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Factors Affecting Patients' Attitudes and Behavioral Intentions Toward Using Hospital Online Services in Shanghai, China

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Abstract

Purpose: This research aimed to examine the factors affecting patients' attitudes and behavioral intentions toward using hospital online services. The conceptual framework is grounded in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). **Research design, data and methodology:** The study employed a non-probability sampling procedure to select participants. A questionnaire was developed using a Five-point Likert scale and tested for content validity and reliability through Item-Objective Congruence (IOC) and Cronbach's Alpha. Confirmatory Factor Analysis (CFA) was conducted to ensure the model's validity, and Structural Equation Modeling (SEM) was utilized to assess the model fit and test the hypotheses. **Results:** The analysis confirmed that satisfaction, social influence, and facilitating conditions have a significant direct impact on behavioral intentions. Perceived usefulness and perceived ease of use influence behavioral intentions indirectly through attitude. **Conclusions:** The findings underscore the importance of improving user satisfaction, simplifying system interfaces, and recognizing the influence of social networks in encouraging online service use. Strengthening these areas can support broader adoption of digital health tools, contributing to more efficient and accessible healthcare delivery. The results offer valuable insights for enhancing the design and implementation of hospital online registration systems.

Keywords: Hospital Online Services, Patient Attitude, Behavioral Intention, Technology Acceptance

JEL Classification Code: D90, I10, L84, M10

1. Introduction

Hospital Online Services in China have undergone rapid growth and transformation in recent years, driven by advancements in technology. These services, which encompass a range of digital healthcare offerings, have become integral to the Chinese healthcare system, enhancing patient care and streamlining administrative processes (Chen & Tan, 2004).

The rationale for studying Hospital Online Services stems from their potential to improve healthcare service quality, optimize the patient experience, and enable the rational allocation of healthcare resources (Anderson & Srinivasan, 2003). With the rapid development of information technology, these services have become a vital direction for healthcare service innovation. Hospital Online Services provide patients with convenient tools for appointments, registration, and inquiries via electronic platforms, significantly improving the efficiency and quality of healthcare delivery (Chen & Tan, 2004). Furthermore, online health consultations and telemedicine offer timely and professional medical assistance, especially in remote areas or emergencies.

While the benefits of Hospital Online Services are evident, a significant gap remains in understanding the factors influencing patient adoption, particularly within China's public hospital context. Many patients still hesitate to use online platforms, often due to concerns about usability,

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trust, or lack of awareness. This underutilization presents a challenge, as it hinders the full realization of digital health's potential.

Hospital Online Services play a crucial role in enhancing the patient experience. Traditional medical processes can be cumbersome and time-consuming, whereas online platforms simplify access to healthcare services and improve communication with providers (Anderson et al., 2004). These platforms also offer health education and self-management resources, empowering patients to make informed decisions about their care.

In addition, these services support the rational allocation of medical resources. By analyzing digital platform data, hospitals can better understand patient needs and behaviors, leading to more efficient service delivery and helping to address resource shortages in underserved areas (Al-Mamary & Shamsuddin, 2015). The growing demand for convenient, technology-enabled healthcare services demonstrates strong market potential (Babin et al., 2023). As public health awareness increases, online platforms are becoming essential tools for healthcare delivery.

Therefore, this study seeks to examine the key factors influencing patients' attitudes and behavioral intentions toward using Hospital Online Services. By applying the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), this research aims to fill existing gaps in understanding patient behavior in a digital healthcare environment. The findings are expected to contribute both to theoretical frameworks and practical strategies for enhancing digital health adoption.

