behavior intention.
H8: Facilitating condition has a significant impact on patients' behavior.
H9: Social influence has a significant impact on behavior intention.
H10: Privacy has a significant impact on behavior intention.
H11: Trust has a significant impact on behavior intention.

3.2 Research Methodology

The study sample was selected using multistage sampling, including judgment, stratified random, and convenient sampling techniques. The questionnaire method was used to collect data. It was distributed to patients who suffered from head and neck, thoracic, abdominal, and pelvic cancer in proportion to the number of patients in the Sichuan Cancer Hospital located in Chengdu. Finally, the data was analyzed using SPSS 26.0 and AMOS 23.0. Item objective congruence (IOC) was used to evaluate the content validity of the questionnaire instrument. The researcher conducted a pilot test with 50 samples to ensure the reliability and consistency of each item. Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) were employed to validate the model's goodness-of-fit and confirm hypotheses from the data of 500 respondents.

3.3 Population and Sample Size

The target population refers to a defined group of individuals or subjects who meet specific criteria for inclusion in research (Rothman et al., 2008). This study's target population was cancer patients without experience using mobile health applications and were treated in Sichuan Cancer Hospital, Chengdu, Sichuan province. According to the primary site of cancer, the target population was divided into head and neck cancer patients, thoracic cancer patients, abdominal cancer patients, and pelvic cancer patients.

The sample size, the number of observations or measurements taken from a population, is a key factor in ensuring the reliability and representativeness of the research results (Saunders et al., 2007; Sullivan, 2022). With 8 latent variables and 30 observed variables, Soper (2021) calculator recommended a minimum sample size of 444. The use of the web-based survey tool Sojump and the collection of 550 valid questionnaires, of which 500 were used for analysis, further bolster the reliability of our findings.

3.4 Sampling Technique

The study employed a multi-stage sampling approach divided into two phases. Initially, researchers utilized a judgmental sampling technique to screen 2,030 students from three majors at Sichuan University of Science & Technology, all of whom had at least one year of experience with Moocs. Following this, 500 respondents were selected from these three majors using a quota selection method to constitute the final sample.

Table 1: Sample Units and Sample Size

Practitioners	Population Size	Proportional Sample Size
Head and neck cancer patients	1236	100
Thoracic cancer patients	3025	245
Abdominal cancer patients	806	65
Pelvic cancer patients	1105	90
Total	**6172**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

As Table 2 shows, among 500 respondents, 47.6% were male, and 52.4% were female. Most of the respondents are middle-aged and elderly patients, which is the onset age of cancer. The respondents who lived in urban areas account for 56.4%, and most of the respondents have secondary education.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	238	47.6%
	Female	262	52.4%
Age (years)	<45	123	24.6%
	≥45 and <60	239	47.8%
	≥60	138	27.6%
Residential area	urban	282	56.4%
	rural	218	43.6%
Educational degree	primary education or l	126	25.2%
	secondary education	243	48.6%
	university education	131	26.2%

4.2 Confirmatory Factor Analysis (CFA)

Confirmatory factor analysis (CFA) is a powerful statistical tool for examining latent constructs' nature and relations (Jackson et al., 2009). Convergent validity and discriminant validity could be satisfied minimum requirements through CFA. The results in Table 3 revealed that the constructs have a coefficient of internal consistency under the rules of thumb. Cronbach's Alpha value surpassed 0.7 (Dikko, 2016), factor loading of each variable was higher than 0.5 (Hair et al., 2017). composite reliability (CR) exceeded 0.7, and the average variance extracted (AVE) was greater than 0.5 for all constructs, according to Fornell and Larcker (1981). In summary, the statistical estimates were significant.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Disease Threat (PDT)	Dou et al. (2017)	3	0.868	0.786 - 0.899	0.870	0.691
Effort Expectancy (EE)	Cao et al. (2020)	4	0.800	0.674 - 0.726	0.801	0.502
Performance Expectancy (PE)	Zhang et al. (2019)	4	0.877	0.724 - 0.844	0.878	0.644
Social Influence (SI)	Zhang et al. (2019)	4	0.843	0.670 - 0.840	0.845	0.578
Facilitating Conditions (FC)	Zhang et al. (2019)	4	0.908	0.807 - 0.861	0.909	0.714
Trust (TR)	Zhao et al. (2018)	5	0.920	0.767 - 0.825	0.922	0.703
Privacy (PR)	Zhang et al. (2019)	3	0.828	0.786 - 0.902	0.830	0.619

