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Factors Impacting Undergraduates' Perceived Value and Behavioral Intention to Use Mobile Health Applications in Sichuan, China

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Abstract

This study examines factors influencing undergraduate students' behavioral intentions to use mobile health (mHealth) applications in Sichuan, China. Focusing on senior students at Sichuan University of Science and Engineering, Perceived Trust, Enjoyment, and Health Literacy were incorporated into the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT). Using structural equation modeling on 500 valid questionnaires, results show that Perceived Usefulness, Perceived Ubiquity, Enjoyment, Perceived Value, Social Influence, Perceived Trust, and Health Literacy positively affect Behavioral Intention, while Perceived Risk does not significantly impact Perceived Value. Enhancing user experience, application credibility, and health education can increase students' willingness to adopt mHealth apps. The study provides valuable insights for promoting mHealth app adoption among university students and offers practical guidance for developers and policymakers.

Keywords: Mobile Health Application, Perceived Value, Behavioral Intention, TAM, UTAUT, College Students.

Introduction

Mobile health (mHealth) denotes the use of mobile and wireless technologies to deliver healthcare information and services through devices such as smartphones and tablets (Moudud-Ul-Huq et al., 2021). Mobile health applications (mHealth apps) are apps that run on a smartphone or tablet and are designed to help users manage and improve their health and fitness. These apps offer many features, including health monitoring, physical activity tracking, diet management, sleep monitoring, mental health support, and more (Barutçu, 2019).With the rapid advancement of information technology and mobile devices, mHealth applications have emerged as a promising solution to address the growing challenges in healthcare. The

increasing prevalence of chronic diseases, the rising costs of healthcare, and the uneven distribution of healthcare resources have led to a significant demand for innovative health management tools. mHealth apps, which leverage the ubiquity and power of smartphones and wearable devices, offer a convenient and cost-effective way to promote health management and disease prevention (Barua & Barua, 2021; Gagnon et al., 2012).

With the widespread adoption of smartphones and mobile networks, mobile health (mHealth) applications have rapidly developed globally, becoming essential tools for college students to manage their own health. These applications not only help users monitor physical activity, diet, and mental health but also provide personalized health interventions and education (M. Z. Alam et al., 2020; Aydin & Silahtaroglu, 2021). However, college students exhibit significant variations in their health app usage behaviors. Their adoption intentions and sustained usage rates are influenced by multiple factors, including perceived usefulness, perceived ease of use, trust in privacy and data security, social influence, and app functional design (M. Z. Alam et al., 2020). Research indicates that app-based health interventions significantly enhance physical activity and improve fitness levels, suggesting that functional design and content scientific rigor directly influence user adoption intent (Wang et al., 2024). Therefore, when selecting and using health apps, college students are influenced not only by technical and functional features but also by a combination of psychological factors, social support, and the health value provided by the application itself.

Despite the potential benefits of mHealth apps, their adoption among Chinese university students remains limited. University students, especially in Sichuan, face unique challenges such as study pressure, irregular lifestyles, and relatively weak health awareness. These factors make them potential major users of mHealth apps. However, research indicates that while Generation Z has a low adoption rate of mHealth apps, they tend to be generally satisfied with the applications they use (Do et al., 2018; Rahman et al., 2021).

This study seeks to analyze the key drivers of behavioral intention (BI) toward mHealth applications among students at universities in Sichuan. By integrating Perceived Trust, Enjoyment, and Health Literacy into the classic Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) models, this study explores the impact of these variables on students' behavioral intentions. Additionally, the study examines the role of perceived risk, perceived ubiquity, perceived usefulness, and perceived value in shaping these intentions. Insights obtained from the study may serve as a useful reference for professionals engaged in designing and improving mHealth applications, public health practitioners, and policymakers to enhance the adoption and effectiveness of mHealth apps among university students.

Literature Review and hypotheses development

Perceived Usefulness (PU)

According to Y. Chen and Barnes (2007), the higher the PU, the stronger the user's BI to adopt the technology. In terms of perceived technology categories, PU is the most influential determinant of initial online trust. Compared to usability, practicality is more important and closely linked together (Y. Chen & Barnes, 2007). In the context of the popularity of mobile health applications, PU is understood as the level of confidence users hold that online consultation services can meet their healthcare needs (Karamchandani et al., 2020). Goyal et al. (2022) found that PU is the main factor influencing people's willingness to use online physician consultation platform applications and services when they first come into contact with them, so developers of online platforms should pay attention to the role of PU in enhancing the perceived value of mHealth platforms. In light of the above discussion, the subsequent hypothesis is formulated:

H1: Perceived Usefulness has significant impact on Perceived Value.