2. Literature Review

2.1 Satisfaction

Satisfaction is a subjective state of mind reflecting an individual's contentment with a service, product, or interaction (Oliver, 1997). It plays a critical role in shaping customer loyalty, repeat purchasing behavior, and brand reputation (Anderson & Srinivasan, 2003). Oliver (1980) emphasized that satisfaction is a key predictor of consumers' future purchasing behavior, as satisfied customers are more likely to consider and act on repeat purchases. Zeithaml et al. (1996) further confirmed the positive relationship between satisfaction and behavioral intention, highlighting that exceeding consumer expectations in service quality fosters satisfaction, which, in turn, encourages repeat purchases or recommendations. Bhattacherjee (2001) demonstrated that satisfaction with information systems significantly influences users' intentions to continue usage, driven by cognitive and emotional factors as well as social influences. Thus, enhancing satisfaction is a powerful strategy to encourage positive behavioral intentions. Based on these insights, the following hypothesis is proposed:

H1: Satisfaction has a significant effect on Behavioral Intention.

2.2 Social Influence

Social influence refers to the impact others have on an individual's attitudes, beliefs, behaviors, or emotions, either directly or indirectly (Cialdini & Goldstein, 2004). Connolly (2017) found that social influence plays a significant role in shaping individuals' consumption decisions, as the opinions and behaviors of others often serve as critical references during decision-making. Social influence is particularly important in determining behavioral intentions, with family and friends' recommendations strongly influencing decisions to use rating websites (Guetz & Bidmon, 2022). Additionally, Ryan (2024) highlighted that social influence mediates the effects of cognitive and normative information on behavioral intentions. Similarly, Lai (2023) demonstrated that peer recommendations and social interaction significantly enhance individuals' willingness to adopt new technologies. These findings underscore the positive role of social influence in promoting behavioral intention within the healthcare context. Based on these insights, the following hypothesis is proposed:

H2: Social Influence has a significant effect on Behavioral Intention.

2.3. Facilitation Conditions

In cognitive psychology, facilitation conditions refer to factors that reduce cognitive load and enhance information processing efficiency. For instance, breaking complex information into smaller, more manageable units through information chunking can significantly improve memory and learning efficiency (Miller, 1956). According to Social Facilitation Theory, the presence of others or favorable external conditions can influence behavior by enhancing internal motivation and improving task performance efficiency. Burnham (2022) observed that the presence of others can either enhance or hinder individual performance, depending on the context. Additionally, group dynamics can affect task focus, serving as either a distracting stimulus or a motivator, with the type of task playing a critical role in determining performance outcomes. This perspective aligns with the role of facilitation conditions in shaping behavioral intention. When external conditions support task completion, individuals are likely to focus more on the task, reduce distractions, and strengthen their willingness to engage, thus enhancing behavioral intention. Bagozzi (2023) further emphasized that favorable external conditions positively influence attitudes, which in turn promote the development of behavioral intention. These insights underscore the critical role of facilitation conditions in shaping attitudes and driving behavioral intentions. Based on these insights, the following hypothesis is proposed:

H3: Facilitation Conditions have a significant effect on Behavioral Intention.

2.4 Perceived Usefulness

Davis (1989) defined perceived usefulness in his Technology Adoption Model (TAM) as "the degree to which a user believes that using a particular technology or system will increase their productivity." According to the model, perceived usefulness has a greater influence on behavioral intention than perceived ease of use. Lee et al. (2013) identified perceived usefulness as a key factor influencing consumers' intentions to adopt mobile commerce, highlighting that consumers are more likely to form positive behavioral intentions when they perceive m-commerce as convenient, time-saving, and productivity-enhancing. Similarly, Kim (2007) examined online banking and found that perceived usefulness significantly impacts users' behavioral intentions, with a positive correlation observed between perceived usefulness and ease of use, which together influence behavioral intention. Hsu and Lu (2004) extended this understanding by studying the influence of perceived usefulness on users' continuous behavioral intentions in the context of online learning systems. Their findings showed that perceived usefulness plays a critical role in consistent usage, as users are more likely to engage with eLearning systems when they believe the systems provide valuable learning resources and support. Based on these insights, the following hypothesis is proposed:

H4: Perceived Usefulness has a significant effect on Attitude.