Table 4 displays absolute fit metrics including GFI, CMIN/DF, RMSEA, and AGFI, as well as incremental fit indices such as NFI, CFI, and TLI. Each metric met the necessary criteria, indicating that all the fit measures yielded satisfactory results in this study's CFA test and are fully acceptable.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<5 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.127
RMSEA	<0.08 (Pedroso et al., 2016)	0.056
GFI	≥0.85 (Sica & Ghisi, 2007)	0.889
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.857
NFI	≥0.80 (Wu & Wang, 2005)	0.892
CFI	≥0.80 (Bentler, 1990)	0.961
TLI	≥0.80 (Sharma et al., 2005)	0.937
Model Summary		**Acceptable Model Fit**

CMIN/DF = The ratio of the chi-square value to degree of freedom, RMSEA = root mean square error of approximation, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index and TLI = Tucker Lewis index and RMSEA

Discriminant validity was evaluated in Table 5. The square root of AVEs was compared with the factor correlations according to Fornell and Larcker (1981), and the results indicated that the values of discriminant validity were all larger than inter-construct correlations; therefore, discriminant validity was acceptable.

Table 5: Discriminant Validity

	PDT	EE	PE	SI	FC	TR	PR	BI
PDT	**0.831**							
EE	0.314	**0.708**						
PE	0.291	0.250	**0.802**					
SI	0.240	0.264	0.359	**0.760**				
FC	0.258	0.201	0.245	0.288	**0.844**			
TR	0.301	0.300	0.295	0.331	0.231	**0.838**		
PR	0.267	0.258	0.300	0.272	0.229	0.381	**0.787**	
BI	0.379	0.307	0.422	0.392	0.296	0.323	0.311	**0.792**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

The structural equation model was a statistical approach used to measure the correlation in structural equations and verify the relationship between structure and hypothesis (Byrne, 2010). The index of goodness of fit of the model for SEM was presented in Table 6, and the results illustrated that CMIN/DF = 2,233, RMSEA = 0.050, GFI = 0.878, AGFI = 0.856, CFI = 0.941 and TLI = 0.934 Compared with the acceptable values, all index values were within the acceptable criterion.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	<5 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	879.977/394 or 2.233
RMSEA	<0.08 (Pedroso et al., 2016)	0.050
GFI	≥0.85 (Sica & Ghisi, 2007)	0.878
AGFI	≥0.80 (Sica & Ghisi, 2007)	0.856
NFI	≥0.80 (Wu & Wang, 2005)	0.898
CFI	≥0.80 (Bentler, 1990)	0.941
TLI	≥0.80 (Sharma et al., 2005)	0.934
Model Summary		**Acceptable Model Fit**

CMIN/DF = The ratio of the chi-square value to degree of freedom, RMSEA = root mean square error of approximation, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index and TLI = Tucker Lewis index and RMSEA