Perceived Risk (PR)

Previous related research literature has found that PR is a negative determinant of whether people take to buy things online and buy drugs online (Aref & Okasha, 2019). In addition to technical factors, PR, frequently regarded as the uncertainty surrounding the potential adverse outcomes associated with the utilization of a product or service, is also perceived as a prominent obstacle that consumers encounter when contemplating the adoption of electronic services (Wei et al., 2018). X. Chen and Li (2017) conceptualize PR as the subjective assessment of users concerning the possibility of encountering losses when utilizing a specific system. Goyal et al. (2022) showed that variables such as patients' PR and subjective norms in the structure of the technology acceptance model play an important function in shaping their perceived value and trust in the product, which affects patients' willingness to use the product. In light of the above discussion, the subsequent hypothesis is formulated:

H2: Perceived Risk has significant impact on Perceived Value.

Perceived Ubiquity (PUb)

The research results of many scholars have proved that ubiquity usually refers to the fact that users can use a certain product or a certain service regardless of time and place, and this situation is called ubiquitous (Chopdar & Balakrishnan, 2020). Anwar et al. (2021) have found positive impacts of ubiquitous perception on consumers' perception of mobile commerce value. Similarly, people are becoming more willing to use online physician consultation platforms, hoping to access healthcare consultations anytime, anywhere. The PUb of online advisory Services Network refers to the efficiency of providing users with services that are not limited by time and location, so PUb is the main driver of the active use of mHealth services, thus increasing the perceived value of online consultations (Sneha & Varshney, 2009). In light

of the above discussion, the subsequent hypothesis is formulated:

H3: Perceived Ubiquity has significant impact on Perceived Value.

Enjoyment (En)

En is considered by some scholars as a source of a mood state (Weber et al., 2009), so when using social networking sites (SNSs), hedonics is often considered as an intrinsic positive stimulus for people, who usually show emotions such as liking, pleasure, etc., and this entertaining experience is usually positively evaluated by users (Lewis et al., 2014). Aydin (2023) studied the impact factors of young people's use of mobile health applications. His findings suggest that the pleasant feelings that mHealth apps bring to users are often overlooked by scholars, and that on the contrary, mHealth apps with En elements will always appeal to the younger generation, making them more likely to use such products. Gwebu et al. (2014) verified through examples that En triggers users' loyalty, which increases people's intention to continue using social networking sites. In light of the above discussion, the subsequent hypothesis is formulated:

H4: Enjoyment has significant impact on Behavioural Intention.

Perceived Value (PV)

The researcher underscored the key contribution of PV to steering consumption behavior and preference formation (Karjaluoto et al., 2019). PV can be elucidated as a comprehensive evaluation undertaken by an individual, encompassing their subjective assessment of the overall utility derived from a product. This evaluation transcends mere objective measurements and incorporates personal preferences, expectations, and experiences. In essence, it represents a holistic judgment of the worthiness of a product, shaped by the individual's unique perception of what has been gained and what has been relinquished (Zeithaml, 1988). Hult et al. (2019) argue that PV is an important construct that influences users' behavioral intentions towards online applications, products, and services. In light of the above discussion, the subsequent hypothesis is formulated:

H5: Perceived Value has significant impact on Behavioural Intention.

Social Influence (SI)

According to UTAUT, SI denotes the perceived expectations of valued others regarding one’s adoption of a particular technology (Aydin, 2023). Results from previous studies have shown that SI exerts a beneficial effect on people's adoption of teleconsultation healthcare, mHealth, and health information technology, as well as playing a significant, positive role in consumers' use of various online shopping applications (M. Alam et al., 2019). J. Cao et al. (2024) proposed an SI model to examine the use intentions of Chinese youth toward mobile healthcare. Their results demonstrated that SI exerted a significant positive effect on young people’s BI, indirectly enhancing their likelihood of adoption by fostering greater trust and

awareness of health-related issues. In light of the above discussion, the subsequent hypothesis is formulated:

H6: Social Influence has significant impact on Behavioural Intention.

Perceived Trust (PT)

Pipitwanichakarn and Wongtada (2019) considered that PT influences consumers' willingness to adopt new technologies. Building on the UTAUT, Chinese scholars have examined shoppers' adoption of digital pharmacy services. According to the findings, consumers' intention to buy medicines online is significantly and directly shaped by performance expectations, SI, PT, and PR (Yin et al., 2016). Chung and Kwon (2009) further elucidated that trust is a manifestation of a sense of security, a tendency to trust an entity or an individual. Schnall et al. (2015) found that the usefulness and ease of use of mHealth technology, as well as patients' PT in mobile health, all promote patients' BI to use mHealth apps. In light of the above discussion, the subsequent hypothesis is formulated:

H7: Perceived Trust has significant impact on Behavioural Intention.