2.5 Perceived Ease of Use

Perceived ease of use refers to users' subjective perception of how simple and intuitive a technology is to operate and master (Davis, 1989). It plays a crucial role in influencing technology acceptance, particularly in the context of rapidly advancing information technology and the adoption of digital tools. Hsu and Lu (2004) emphasized that when users perceive a system as easy to use, they are more likely to develop the intention to continue using it. Perceived ease of use exerts a significant positive influence on behavioral intention, both directly and indirectly, by shaping users' attitudes toward the technology. Similarly, Moon and Kim (2001) found that perceived ease of use significantly impacts purchase intentions, demonstrating that users are more inclined to make purchases on e-commerce platforms that are simple and user-friendly. Based on these insights, the following hypothesis is proposed:

H5: Perceived Ease of Use has a significant effect on Attitude.

2.6 Attitude

Attitude is a multidimensional construct encompassing an individual's affective feelings and cognitive evaluation of an object or situation. It reflects a subjective disposition and tendency toward a particular object, often shaped by personal experiences, values, and emotional responses (Eagly & Chaiken, 1993). Attitude is recognized as one of the primary determinants of behavioral intention. For instance, Fishbein and Ajzen (1975) demonstrated that a positive attitude toward a brand significantly strengthens a consumer's intention to purchase its products. Similarly, Ajzen's (1991) study on environmental behavior revealed that individuals with positive attitudes toward environmental practices were significantly more likely to engage in environmental activities. Furthermore, Venkatesh et al. (2003) highlighted in their study on information systems that employees with positive attitudes toward a system were more inclined to adopt and use it. These findings underscore the critical role of attitude in shaping behavioral intentions across diverse contexts. Based on these insights, the following hypothesis is proposed:

H6: Attitude has a significant effect on Behavioral Intention.

2.7 Behavioral Intention

Behavioral Intention refers to an individual's anticipated or planned course of action in the future. Fishbein (1980) emphasized that Behavioral Intention serves as a significant predictor of actual behavior, linking cognitive and motivational processes to observable actions. Jidong (2010) further elaborated that Behavioral Intention represents the likelihood of a consumer engaging with a company's products or services after exposure to relevant information, ultimately leading to specific behaviors related to the company or product. This likelihood is shaped by factors such as the consumer's attitude, beliefs, and anticipated satisfaction with the product or service. Kim (2019) expanded the concept of Behavioral Intention by examining its broader determinants. They argued that it is influenced not only by intrinsic factors, such as individual attitudes and preferences, but also by external factors, including the social environment, cultural context, and situational dynamics. Consequently, to fully understand and predict an individual's Behavioral Intention, a comprehensive approach that incorporates both intrinsic and extrinsic influences is essential.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework in this study is primarily based on the following theoretical foundations: the Technology Acceptance Model (TAM) proposed by Davis (1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT), an influential theoretical model in the field of information technology acceptance introduced by Venkatesh et al. in 2003.

This framework emphasizes the interactions between these core concepts, illustrating the complex processes through which they collectively shape individual behavioral intentions. The study includes five independent variables—Satisfaction, Social Influence, Facilitation Conditions, Perceived Usefulness, and Perceived Ease of Use—one mediating variable, Attitude, and one dependent variable, Behavioral Intention By gaining a deeper understanding of these concepts and their interrelationships, it becomes possible to more effectively predict and influence individuals' behavioral decision-making processes.

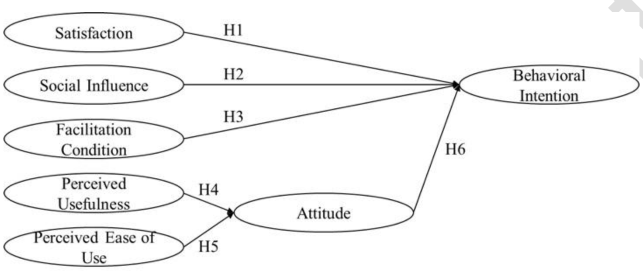

Figure 1: Conceptual Framework

3.2 Research Methodology

The research design for this study is quantitative, employing a cross-sectional survey to gather data. It is anchored on the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), aiming to understand the factors that could influence patients' behavioral intentions when engaging with online hospital services.