4.4 Research Hypothesis Testing Result

The significance of the relationship between variables was measured from its regression weights variances in the structural model. The results indicated that proposed hypotheses H1, H4, H5, H7, and H9 were supported, while others were not supported in this research. Performance expectancy was the strongest predictor of behavioral intention, followed by social influence and perceived disease threat. Moreover, social influence and perceived disease threat satisfaction positively affected behavioral intention mediated through performance expectancy. The causal relationships among the variables are presented in Table 7.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: PDT→PE	0.186	3.880*	Supported
H2: EE→PE	0.146	2.894	Not Supported
H3: FC→PE	0.132	2.803	Not Supported
H4: SI→PE	0.323	6.442*	Supported
H5: PDT→BI	0.235	4.685*	Supported
H6: EE→BI	0.121	2.359	Not Supported
H7: PE→BI	0.231	4.154*	Supported
H8: FC→BI	0.112	2.347	Not Supported
H9: SI→BI	0.231	4.316*	Supported
H10: PR→BI	0.105	2.145	Not Supported
H11: TR→BI	0.093	1.993	Not Supported

Note: * p<0.05
Source: Created by the author

The results of the structural path from Table 7 could be summarized as follows:

H1: Patients' perceived disease threat positively affects performance expectancy. With a standardized path coefficient of 0.186 and a t-value of 3,880*. The hypothesis is supported by UTAUT (Venkatesh et al., 2003) and previous empirical studies (Dou et al., 2017; Schomakers et al., 2022; Zhang et al., 2019) that the patients perceive mobile health applications for chronic disease management as useful when the technology is understandable and easy to operate.

H2: The standardized path coefficient between patients' effort and performance expectancy is 0.146, and the t-value is 2.894. Therefore, the result indicates that patients' effort expectancy does not affect performance expectancy. However, the finding contradicted Ajzen and Fishbein (1980) and Zhang et al. (2019) statement that effort expectancy had moderate effects on performance expectancy. It is different from the consumer context. Patients strongly believe that medical apps are useful and that they can learn to use mobile health applications, so performance expectancy should not be influenced by ease of use (EE).

H3: The hypothesis is not supported that facilitating conditions positively affect performance expectancy. The standardized path coefficient is 0.132 at a t-value of 2.803. The finding contradicted Rho et al. (2015) and Zhang et al. (2019) statement that facilitating conditions promotes system acceptance and using behavior mediated by performance expectancy. It is attributable to the current widespread use of mobile devices and the support of information technology by the relevant government and healthcare institutions. The facilitating condition is not a significant influencing factor.

H4: Social influence positively affects performance expectancy with a standardized path coefficient of 0.323 and a t-value of 6,442*. Most cancer patients, especially the newly diagnosed patients, were very anxious about their disease, and they lacked medical oncology knowledge, so they were always looking for help from doctors and ward mates. The advice of doctors, nurses, and ward mates is very important for cancer patients. It can explain that social influence has a positive effect on performance expectancy. The findings of the study aligned with the previous empirical research (Apolinário-Hagen et al., 2018; Zhang et al., 2019)

H5: Patients' perceived disease threat positively affects behavioral intention to use mobile health applications for cancer management. The standardized path coefficient is 0.235, and the t-value is 4.685*. TAM (Davis, 1989) and previous empirical studies (Breil et al., 2022; Dou et al., 2017; Zhang et al., 2019) supported the hypothesis that people who were aware and concerned about their poor health conditions were more likely to adopt new tech.

H6: The standardized path coefficient between facilitating condition and performance expectancy is 0.121, and the t-value is 2.359. Therefore, the result indicates that patients' effort expectancy does not affect behavioral intention to use mobile health applications for cancer management. However, the finding contradicts Rho et al. (2015), whose statements that facilitating conditions indirectly affected behavioral intention mediated by performance expectancy. However, the finding aligned with the findings of Venkatesh et al. (2003).

H7: Performance expectancy positively affects behavioral intention to use mobile health applications for cancer management. The standardized path coefficient is 0.231, and the t-value is 4.154*. The hypothesis was supported by UTAUT (Venkatesh et al., 2003) and previous empirical studies (Zhang et al., 2019) that performance expectancy was a major determinant of the intention to use health information technologies. In the context of cancer management, mobile health applications are more useful; the patients will have a stronger intention to use mobile health applications. That is why performance expectancy can influence behavioral intention.

