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Research Article

DETERMINANTS OF MEDICAL STUDENT'S ATTITUDE TOWARD MOBILE ENGLISH LEARNING IN CHENGDU, CHINA

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Abstract

This study aims to examine the factors influencing the attitudes and behavioral intentions of medical students in Chengdu, China, regarding their engagement in mobile English learning. The conceptual framework posits direct and indirect relationships among performance expectations (PE), social influence (SI), facilitating conditions (FC), perceived playfulness (PP), attitude (ATT), perceived usefulness (PU), perceived ease of use (PEOU), and behavioral intention (BI). A quantitative survey was conducted involving 500 undergraduate medical students. The data were analyzed using structural equation modeling (SEM) and confirmatory factor analysis (CFA). The findings indicate that attitude, perceived usefulness, and perceived ease of use are significant predictors of behavioral intention, with perceived usefulness exerting the strongest impact ($\beta = 0.634$, $p < 0.001$). Performance expectations, social influence, facilitating conditions, and perceived playfulness collectively account for 12.9% of the variance in attitude ($R^2 = 0.129$). Furthermore, perceived usefulness, perceived ease of use, and attitude explain 43.9% of the variance in behavioral intention ($R^2 = 0.439$). The statistical results substantiate the seven research hypotheses and the final recommendations. To enhance the adoption of mobile English learning, it is recommended that institutions invest in reliable technological infrastructures, design user-friendly and interactive learning platforms, and promote positive social interactions to improve students' attitudes and behavioral intentions. Additionally, further studies are necessary to explore the long-term impact of mobile learning on academic performance and professional development, as well as to investigate the potential of emerging technologies, including artificial intelligence and virtual reality, in enhancing mobile learning experiences.

Keywords: Performance Expectations (PE), Social Impact (SI), Facilitation (FC), Perceived Playfulness (PP), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude (ATT), Behavioral Intentions (BI)

Introduction

The trajectory of mobile learning (m-learning) has spanned three distinct technological eras, evolving from rudimentary Personal Digital Assistants systems (PDAs) in the 1990s to today's interconnected smart ecosystems (Kukulska-Hulme & Traxler, 2005). Yet within medical education, particularly in English language acquisition, this technological progression masks persistent disciplinary oversights. While frameworks emphasizing collaborative learning and personalization (Kearney et al., 2012) dominate general pedagogy, they stumble when confronting medical English's unique demands—those requiring precise navigation of clinical jargon like International Classification of Diseases (ICD) coding conventions alongside strict adherence to World Health Organisation (WHO) documentation protocols. Curiously, research patterns reveal a paradoxical fixation: 87% of studies obsess over device accessibility metrics (Al-Balasd et al., 2020) while sidestepping the cognitive challenges of sustaining engagement with complex medical lexicons.

This disconnect grows more pronounced when considering pandemic-era shifts. Post-COVID scholarship remains preoccupied with emergency remote teaching models (Bernacki et al., 2019), creating a temporal blind spot regarding hybrid learning's long-term impacts on diagnostic communication skills. The irony lies in medical education's globalized reality—where WHO records show a 68% plunge in international clinical rotations since 2020, precisely when Belt and Road Initiative (BRI) healthcare collaborations demand more anglophone-competent Chinese clinicians (Wang et al., 2017).

Traditional TAM models, often misapplied as generic language learning templates (Sari, 2020), prove particularly inadequate here. Our modified framework injects medical specificity through three novel constructs: residency-driven language benchmarks mirroring TOEFL/IELTS requirements, gamified patient interview simulators addressing clinical pragmatics, and case report interpretation modules aligned with International Committee of Medical Journal Editors (ICMJE) standards.

The Study at Chengdu Medical College study is both representative and unique. As China is a major source of English-speaking proficient medical professionals in the Belt and Road Initiative (BRI) partner countries, the m-learning patterns of these students have important policy implications. The findings reveal interesting trends: on one hand, Accreditation Council for Continuing Medical Education (ACCME) are gaining popularity(Macario, 2019); on the other hand, hospitals accredited by international healthcare organizations (JCI) increasingly favor learning platforms that integrate preparation tools for Medical Licensing Examination(USMLE) and the Professional and Linguistic Assessments Board (PLAB). However, a seemingly paradoxical trend is emerging: simply increasing infrastructure investments is yielding diminishing returns. This suggests that next-generation educational technology solutions must go beyond technical upgrades and address the complexities of medical discourse itself. The tension between global standardization and disciplinary specificity is redefining what constitutes effective mobile pedagogy in post-pandemic medical education.

Objectives

1. Identify the key factors influencing medical students' attitudes and behavioral intentions toward mobile learning.

2. Examine how attitudes mediate the relationship between these factors and behavioral intentions, elucidating both direct and indirect pathways.

3. Assess the model's predictive power regarding students' behavioral intentions, providing a robust framework for understanding mobile learning adoption.

4. Provide evidence-based recommendations for educational institutions, policy makers, and educational technologists to enhance technological infrastructure, design engaging content, and promote supportive environments.