A quantitative approach is adopted by using non-probability sampling procedure to collect data from patients in selected three hospitals. In the development of the questionnaire, a five-point Likert scale was primarily used, and Item-Objective Congruence (IOC) testing was conducted by three experts to ensure content validity. Before formal data collection, a pilot test with 50 samples was conducted to evaluate internal consistency and reliability. Following this, a formal survey was implemented, distributing a total of 500 questionnaires.

This study employed a combination of descriptive analysis and inferential statistics to test the proposed hypotheses using structural equation modeling (SEM). To ensure the accuracy and scientific rigor of the model, SPSS and AMOS software were utilized for data analysis. Confirmatory Factor Analysis (CFA) was conducted to evaluate the reliability, convergent validity, and discriminant validity of the measurement model. Structural Equation Modeling (SEM) was subsequently applied to validate the relationships among the key variables, including Satisfaction, Social Influence, Facilitation Conditions, Perceived Usefulness, Perceived Ease of Use, Attitude, and Behavioral Intention.

3.3 Population and Sample Size

This study focused on users from three hospitals in Shanghai, China, where many patients utilize online hospital registration systems for their treatment. The sample size was determined to meet the research requirements. The study investigated factors affecting patients' attitudes and behavioral intentions toward using hospital online services through an online data collection process. The three hospitals selected for this study were Renji Hospital Shanghai, Shanghai Jiao Tong University Ruijin Hospital, and Zhongshan Hospital of Fudan University.

A non-probability sampling method was employed to select participants for this study. A survey was conducted targeting patients with prior experience using online hospital registration services in Shanghai. The specific sampling details are presented in Table 1.

Table 1: Population and sample size from the selected hospitals

Hospital	Number of Patients per Day	Proportional Sample Size
Renji Hospital Shanghai	7,031	137
Shanghai JiaoTong University Ruijing Hospital	7,397	144
Zhongshan Hospital of Fudan University	11,297	219
Total	**25,725**	**500**

Source: Constructed by author

Data for this study were obtained through a questionnaire survey, which facilitated the standardized collection of feedback from a large number of participants within a specific time period. The data collection process involved two key steps: pilot testing and the primary investigation. The preliminary test results indicated that the scale items used in this study demonstrated good reliability and internal consistency. Based on these findings, a large-scale questionnaire survey was conducted, resulting in the distribution and collection of data from 500 participants.

4. Results and Discussion

4.1 Demographic Profile

The demographic information collected from participants is summarized in Table 2. From a gender perspective, the sample included 244 males (49.29%) and 251 females (50.71%).

In terms of age distribution, participants aged 18–30 accounted for 164 individuals (33.13%), those aged 31–50 comprised 192 individuals (38.79%), and participants aged above 50 totaled 139 individuals (28.08%).

In terms of occupation, the distribution was as follows: students (99 participants, 20%), employed/worker (155 participants, 31.3%), retirees (114 participants, 23.0%), and others (127 participants, 25.7%).

Regarding education level, the majority of respondents were junior college (153 participants, 30.9%), undergraduate (101 participants, 20.4%), and graduate-level or above (143 participants, 28.9%).

Table 2: Demographic Profile

Demographic and Behavior Data (N=500)		Frequency	Percentage
Gender	Male	244	49.3
	Female	251	50.7
Age	18-30	164	33.1
	31-50	192	38.8
	Above 50	139	28.1
Occupation	Student	99	20.0
	Employed/Worker	155	31.3
	Retiree	114	23.0
	Other	127	25.7
Educational Level	High School and below	98	19.8
	Junior College	153	30.9
	Undergraduate	101	20.4
	Graduate Students and above	143	28.9

4.2 Confirmatory Factor Analysis (CFA)

To validate the research model, confirmatory factor analysis (CFA) was conducted to test the fit of the measurement model and ensure the constructs were well-represented by the observed variables.