H8: The standardized path coefficient between facilitating condition and behavior intention is 0.112, and the t-value is 2.347. Therefore, the result indicates that facilitating conditions do not affect the intention to use mobile health applications. In the UTAUT model, facilitating condition was considered the basis of the use of info using information technology was not a strong factor towards initial intention. The finding also aligned with the original UTAUT model (Venkatesh et al., 2003).

H9: Social influence has a positive effect on behavioral intention to use mobile health applications, with a standardized path coefficient of 0.231 and a t-value of 4.316*. AUT (Venkatesh et al., 2003) and previous empirical studies (Zhang et al., 2019) supported the hypothesis that patients' intention to adopt a health behavior was often influenced by their physicians, peers with the same disease, and family members.

H10: The standardized path coefficient between privacy and behavior intention is 0.105, and the t-value is 2.145. Therefore, the result indicates that privacy does not affect behavioral intention to use mobile health applications. However, the finding contradicted Zhang et al. (2019) and Schomakers et al. (2022), indicating that privacy influences system acceptance and use. It was due to the population of this study; most of the cancer patients included in this study were older adults, and maybe they were less conscious of privacy.

H11: Trust has no positive impact on behavioral intention, with a standardized path coefficient of 0.093 and a t-value of 1.993. However, the finding contradicted Schomakers et al. (2022) and Jacob et al. (2022), whose statements were that TR predicts the acceptance of mobile health applications. In this study, patients included were those who did not have experience using mobile health applications, so they still needed to understand the applications' functionality and were unsure whether they could trust mHealth applications.

5. Conclusion and Recommendation

5.1 Conclusion

The researcher aims to investigate factors influencing cancer patients' behavioral intention to use mobile health applications for cancer management. The sampling units in the study were cancer patients who were treated at Sichuan Cancer Hospital, and the primary site of the tumor was the head and neck, thoracic, abdominal, or pelvic. Eight variables and eleven hypotheses were utilized to demonstrate how perceived disease threat, effort expectancy, performance expectancy, social influence, facilitating condition, trust, and privacy affected behavioral intention to use mobile health applications. This research was quantitative research, and a questionnaire was an instrument for collecting data. IOC was applied for the pilot test, and CFA and SEM were used to examine the content validity and reliability of the proposed conceptual framework.

The findings from the statistical results, which are significant, were summarized as follows:

First, using mobile health applications for cancer management was mostly determined by behavioral intention according to the theory of the UTAUT model (Venkatesh et al., 2003), and the original UTAUT can explain 70% of the variable of behavioral intention. In this study, the researcher based on the UTAUT model to explore the determinations of behavioral intention. Former research has revealed that user's intention to use an information system was affected by four core constructs: performance expectancy, effort expectancy, social influence, and facilitating condition. In empirical research on adopting diabetes mHealth applications, the UTAUT model can explain 32.8-57.1% of the variance in behavioral intention. In this research, the UTAUT model can explain 27.8% of the variance in behavioral intention to use mobile health applications for cancer management so that other important factors may impact behavioral intention.

Second, performance expectancy was defined as the degree to which a specific technology benefits users played a vital role in behavioral intention. It liked the usefulness of a specific technology in the acceptance model; the more useful the technology expected, the stronger the use behavior. Most previous studies indicated that performance expectancy positively affected behavioral intention and mediated EE, FC, SI, and PDT on behavioral intention (Dou et al., 2017; Zhang et al., 2019). In this research, PDT and SI variables have been verified to affect behavioral intention to use mobile health applications for cancer management, mediated by performance expectancy.

Third, some research used social influence as the core variable in UTAUT to predicate the affection of behavioral intention toward mobile health applications (Zhang et al., 2019; Zhu et al., 2023). Additionally, another study stated that it had no significant influence on behavioral intention in mobile health (Schretzlmaier et al., 2022). In this study, social influence is confirmed to have a positive direct and indirect effect on behavioral intention mediated by performance expectancy.