Health Literacy (HL)

Levy and Janke (2016) believe that adapting to different users' levels of health knowledge is one of the key communication elements to improve the acceptance and effectiveness of mobile healthcare system users. According to the World Health Organization (WHO), HL refers to the cognitive and social abilities that influence an individual's drive and capability to access, interpret, and utilize information in ways that support and sustain physical health (Nutbeam & Kickbusch, 1998). HL encompasses the extent of an individual's capability to gather, analyze, comprehend, and convey health information vital for making well-informed choices about their health, thereby empowering them to manage their wellbeing more effectively (Berkman et al., 2010). The research has demonstrated that a person's HL is a major determinant of their willingness to recommend others to use the information, and a person's HL reflects their understanding of medical information, their discriminatory acceptance of different medical knowledge, and thus their behavioral willingness to use mHealth products (Kerr et al., 2021). In light of the above discussion, the subsequent hypothesis is formulated:

H8: Health Literacy has significant impact on Behavioural Intention.

Behavioural Intention (BI)

F. D. Davis et al. (1989) proposed an existing notable relationship linking the BI of using a system and the amount of usage. BI stands as the primary driver of user actions, with other variables exerting their influence on user behavior in an indirect manner, mediated through this pivotal concept of intention. BI refers to the subjective possibility that a person will perform certain actions (Douglass, 1977). BI is defined as "a signal of whether the customer is staying or withdrawing from the relationship with the service provider (Naik

Jandavath & Byram, 2016). Ajzen (1991) found that, in the UTAUT, TPB, and related literature, BI is typically regarded as a direct precursor to actual behavior, a view supported by numerous studies conducted across various e-health settings (Dwivedi et al., 2016).

Conceptual Framework

This research incorporates three theoretical frameworks: the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Stimulus-Organism-Response (S-O-R) framework. TAM, initially developed by Davis in 1985 (Davis, 1985) and later refined by Venkatesh in 2000 (Venkatesh & Davis, 2000), has been extensively utilized to interpret how individuals adopt information technologies. It highlights the roles of perceived usefulness, perceived ease of use, and the resulting intention to engage with technology (Chuttur, 2009). The Mobile Health TAM (MoHTAM) highlighted the role of system design and user perceptions in shaping mHealth adoption (Mohamed et al., 2011).

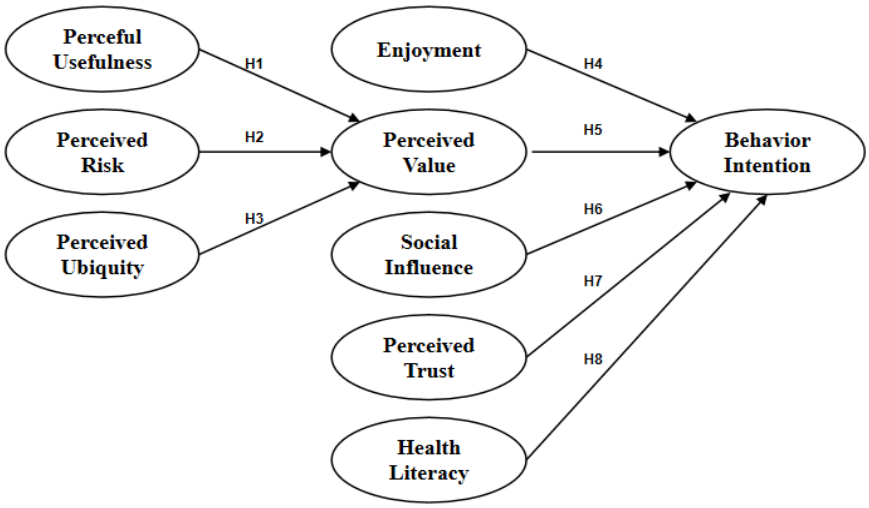
UTAUT, developed by Venkatesh et al. (2003), integrates multiple adoption perspectives and has been adapted for healthcare contexts. Variables such as situational constraints and health consciousness were added to enhance its predictive power for mobile healthcare behavior (Barua & Barua, 2021; Gagnon et al., 2012).

The S-O-R model explains behavior as responses to stimuli mediated by internal states. In mobile health studies, information and system overload were found to increase fatigue and resistance, while intergenerational support reduced these effects (Y. Cao et al., 2020).

This study focuses on factors affecting college students' intention to adopt mHealth in Sichuan Province, drawing on these three frameworks. Specifically, S-O-R supports the analysis of PU, PR, PUb, PV, and BI (Goyal et al., 2022). UTAUT contributes variables such as SI, PT, and HL (Sabbir et al., 2021), while En is added as another determinant of BI (Aydin, 2023). The conceptual framework of this study is shown in Figure 1.