The reliability of the measurement model was assessed using Cronbach's Alpha and composite reliability (CR). Cronbach's Alpha measures the internal consistency of items within a construct, with values above 0.7 indicating acceptable reliability and values above 0.8 suggesting strong reliability (Nunnally, 1978). As shown in Table 3, all constructs meet or exceed this threshold, indicating good internal consistency.

Composite reliability (CR) values above 0.6 further confirmed the constructs' reliability (Fornell & Larcker, 1981). For validity, both convergent and discriminant validity were assessed. Convergent validity was supported by average variance extracted (AVE) values exceeding 0.4, while discriminant validity was confirmed as all AVE values were greater than the squared correlations between constructs. Table 3 presents the CFA results, confirming that the measurement model demonstrates good reliability and validity.

Furthermore, an analysis of the relationship between participants' demographic characteristics and influencing factors reveals that younger, more educated participants may perceive online hospital services as more useful and easier to use. In contrast, older adults and retirees may rely more on facilitating conditions and support, highlighting the need for user-friendly system designs and assistance.

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

Variable	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factor Loading	CR	AVE
Satisfaction (SA)	Hossain et al. (2023)	3	0.833	0.754-0.856	0.836	0.63
Social Influence (SI)	Tugiman et al. (2023)	4	0.848	0.716-0.838	0.849	0.585
Facilitation Condition (FC)	Tugiman et al. (2023)	4	0.815	0.673-0.814	0.816	0.527
Perceived Usefulness (PU)	Tu et al. (2022)	4	0.885	0.789-0.834	0.885	0.659
Perceived Ease of Use (PE)	Tu et al. (2022)	4	0.879	0.773-0.838	0.879	0.646
Attitude (AT)	Tu et al. (2022)	3	0.832	0.767-0.807	0.832	0.623
Behavioral Intention (BI)	Tu et al. (2022)	3	0.802	0.751-0.756	0.802	0.574

Note: CR = Composite Reliability, AVE = Average Variance Extracted

As shown in Table 4, the diagonal values representing the square roots of AVE are used to determined discriminant validity of the model. Discriminative validity refers to the accuracy and validity of a measurement tool or evaluation method in evaluating or measuring a particular concept.

The values AVE square roots are all larger than the corresponding values in the same columns, indicating that the questionnaire demonstrates good discriminant validity.

Table 4: Discriminant Validity

Variable	Factor Correlations						
	SA	SI	FC	PU	PE	AT	BI
SA	**0.793**						
SI	0.205	**0.765**					
FC	0.196	0.193	**0.726**				
PU	0.122	0.207	0.326	**0.812**			
PE	0.141	0.227	0.225	0.431	**0.804**		
AT	0.238	0.366	0.313	0.322	0.347	**0.789**	
BI	0.283	0.327	0.382	0.352	0.26	0.601	**0.758**

Note: The diagonally listed value is the AVE square roots of the variables

4.3 Structural Equation Model (SEM)

Structural equation modeling (SEM) was used to address the research objectives of this study and validate the relationships among the variables. To ensure the fitness of the structural model, the goodness-of-fit indices were evaluated. The results in Table 5 showed CMIN/DF = 1.707, GFI = 0.935, AGFI = 0.919, NFI = 0.929, CFI = 0.969, TLI = 0.964, and RMSEA = 0.038. These values fall within the acceptable thresholds, confirming the model's fitness and allowing for further path analysis to be conducted.