Fourth, according to the Health Belief Model, individuals will not take health-related actions unless they feel susceptible to or experience the severity of a disease. In the context of cancer management, perceived disease threat, a patient's awareness of his/her cancer condition and concern for its potential consequences, plays a crucial role. It influences the perceived usefulness of health-related technology and is recognized as a significant driver for the acceptance and use of mHealth applications. In this research, perceived disease threat has been identified as a significant impact on behavioral intention toward mHealth applications for cancer management, underscoring its importance.

In summary, the UTAUT model, while a powerful tool, only partially predicts behavior intention towards mobile health applications. This finding underscores the need for an extended UTAUT model that incorporates perceived disease threats to better predict mHealth acceptance. This opens up an exciting avenue for future research to investigate additional mHealth acceptance factors.

5.2 Recommendation

This study proved the Unified Theory of Acceptance and Use of Technology (UTAUT) and expanded the perceived disease threat (PDT) variable for theoretical implications. The results confirmed that performance expectancy, social influence, and perceived disease threat were three significant elements that impact and predict users' behavioral intention toward mobile health applications for cancer management. This study indicates that performance expectancy positively influences cancer patients' behavioral intention to use mobile health applications. Besides, social influence and perceived disease threat are important factors that directly impact cancer patients' behavioral intentions. Moreover, social influence and perceived disease threat indirectly influence cancer patients' behavioral intention to use mobile health applications for cancer management mediated through performance expectancy. However, other variables like effort expectancy, facilitating condition, privacy, and trust show insignificant impact on behavioral intention to use mobile health applications for cancer management in this study, which is in contrast with some other research in the context of medical care.

For practical implications, the study demonstrates that the usefulness of developing systems and platforms for cancer management is very important for patients' behavioral intentions. Although there are recommendations from peers of cancer patients, physicians, and family members, manufacturers must carry out research to provide clinical evidence for the effectiveness of these applications because the mediation of performance expectancy can moderate the effects of perceived disease threat and social influence on behavioral intention. Perceived usefulness enhances perceived disease threat, social influence, behavioral intentions, and cancer patients' acceptance of mHealth. On the other hand, social influence had a direct significant effect on behavioral intention, so for developers or healthcare managers, strengthening the training of relevant personnel and promoting the use of mHealth is another way to improve patient acceptance. Additionally, this study shows that although privacy and trust are not related to behavioral intentions, most of the literature shows that privacy and trust strongly impact willingness to use mobile health applications. The reason may be that the study population was predominantly middle-aged and elderly patients who lacked a sense of security regarding the privacy of information technology and whose trust in the applications was mainly derived from their trust in doctors and nurses.

5.3 Limitation and Further Study

The limitation of the study lies in the population the researcher selected for the research. The target population in this study were patients who had no experience using mHealth apps, and this was a pilot study in Sichuan Cancer Hospital. Moreover, to expand coverage of the survey and make the results more accurate and representative, the researcher might choose other hospitals in Sichuan province or even other provinces as research objects, which might bring some new findings in the field of using mobile health applications for cancer management.

References

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior* (1st ed.). Prentice-Hall.

Alam, M. Z., Hu, W., Kaium, M. A., Hoque, M. R., & Alam, M. M. D. (2020). Understanding the determinants of mHealth apps adoption in Bangladesh: A SEM-Neural network approach. *Technology in Society*, *61*, 101255. https://doi.org/10.1016/j.techsoc.2020.101255

AlBar, A. M., & Hoque, M. R. (2019). Patient acceptance of e-health services in Saudi Arabia: an integrative perspective. *Telemedicine and e-Health*, *25*(9), 847-852. https://doi.org/10.1089/tmj.2018.0107

Al-Mamary, Y. H., & Shamsuddin, A. (2015). Testing of the technology acceptance model in context of Yemen. *Mediterranean Journal of Social Sciences, 6*(4), 20-34. https://doi.org/10.5901/mjss.2015.v6n4s1p268