Figure 1

Conceptual framework



Source: Constructed by the Author

Research Methodology

Sampling and Data Collection

This study aims to explore the factors influencing university students' use of mobile health applications. The target participants were senior students from Sichuan University of Science and Engineering, the university with the largest student population in Zigong, Sichuan Province. These students had used mobile health apps for at least three months prior to data collection. Because the total number of mobile health app users in the Zigong area was not clearly identified, the sampling procedure was carried out in three stages. In the first stage, purposive sampling was applied to define the scope of the study and identify participants whose characteristics aligned with the research objectives. The second stage involved stratified random sampling, where the student population was grouped by academic department to enhance sample representativeness and balance. Finally, a combination of purposive and convenient sampling was used to ensure data collection feasibility and efficiency. Questionnaires were distributed through QQ, WeChat, and in-person interactions during class breaks to students from four representative majors—Biopharmaceutical Engineering, Computer Science, Engineering Management, and Chemical Engineering and Technology.

Taherdoost (2017) noted that sample size is a crucial component of any empirical study, as it aims to draw conclusions about the sample population. This study utilized online sample size calculation. The study considered factors such as the expected effect size, required statistical power level, number of latent variables, number of observed variables, and probability level, successfully determining the minimum sample size required for structural

equation modeling (SEM). The computed sample requirement amounted to 460; to ensure data reliability and the objectivity of data analysis, the sample size for this study was set at 500. To draw valid conclusions from a random sample and reduce the risk of bias or sampling mistakes, the researchers distributed 682 questionnaires through both online and offline channels, collected 500 valid questionnaires, and used SEM to investigate the sample data. The demographic information collected from these questionnaires is shown in Table 1.

Table 1

Demographic Information

Characteristic	Value	Frequency	Percentage
Students' school	Sichuan University of Science and Engineering	500	100%
Students' major	Biopharmaceutical Engineering students	50	10%
	Computer Science students	251	50.2%
	Engineering Management students	100	20%
	Chemical Engineering and Technology students	99	19.8%
Time of using mHealth apps	using a mobile health APP for more than three months	500	100%
gender	Male	303	60.6%
	Female	197	39.4%
Age	18- 20 years old	0	0
	21-22 years old	361	72.2%
	More than 22 years old	139	27.8%
state of health	Healthy	361	72.2%
	Sub-healthy	123	24.6%
	Minor illnesses	11	2.2%
	Chronic diseases	5	1.0%
Times of exercise per week	Less than once a week	201	40.2%
	twice a week	118	23.6%
	three times a week	74	14.8%
	More than three times	107	21.4%

Source: Constructed by the Author

Questionnaire Development

Before the questionnaire survey, the researchers explained the purpose and scope of the questionnaire study to the participants. All college students who participated in the survey did so voluntarily, and the researchers did not offer any incentives to the participants. First, the researchers used three screening questions to exclude respondents who did not meet the professional requirements and those who had never used a mobile health application. Then, questions were posed regarding the factors influencing college students' behavioral intentions toward using mobile health applications. Lastly, demographic items were included, and the survey instrument was completed. This study employed the Item-Objective Congruence (IOC) method, with three experts scoring each item in the questionnaire to ensure consistency

between each item and the research objectives or testing objectives. Prior to the large-scale questionnaire survey, the researchers conducted a pilot survey with 50 sample questionnaires to test the questionnaire design, question wording, and data collection process for reasonableness and effectiveness.

Data Analysis

This study employs SEM as its core analytical method to systematically examine college students' intention to use mobile health applications in Zigong City and the underlying influencing factors. To meet the prerequisites for statistical analysis, we conducted normality tests, primarily relying on skewness and kurtosis results to evaluate data distribution normality. Additionally, the measurement instruments' scientific validity was tested through confirmatory factor analysis (CFA). CFA helped us confirm the pre-established relationships among variables and systematically assess model fit, convergent validity, and discriminant validity. During the SEM analysis phase, multiple fit indices were employed to comprehensively evaluate model adequacy. These metrics collectively validated the model's interpretive power over the data, ensuring its validity. Data collection was conducted via a questionnaire survey utilizing a five-point Likert scale to quantify respondents' usage intentions toward mobile health applications, thereby establishing the empirical foundation for this study.

Results and Discussion

Cronbach's Alpha Reliability (CA)

In this study, the reliability of the scale was evaluated using the Cronbach's Alpha (CA) approach, and the final Cronbach's Alpha values measured for the dimensions ranged from 0.774 to 0.938. These values reflect the level of internal consistency between the constructs and their corresponding measurement entries. According to the rule of thumb for reliability testing, Cronbach's Alpha scores of at least 0.70 are viewed as adequate(Dikko, 2016).