Table 5: Goodness of Fit for Structural Model

Index	Criterion	Statistical Value
CMIN/DF	< 5.00 (Wheaton et al., 1977)	1.707
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.935
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.919
NFI	≥ 0.80 (Wu & Wang, 2006)	0.929
CFI	≥ 0.80 (Bentler, 1990)	0.969
TLI	≥ 0.80 (Sharma et al., 2005)	0.964
RMSEA	< 0.08 (Pedroso et al., 2016)	0.038

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

4.4 Research Hypothesis Testing Result

The significance of the relationships among the constructs was assessed through regression weights, standardized path coefficients, t-values, and R^2 variances. Hypotheses were deemed supported if the p-value was less than 0.05 and the t-value exceeded 1.96. The findings of the analysis are summarized in Table 6 and illustrated in Figure 2, with all proposed hypotheses being statistically validated.

Table 6: Hypothesis Testing Result

Hypothesis	Standardized path coefficients (β)	t-value	Test Result
H1: SA → BI	0.135	2.93*	Supported
H2: SI → BI	0.097	2.115*	Supported
H3: FC → BI	0.236	4.876*	Supported
H4: PU → AT	0.263	4.577*	Supported
H5: PE → AT	0.282	4.895*	Supported
H6: AT → BI	0.612	11.039*	Supported

Note: *=p-value<0.05

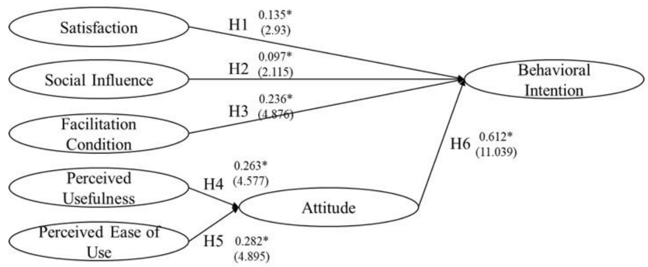

Figure 2: Results of Research Framework
Note: Solid line reports the Standardized Coefficient with * as $p<0.05$, and t-value in Parentheses

The analysis result in Table 6 presents that the proposed hypotheses were supported.

H1: Satisfaction has a significant effect on behavioral intention as demonstrated with a standardized coefficient value of 0.135. Individual satisfaction is leveled by personal experience, environment, and social factors. When individuals are recognized and supported in a social environment, their Satisfaction is enhanced, which in turn promotes the generation of positive behavioral intentions (Bhattacherjee, 2001; Zeithaml et al., 1996)

H2: Social influence has a significant effect on behavioral intention as demonstrated with a standardized coefficient value of 0.097. Social norms and peer pressure positively influence users' behavioral intentions. This indicates that social influence is an important driver of sustained usage and adoption of technologies (Guetz & Bidmon, 2022; Ryan, 2024)

H3: Facilitation Conditions have a significant effect on behavioral intention as demonstrated with a standardized coefficient value of 0.236. When external conditions are conducive to the individual's completion of the task, the individual's behavioral intention may be enhanced, which in turn promotes the formation of his behavioral intention (Ajzen & Fishbein, 1980).

H4: Perceived usefulness has a significant effect on attitude as demonstrated with a standardized coefficient value of 0.263. Designing and promoting new technologies or systems requires full consideration of ways to enhance users' perceived usefulness to encourage positive behavioral intentions and continuous use behaviors (Hsu & Lu, 2004; Kim, 2007).

H5: Perceived ease of use has a significant effect on attitude as demonstrated with a standardized coefficient value of 0.282. The findings indicate that perceived ease of use is a key factor influencing users continued use of technology. Users who perceive the technology as easy to use are more likely to develop an intention to continue using it (Hsu & Lu, 2004; Moon & Kim, 2001).

H6: Attitude has a significant effect on behavioral intention as demonstrated with a standardized coefficient value of 0.612. This indicated that patients were more likely to use the systems when they held positive attitudes toward them (Venkatesh et al., 2003).