Anderson, L. A., & Dedrick, R. F. (1990). Development of the Trust in Physician scale: a measure to assess interpersonal trust in patient-physician relationships. *Psychological reports*, *67*(3), 1091-1100. https://doi.org/10.2466/pr0.1990.67.3f.1091

Apolinário-Hagen, J., Harrer, M., Kählke, F., Fritsche, L., Salewski, C., & Ebert, D. D. (2018). Public attitudes toward guided internet-based therapies: web-based survey study. *JMIR mental health*, *5*(2), e10735. https://doi.org/10.2196/10735

Awang, Z. (2012). Research methodology and data analysis second edition (1st ed.). UiTM Press.

Baek, H., Gordon, P. C., & Choi, W. (2024). Effects of age and word frequency on Korean visual word recognition: Evidence from a web-based large-scale lexical-decision task. *Psychology and Aging, 39*(3), 231-244. https://doi.org/10.1037/pag0000793

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological bulletin*, *107*(2), 238-246. https://doi.org/10.1037/0033-2909.107.2.238

Breil, B., Salewski, C., & Apolinário-Hagen, J. (2022). Comparing the acceptance of mobile hypertension apps for disease management among patients versus clinical use among physicians: cross-sectional survey. *JMIR cardio*, *6*(1), e31617. https://doi.org/10.2196/31617

Byrne, B. M. (2010). *Structural Equation Modeling with Amos: Basic Concepts, Applications, and Programming* (2nd ed.). Taylor and Francis Group.

Cao, Y., Zhang, J., Ma, L., Qin, X., & Li, J. (2020). Examining user's initial trust building in Mobile online health community adopting. *International journal of environmental research and public health*, *17*(11), 3945. https://doi.org/10.3390/ijerph17113945

Davis, F. D. (1989). *Perceived usefulness, perceived ease of use, and user acceptance of information technology*. *MIS Quarterly, 13*(3), 319-340. https://doi.org/10.2307/249008

Deng, Z., Hong, Z., Ren, C., Zhang, W., & Xiang, F. (2018). What predicts patients' adoption intention toward mHealth services in China: empirical study. *JMIR mHealth and uHealth*, *6*(8), e9316. https://doi.org/10.2196/mhealth.9316

Dikko, M. (2016). Establishing Construct Validity and Reliability: Pilot Testing of a Qualitative Interview for Research in Takaful (Islamic Insurance). *Qualitative Report, 21*(3), 34-67. https://doi.org/10.46743/2160-3715/2016.2243

Dou, K., Yu, P., Deng, N., Liu, F., Guan, Y., Li, Z., & Duan, H. (2017). Patients' acceptance of smartphone health technology for chronic disease management: a theoretical model and empirical test. *JMIR mHealth and uHealth, 5*(12), e177. https://doi.org/10.2196/mhealth.7886

Fischer, S. H., David, D., Crotty, B. H., Dierks, M., & Safran, C. (2014). Acceptance and use of health information technology by community-dwelling elders. *International journal of medical informatics*, *83*(9), 624-635. https://doi.org/10.1016/j.ijmedinf.2014.06.005

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research, 18*(1), 39-50. https://doi.org/10.1177/002224378101800104

Guo, Y. (2022). Digital Trust and the Reconstruction of Trust in the Digital Society: An Integrated Model based on Trust Theory and Expectation Confirmation Theory. *Digital Government: Research and Practice*, *3*(4), 1-19. https://doi.org/10.1145/3543860

Hair, J., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. L. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial management & data systems*, *117*(3), 442-458. https://doi.org/10.1108/imds-04-2016-0130

Hoque, M. R. (2016). An empirical study of mHealth adoption in a developing country: the moderating effect of gender concern. *BMC medical informatics and decision making*, *16*(1), 1-10.