Table 2

The Reliability Statistics of the Model

Variable	Number of Items	Cronbach's Alpha	Strength of Association
PU	3	0.774	Acceptable
PR	4	0.938	Excellent
PUb	5	0.893	Good
En	3	0.802	Good
PV	4	0.891	Good
SI	4	0.839	Good
PT	3	0.790	Acceptable
HL	3	0.798	Acceptable
BI	3	0.815	Good

Source: Constructed by the Author

The results of the study show that the reliability coefficients of all relevant dimensions satisfy this criterion, indicating that the scale has a reliable internal consistency. Specifically (Table 2), the Cronbach's alpha values and ratings for the dimensions are as follows: the PU is 0.774 (Acceptable), the PR is 0.938 (Excellent), the PUb is 0.893 (Good), the En is 0.802 (Good), the PV is 0.891 (Good), the SI is 0.839 (Good), and the PT is 0.790 (Acceptable), HL is 0.798 (Acceptable), and BI is 0.815 (Good). The reliability of each dimension reached the “good” level, which further verified the reliability of this study's scale.

Measurement Model Assessment

Before constructing the Structural Equation Model (SEM), the researchers first validated the measurement model through the Confirmatory Factor Analysis (CFA). This step not only confirmed the predefined relationships among variables in the theoretical framework but also systematically assessed the model's goodness-of-fit, validity related to convergence, and validity related to discrimination.

Table 3

Acceptable Criteria of Goodness-of-Fit Indices

Index	Acceptable Values	Source	Statistical Values
CMIN/df	< 3.00	(Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.804
GFI	≥ 0.85	(Sica & Ghisi, 2007)	0.908
AGFI	≥ 0.80	(Sica & Ghisi, 2007)	0.887
NFI	≥ 0.80	(Wu, 2005)	0.936
CFI	≥ 0.80	(Bentler, 1990)	0.970
TLI	≥ 0.80	(Sharma et al., 2005)	0.965
RMSEA	< 0.08	(Pedroso et al., 2016)	0.04
Model Summary			Acceptable Model Fit

Source: Constructed by the Author

The evaluation demonstrated that all fit indices of the proposed model fulfilled the recommended statistical criteria. As summarized in Table 3, the CMIN/df was 1.804, GFI equaled 0.908, AGFI reached 0.887, NFI was 0.936, CFI stood at 0.970, TLI was 0.965, and RMSEA was observed at 0.04. Together, these metrics demonstrate that the model does not require corrective adjustments and that all fit values satisfy the validation requirements for convergent and discriminant validity. The study provides solid empirical support for the theoretical model by integrating CFA and SEM analysis.

Convergent validity

Convergent validity assesses the consistency of relationships between constructs. Key measures include Cronbach's Alpha, factor loadings, composite reliability (CR), and Average Variance Extracted (AVE). In conducting CFA, the researchers employed SEM to assess the validity of the measurement model. CFA results indicated that all measurement items for each construct achieved statistical significance (factor loadings exceeding 0.50 and p-values below 0.05), demonstrating substantial associations between these items and their respective constructs. Furthermore, to further assess discriminant validity, we calculated CR and AVE as recommended by Fornell and Larcker (1981). Results showed that CR values for all constructs exceeded 0.7, and AVE values exceeded 0.4. These metrics met the recommended standards, thereby confirming the discriminant validity of the measurement framework.

Table 4

Results of the CFA, along with CR and AVE

Variable	Factors Loading	CR	AVE
PU	0.687-0.786	0.778	0.539
PR	0.736-1.000	0.944	0.812
PUb	0.583-0.992	0.879	0.607
En	0.719-0.791	0.802	0.575
PV	0.620-0.996	0.895	0.690
SI	0.726-0.772	0.839	0.566
PT	0.743-0.752	0.792	0.559
HL	0.748-0.760	0.799	0.569
BI	0.735-0.823	0.817	0.599

Source: Constructed by the Author

Table 4 shows that the factor loadings of all measurement items across variables were higher than 0.5 and the CR values for each variable ranged from 0.778-0.944 and were all greater than 0.7; the AVE values for each variable ranged from 0.539-0.812 and were all greater than 0.4, both exceeding their respective thresholds. These findings suggest the constructs have good internal consistency and are suitable for use.

Discriminant Validity

According to Fornell and Larcker (1981), discriminant validity is tested by calculating the square root of the AVE for each construct. In this study, the square roots of the AVE values for all constructs exceeded the correlations between the constructs, demonstrating support for

discriminant validity. Furthermore, when the correlations among related constructs are smaller than their respective AVE square roots, discriminant validity is considered acceptable. This conclusion is reinforced by the data presented in Table 5, where the diagonal elements representing the AVE square roots of all constructs are higher than their inter-construct correlations. Collectively, these findings confirm that the structural model employed in this study exhibits satisfactory discriminant validity.