5. Conclusions and Recommendation

5.1 Conclusions

This study examined the factors significantly influencing patients' attitudes and behavioral intentions toward using online registration systems in municipal hospitals in Shanghai. The research highlighted both the theoretical and practical significance of these factors and explored how they collectively shape patient behavior. A quantitative research approach was employed, utilizing questionnaires to collect data, which were analyzed using CFA and SEM. The results revealed that several key drivers had a significant impact on patients' attitudes and intentions.

Patient satisfaction with the online registration system was found to significantly affect their behavioral intention to continue using the system. This finding aligns with Oliver's (1980) assertion that satisfaction influences future behavioral intentions. Additionally, social influence from family, friends, and medical institutions played a crucial role in shaping patients' intentions to adopt online registration systems. This finding supports the UTAUT model proposed by Venkatesh et al. (2003), which identifies social influence as a key determinant of technology adoption. Facilitating conditions, such as access to resources, knowledge, and support, were also shown to be highly influential. This result is consistent with the observations of Taylor and Todd (1995), who noted that external support is critical for technology acceptance.

Furthermore, perceived usefulness and ease of use were found to significantly affect patients' attitudes toward online registration systems. These findings confirm the basic premises of the TAM model by Davis (1989) and align with Venkatesh and Davis's (1989) work on predicting user technology acceptance behavior. Collectively, these factors provide an integrated view of how satisfaction, social influence, facilitating conditions, perceived usefulness, and perceived ease of use interact to influence the complex decision-making process of patients in adopting online registration systems.

By examining these variables, the study successfully fulfilled its objective of identifying the key determinants of patients' attitudes and behavioral intentions toward hospital online registration systems. The findings offer empirical evidence that addresses the research problem—namely, the underutilization of digital health tools—and highlight the conditions that can enhance user acceptance.

Overall, the findings of this study correspond to previously published literature, affirming the applicability of established models like TAM and UTAUT in the context of hospital online registration systems. At the same time, the research contributes context-specific insights by revealing how cultural elements such as collectivism and social norms strongly influence technology adoption among Chinese patients. The study concludes that enhancing satisfaction, social influence, facilitating conditions, perceived usefulness, and perceived ease of use are essential precursors to the successful adoption of online registration systems. These factors not only influence a patient's attitude and intentions individually but also interactively contribute to shaping their behavior. Thus, the study not only advances theoretical understanding but also offers actionable knowledge to support the effective implementation of digital health services.

5.2 Recommendations

Policymakers should prioritize increasing digital literacy among patients, particularly in rural and economically disadvantaged areas, to bridge the digital divide and ensure equitable access to online healthcare services. Furthermore, strong regulatory frameworks for data security are essential to protect patients' sensitive information and build confidence in online healthcare systems. Policies should also incentivize the adoption and enhancement of hospital online registration systems. This could involve initiatives to make these systems more convenient, user-friendly, and accessible, thereby encouraging broader utilization by patients.

From a practical perspective, online registration systems should focus on enhancing user experience by addressing technical issues, simplifying processes, and providing clear operational instructions. Leveraging the power of social networks and media could further promote awareness of online registration systems and their benefits, utilizing word-of-mouth publicity and patient testimonials. Comprehensive technical support, such as online tutorials and 24-hour hotlines, should be made available to assist patients with limited technical skills in effectively using the systems. Additionally, continuous system innovation and regular updates based on user feedback are crucial for improving functionality and ensuring patient satisfaction.

5.3 Limitation and Further Study

Future studies should consider expanding the model by including additional factors such as patients' health status, trust in technology, and concerns related to privacy and data security. These factors could contribute to the development of a more comprehensive model for understanding patient behavioral intentions. Additionally, longitudinal research methods are recommended to track changes in patient attitudes and intentions over time, allowing for the identification of long-term influencing factors and trends. Cross-cultural analyses could also play a critical role by comparing different regions and examining the impact of socio-cultural backgrounds on patients' intentions toward online healthcare services.

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