Hoque, M. R., Bao, Y., & Sorwar, G. (2017). Investigating factors influencing the adoption of e-Health in developing countries: A patient's perspective. *Informatics for Health and Social Care*, *42*(1), 1-17. https://doi.org/10.1186/s12911-016-0289-0

Jackson, D. L., Gillaspy, J. A., & Purc-Stephenson, R. (2009). Reporting practices in confirmatory factor analysis: an overview and some recommendations. *Psychological methods*, *14*(1), 6-23. https://doi.org/10.1037/a0014694

Jacob, C., Sezgin, E., Sanchez-Vazquez, A., & Ivory, C. (2022). Sociotechnical factors affecting patients' adoption of mobile health tools: systematic literature review and narrative synthesis. *JMIR mHealth and uHealth*, *10*(5), e36284. https://doi.org/10.2196/36284

Palos-Sanchez, P. R., Saura, J. R., Rios Martin, M. A., & Aguayo-Camacho, M. (2021). Toward a better understanding of the intention to use mHealth apps: exploratory study. *JMIR mHealth and uHealth*, *9*(9), e27021. https://doi.org/10.2196/27021

Pedroso, R., Zanetello, L., Guimarães, L., Pettenon, M., Gonçalves, V., Scherer, J., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry (São Paulo), 43,* 37-40. https://doi.org/10.1590/0101-60830000000081

Portz, J. D., Bayliss, E. A., Bull, S., Boxer, R. S., Bekelman, D. B., Gleason, K., & Czaja, S. (2019). Using the Technology Acceptance Model to Explore User Experience, Intent to Use, and Use Behavior of a Patient Portal Among Older Adults with Multiple Chronic Conditions: Descriptive Qualitative Study. *Journal of medical Internet research, 21*(4), e11604. https://doi.org/10.2196/11604

Quaosar, G. M. A. A., Hoque, M. R., & Bao, Y. (2018). Investigating Factors Affecting Elderly's Intention to Use m-Health Services: An Empirical Study. *Telemedicine journal and e-health: the official journal of the American Telemedicine Association, 24*(4), 309-314. https://doi.org/10.1089/tmj.2017.0111

Rahimi, B., Nadri, H., Afshar, H. L., & Timpka, T. (2018). A systematic review of the technology acceptance model in health informatics. *Applied clinical informatics*, *9*(3), 604-634. https://doi.org/10.1055/s-0038-1668091

Rasche, P., Wille, M., Bröhl, C., Theis, S., Schäfer, K., Knobe, M., & Mertens, A. (2018). Prevalence of health app use among older adults in Germany: national survey. *JMIR mHealth and uHealth*, *6*(1), e8619. https://doi.org/10.2196/mhealth.8619

Rasiah, S., Jaafar, S., Yusof, S., Ponnudurai, G., Chung, K. P. Y., & Amirthalingam, S. D. (2020). A study of the nature and level of trust between patients and healthcare providers, its dimensions, and determinants: a scoping review protocol. *BMJ open*, *10*(1), e028061. https://doi.org/10.1136/bmjopen-2018-028061

Rho, M. J., Kim, H. S., Chung, K., & Choi, I. Y. (2015). Factors influencing the acceptance of telemedicine for diabetes management. *Cluster Computing*, *18*(1), 321-331. https://doi.org/10.1007/s10586-014-0356-1

Rothman, K. J., Greenland, S., & Lash, T. L. (2008). *Modern epidemiology* (3st ed.). Wolters Kluwer Health/Lippincott Williams & Wilkins.

Saunders, M., Lewis, P., & Thornhill, A. (2007). *Research methods for business students* (4th ed., pp. 12-18). Pearson.