Table 5

Discriminant Validity

Variables	PU	PR	PUb	En	PV	SI	PT	HL	BI
PU	0.734								
PR	-0.039	0.901							
PUb	0.264	0.011	0.779						
En	0.296	0.048	0.282	0.758					
PV	0.356	-0.028	0.394	0.327	0.831				
SI	0.205	0.004	0.231	0.208	0.341	0.752			
PT	0.161	0.029	0.172	0.243	0.327	0.252	0.748		
HL	0.102	-0.051	0.125	0.238	0.278	0.270	0.219	0.754	
BI	0.118	-0.010	0.227	0.348	0.388	0.377	0.334	0.304	0.774

Source: Constructed by the Author

Structural Equation Modeling Analysis

In this study, the researcher evaluated the goodness-of-fit of the structural model using AMOS statistical software. To provide a comprehensive measure of model fit, the researchers chose the same fit metrics as in the CFA, specifically the chi-square to degrees of freedom ratio (CMIN/df), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), normal fit index (NFI), comparative fit index (CFI), Tucker-Lewis index (TLI), and root mean square Error Approximation (RMSEA). These indices were used to assess the relationship between the nine potential variables involved in this study.

Table 6

Goodness-of-Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
χ^2/d*f* (CMIN/dF)	<5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	2.404
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.859
AGFI	≥ 0.80(Sica & Ghisi, 2007)	0.837
NFI	≥ 0.80(Wu, 2005)	0.909
CFI	≥ 0.80 (Bentler, 1990)	0.944
TLI	≥ 0.80 (Sharma et al., 2005)	0.940
RMSEA	< 0.08(Pedroso et al., 2016)	0.053
Model Summary	**Acceptable Model Fit**	

Fit Index	Acceptable Criteria	Statistical Values
(Before Adjustment)		

Source: Constructed by the Author

Table 6 shows the model fit indices: CMIN/df = 2.404, GFI = 0.859, AGFI = 0.837, NFI = 0.909, CFI = 0.944, TLI = 0.940, and RMSEA = 0.053. All values meet the recommended thresholds, indicating that the structural equation model fits the data well and the relationships among variables are adequately supported.

Hypothesis Testing Findings

To measure the strength of the links between independent and dependent variables, the researcher utilized regression and standardized path coefficients. According to the data in Table 7 and Figure 2, all eight hypotheses proposed in this study were validated and supported by empirical data.

Table 7

Analysis Results of the Structural Model Hypotheses

Hypothesis	Paths	Standardized Path Coefficients (β)	T-value	p-value	Testing Result
H1	PU→PV	0.282	5.488	0.000 ***	Supported
H2	PR→PV	-0.014	-0.336	0.737	Not Supported
H3	PUb→PV	0.303	6.200	0.000 ***	Supported
H4	En→BI	0.273	5.047	0.000 ***	Supported
H5	PV→BI	0.181	3.791	0.000 ***	Supported
H6	SI→BI	0.285	5.373	0.000 ***	Supported
H7	PT→BI	0.221	4.154	0.000 ***	Supported
H8	HL→BI	0.169	3.234	0.001 **	Supported

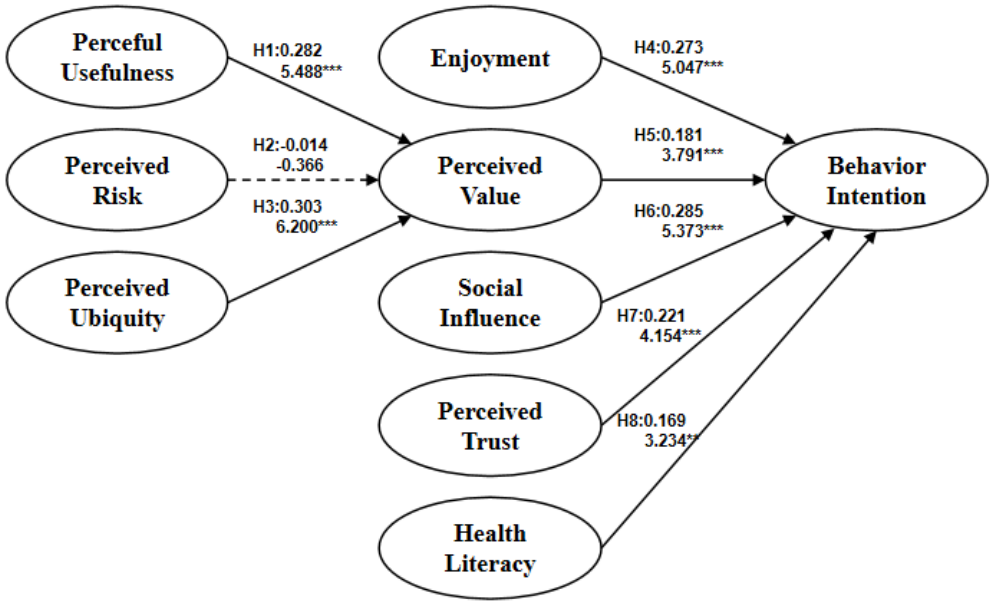
Source: Constructed by the Author
Notes: Significance levels: *=p < 0.05; **=p < 0.01; ***=p < 0.001.

The strongest effect identified in this study was the positive impact of PUb on PV. Beyond evaluating the significance of the paths, effect sizes were calculated to quantify the magnitude of the influences represented by the path coefficients. Effect sizes below 0.02 were deemed negligible, values between 0.02 and 0.15 represented a weak effect, 0.15 to 0.35 indicated a moderate effect, and those exceeding 0.35 reflected a strong effect (Cohen, 1992). In this study, except for the path effect strength of PR on PV, which was less than 0.02 and thus considered insignificant, all other path coefficients fell between 0.15 and 0.35, indicating a

moderate effect.

Figure 2

Result of the Structural Model



Source: Constructed by the Author
Note: In the diagram, solid lines indicate standardized path coefficients, with * = $p < 0.05$, ** = $p < 0.01$, and *** = $p < 0.001$; dashed lines mark paths lacking statistical significance.

Discussion

This study employs empirical data to conduct an in-depth analysis of the key factors influencing the behavioral intentions of college students in Zigong, China, toward using mobile health applications. By constructing structural models for each variable, the relationships among these variables are systematically validated. The following sections discuss each research hypothesis and, drawing on relevant prior research findings, further elucidate the theoretical basis and practical significance of this study's results.

H1: PU has significant positive effect on PV (standardized path coefficient $\beta = 0.282$, T-value = 5.488, significance level***), which suggests that the more useful college students perceive mHealth APPs to be, the more value they perceive in them.

Chairina (2021) reported that in studying factors affecting Pt. Garuda Indonesia Tbk's online services, PU may exert an indirect influence on actual usage, while PV can moderate the effect of PU on actual usage. Higher PU leads to higher PV. Yang et al. (2016) noted in their study that PU significantly positively influences PV. Yu et al. (2017) also indicated that PU significantly positively impacts PV. Our findings are consistent with those reported in the

existing literature.

H2: PR has negative impact on PV, but this effect is not statistically significant (β = -0.014, T value = -0.336, P = 0.737), which may suggest that college students consider potential risks such as privacy leaks when evaluating mobile medical apps, and that their perception of these risks may not affect their assessment of the value of mobile health apps.

According to Thakur and Srivastava (2014), PR negatively influences the adoption of mobile payment and banking systems, thereby reducing the PV of technology-enabled service platforms for users. Our study also found that PR exerts a negative influence on PV, though this effect was not statistically significant. This indicates that the PR associated with mobile health apps among university students does not substantially diminish the PV of these apps within their cognitive framework, and thus does not significantly impact their BI to adopt the technology. This finding aligns with the research results of Chang and Tseng (2013). Although PR is commonly regarded as a factor limiting consumers' online purchase intentions, their study revealed that PR did not significantly moderate the relationship between PV and purchase intention. This may imply that in the Taiwanese sample, while consumers' perception of risks associated with online shopping exists, these risks were not sufficiently strong to alter the path of value influencing intention. It can be inferred that in the sample of university students in Zigong, China, PR was also not strong enough to affect their BI to adopt mobile health apps.

H3: PUb has significant positive effect on PV (β = 0.303, T-value = 6.200, significance level***), which suggests that the higher the PUb of the mHealth APP by college students, the higher their perception of its value.

Research indicates that PUb significantly influences consumers' decisions regarding online services or e-commerce platforms (Goyal et al., 2022). A study of Hsiao and Tang (2015) confirms that older adults' perception of mobile health watches' ubiquity positively impacts their willingness to use such devices. Anwar et al. (2021) further validated the positive effect of PUb on consumers' PV of mobile commerce. As our research confirms, PUb positively correlates with PV, consequently influencing the intention of college students to engage with mHealth apps.

H4: En has significant positive effect on BI (β = 0.273, T-value = 5.047, significance level***), which suggests that the more En college students feel when using the mHealth APP, the stronger their BI to use the APP.

Chin et al. (2003) showed that IT users' intention to use and beliefs about use are moderated by the dual moderating effect of En. Many scholars believe that "enjoyment" is an emotional factor influencing people's behavioral intentions, positively impacting participation and engagement in online communities (Gong et al., 2019; Lowry et al., 2013). Certain mobile health apps incorporate entertainment and social networking features, and the stronger the pleasurable experience these apps provide users, the more they enhance users' behavioral intentions to use them. Our research also found that the more enjoyment college

students experience in mobile health applications, the more it increases their behavioral intentions to use these apps.

H5: PV has significant positive effect on BI (β = 0.181, T-value = 3.791, significance level***), indicating that greater PV of the mHealth apps are associated with increased BI to adopt the apps.

Goyal et al. (2022)argue that PV and trust have a significant impact on users' BI to use online doctor consultation platforms. Several studies have underscored the notable correlation between PV and users' BI to utilize smartphones for online health-related activities (Boontarig et al., 2012). In our study of college students' use of mHealth apps, the higher the PV among college students, the stronger their BI toward mHealth apps.