Schomakers, E. M., Lidynia, C., Vervier, L. S., Valdez, A. C., & Ziefle, M. (2022). Applying an Extended UTAUT2 Model to Explain user acceptance of lifestyle and therapy mobile health apps: survey study. *JMIR mHealth and uHealth, 10*(1), e27095. https://doi.org/ 10.2196/27095

Schomakers, E.-M., & Ziefle, M. (2022). Privacy vs. Security: Trade-Offs in the Acceptance of Smart Technologies for Aging-in-Place. *International Journal of Human-Computer Interaction, 39*(5), 1043-1058. https://doi.org/10.1080/10447318.2022.2078463

Schretzlmaier, P., Hecker, A., & Ammenwerth, E. (2022). Extension of the Unified Theory of Acceptance and Use of Technology 2 model for predicting mHealth acceptance using diabetes as an example: a cross-sectional validation study. *BMJ Health & Care Informatics*, *29*(1), e100640. https://doi.org/10.1136/bmjhci-2022-100640

Semiz, B. B., & Semiz, T. (2021). Examining consumer use of mobile health applications by the extended UTAUT model. *Business & Management Studies: An International Journal*, *9*(1), 267-281. https://doi.org/10.15295/bmij.v9i1.1773

Sharma, S., Mukherjee, S., Kumar, A., & Dillon, W. R. (2005). A simulation study to investigate the use of cutoff values for assessing model fit in covariance structure models. *Journal of business research*, *58*(7), 935-943. https://doi.org/10.1016/j.jbusres.2003.10.007

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. *Leading-edge psychological tests and testing research* (pp. 27-50). Nova Science Publishers.

Soper, D. (2021). *A-Priori Sample Size for Structural Equation Models.* Free Statistics Calculators. https://www.danielsoper.com/statcalc/calculator.aspx?id=89

Sullivan, L. M. (2022). *Essentials of biostatistics for public health* (1st ed.). Jones & Bartlett Learning.

Sung, H., Ferlay, J., Siegel, R. L., Laversanne, M., Soerjomataram, I., Jemal, A., & Bray, F. (2021). Global cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. *CA: a cancer journal for clinicians*, *71*(3), 209-249. https://doi.org/10.3322/caac.21660

Uncovska, M., Freitag, B., Meister, S., & Fehring, L. (2023). Patient Acceptance of Prescribed and Fully Reimbursed mHealth Apps in Germany: An UTAUT2-based Online Survey Study. *Journal of medical systems*, *47*(1), 14. https://doi.org/10.1007/s10916-023-01910-x

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178. https://doi.org/10.2307/41410412

Warren, S. D., & Brandeis, L. D. (1890). The right to privacy. *Harvard Law Review, 4*(5), 193-220. https://doi.org/10.2307/1321160

Wu, J. H., & Wang, S. C. (2005). What drives mobile commerce? An empirical evaluation of the revised technology acceptance model. *Information & management*, *42*(5), 719-729. https://doi.org/10.1016/j.im.2004.07.001

Yang, L., Wu, J., Mo, X., Chen, Y., Huang, S., Zhou, L., & Xie, X. (2023). Changes in Mobile health apps usage before and after the COVID-19 outbreak in China: Semi longitudinal survey. *JMIR Public Health and Surveillance*, *9*(1), e40552. https://doi.org/10.2196/40552

Zhang, Y., Liu, C., Luo, S., Xie, Y., Liu, F., Li, X., & Zhou, Z. (2019). Factors Influencing Patients' Intentions to Use Diabetes Management Apps Based on an Extended Unified Theory of Acceptance and Use of Technology Model: Web-Based Survey. *Journal of medical Internet research*, 21(8), e15023. https://doi.org/10.2196/15023

Zhao, Y., Ni, Q., & Zhou, R. (2018). What factors influence the mobile health service adoption? A meta-analysis and the moderating role of age. *International Journal of Information Management*, *43*, 342-350. https://doi.org/10.1016/j.ijinfomgt.2017.08.006

Zhu, Y., Zhao, Z., Guo, J., Wang, Y., Zhang, C., Zheng, J., & Liu, W. (2023). Understanding use intention of mHealth applications based on the unified theory of acceptance and use of technology 2 (UTAUT-2) model in China. *International journal of environmental research and public health*, *20*(4), 3139. https://doi.org/10.3390/ijerph20043139