H6: SI has significant positive effect on BI (β = 0.285, T-value = 5.373, significance level***), which indicates that the more college students are influenced by people around them, the stronger their BI to use the mHealth APP.

Alalwan et al. (2018) studied the most important factors that may affect Jordanians' intention to use mobile health (mHealth), collected 365 convenient sample size data. The findings revealed that PU, SI, awareness, and innovation were identified as the four key predictors of BI. J. Cao et al. (2024) developed an SI model to investigate the BI of young people in China to adopt mobile healthcare. The findings indicated that SI had a significantly positive influence on the BI of young people to embrace mobile healthcare. The findings of this study also corroborate this view.

H7: PT has significant positive effect on BI (β = 0.221, T-value = 4.154, significance level***), which suggests that the more college students trust the mobile health APP, the stronger their BI to use it.

Gallardo et al. (2024) researched the elderly people in the Philippines to use telemedicine. The results showed that initial trust was a key factor affecting the intention of elderly people to use telemedicine. Enhancing initial trust is essential for shaping older adults' attitudes and intentions, underscoring its significance in technology adoption. Our study found that when mobile health apps provide more accurate information, they enhance users' perceived information security, strengthen college students' PT, and increase their BI to use mobile health apps. This aligns with the findings of two researchs, which argued that trust has a direct or indirect mediating effect on users' intention to adopt or use new technologies (Shareef et al., 2011; Yoon, 2009). It also supports the findings of Al-Sharafi et al. (2017), who discovered that trust mediates the relationship between PU and users' intention.

H8: HL has significant positive effect on BI (β = 0.169, T-value = 3.234, significance level **), which indicates that the higher the HL of college students, the stronger their BI to use the mobile health APP.

HL is a self-motivating independent variable that often promotes people's embracing of health IT and making positive usage intentions (Hsieh & Lai, 2020). Existing studies reveal

that individuals with elevated HL are more prone to engage in the active sharing of health information. This information-sharing behavior further strengthens their behavioral intentions, thereby promoting the implementation of health behaviors (Crook et al., 2016). College students, as individuals possessing relatively comprehensive knowledge, belong to a group with higher HL. Consequently, our research also found that college students' HL positively influences their BI to use mobile health apps. This aligns with the findings of Sabbir et al. (2021), another scholar, who observed that the higher the HL level among younger generations, the stronger their BI to use online pharmacies.

In summary, the research underscores the pivotal role of perceived usefulness, perceived ubiquity, social influence, and enjoyment in molding the perceived value and behavioral intentions of college students. These insights enrich the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) by highlighting the emotional and contextual aspects of mobile health (mHealth) adoption.

Conclusion and Recommendations

The study focuses on understanding the behavioral intentions and determinants influencing the use of mobile health applications among college students in Zigong City, Sichuan Province. This framework systematically examined the mechanisms through which eight variables—PU, PR, PUb, En, PV, SI, PT, and HL—influence BI. The findings reveal that perceived usefulness and perceived ubiquity significantly and positively influence PV, while PR does not significantly affect PV. PV, En, SI, trust, and HL all significantly and positively influenced college students' usage intention. This indicates that enhancing user experience, strengthening application credibility, and reinforcing health education all contribute to increasing their willingness to use the app. This model enriches the theoretical perspective on mobile health applications, enhances the explanatory and predictive power of the theory, and validates the applicability of multidisciplinary integrated theories in this field.

Practically, the study offers actionable recommendations for developing and promoting mHealth applications. Developers should prioritize functional utility and user experience while ensuring data privacy and security. Simultaneously, leveraging social networks and HL education can enhance user retention and engagement. Additionally, increasing the interactivity and enjoyment of the application can motivate sustained usage.

Wang et al. (2024)reported that interventions delivered through mobile health applications can substantially enhance adolescents’ overall physical activity levels while reducing sedentary behaviors. Their findings highlight the potential of mobile health apps to encourage healthier habits and more active lifestyles among young populations. In a related study, M. Z. Alam et al. (2025) demonstrated that both age and gender significantly influence individuals’ willingness to adopt mHealth services, with younger users and males showing

greater intention to use such technologies. Furthermore, Nassar et al. (2019) found a positive association between information and communication technology (ICT) accessibility and mental well-being among older adults in South Korea. Our findings, together with these research results, collectively indicate that advancing the widespread use of mHealth apps across different age groups can improve personal health outcomes while narrowing digital and health disparities, ultimately contributing to the overall well-being of society.

Despite achieving relatively systematic outcomes, the study has limitations, such as restricted geographical sampling and relatively homogeneous participant groups. Future research could expand samples to diverse regions, cultural backgrounds, and socioeconomic groups to enhance the generalizability of findings. Additionally, incorporating variables like technological performance, lifestyle, social support, and health goals, alongside optimizing measurement tools, could facilitate the construction of more interpretable and stable behavioral prediction models.

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