Hypothesis

1. H1 Performance Expectancy has a significant impact on attitude.
2. H2 Social influence has a significant impact on attitude.
3. H3 Facilitating Condition has a significant impact on attitude.
4. H4 Perceived Playfulness has a significant impact on attitude.
5. H5 Attitude has a significant impact on behavioural intention.
6. H6 Perceived Usefulness has a significant impact on behavioural intention.
7. H7 Perceived Ease of Use has a significant impact on behavioural intention.

Conceptual Framework

This study draws on a robust foundation of established theories to explore the complex dynamics influencing medical students' attitudes and behavioral intentions toward mobile English learning. Key theories referenced include the Theory of Reasoned Action (TRA) (Fishbein & Ajzen, 1975), which posits that attitudes and subjective norms shape behavioral intentions; the Theory of Planned Behavior (TPB) (Ajzen, 1991), which extends TRA by incorporating perceived behavioral control; the Technology Acceptance Model (TAM) (Davis et al., 1989), which emphasizes perceived usefulness and ease of use as critical determinants of technology adoption; and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), which integrates multiple theories to provide a comprehensive view of technology acceptance. Additionally, the study incorporates the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) (Tseng et al., 2022), which further expands UTAUT by considering new factors such as hedonic motivation and social influence. Based on this, the researchers developed a new conceptual framework, as illustrated in Figure 1.

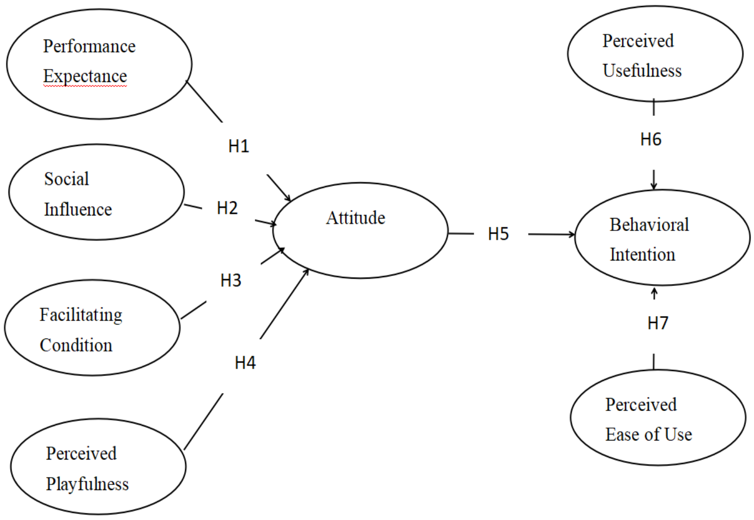

Figure 1 *Conceptual Framework*

Source: Created by the author.

The current study develops its conceptual framework by integrating key constructs from both the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), providing a comprehensive view of the factors influencing medical students' attitudes and behavioral intentions regarding mobile English learning. The framework includes Performance Expectancy (PE), Social Influence (SI), Facilitating Conditions (FC), Perceived Playfulness (PP), Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude (ATT), and Behavioral Intention (BI).

This research is based on two well - established models. TAM suggests that PU and PEOU are crucial for technology acceptance. UTAUT expands TAM by adding dimensions such as PE, Effort Expectancy (related to PEOU), SI, and FC. By using these frameworks, the study explores the complex interplay of factors affecting medical students' attitudes and behavioral intentions toward mobile English learning. The integrated framework provides a strong basis for understanding and potentially improving the adoption of mobile English learning among medical students.

Research Methodology

Population and Sample Size

In this study, we disseminated questionnaires via an online platform to medical undergraduates from five specializations of medical colleges in Chengdu, China. The specific majors included Clinical Medicine, Anesthesiology, Pediatrics, Preventive Medicine, and Pharmacy, with a total population size of 6459 students. To ensure a representative sample, a combination of judgment sampling, stratified random sampling, and convenience sampling was employed. The sample size was determined based on the population size and the desired confidence level, resulting in a total of 500 valid responses. The study's exact sampling is displayed in Table 1.

Table 1 *Population and sample size of the five majors of Chengdu Medical College*

Five Main majors	Population Size	Proportional Sample Size
Clinical Medicine	4367	345
Anesthesiology	259	19
Paediatrics	271	20
Preventive Medicine	286	21
Pharmacy	1276	95
Total	**6459**	**500**

Source: Created by the author.

Data Collection

Transitioning from the population and sample size to data collection, the next step involved distributing questionnaires to the selected participants. Utilizing an online questionnaire platform (Steffens et al., 2014), we reached out to the target population to gather comprehensive feedback on their attitudes and behavioral intentions toward mobile English learning. The questionnaire was designed with three distinct sections: screening questions to qualify respondents, a Likert scale to assess the study's key variables, and demographic questions to provide context for the analysis. Before launching the full-scale survey, a pilot test with 50 respondents was conducted to validate the questionnaire's structure and ensure item-objective consistency (IOC), as evaluated by experts. This preliminary step was crucial in refining the instrument and ensuring its reliability and validity for the broader study.

Questionnaire Validation and Data Analysis

Building on the foundation laid by the population and sample size and the data collection process, the subsequent phase focused on validating the questionnaire and analyzing the collected data. The questionnaire's validity and reliability were rigorously tested using Cronbach's alpha (Hair et al., 2007), with values exceeding 0.70, indicating high internal consistency. This validation step was essential in ensuring that the data would be both reliable and valid, providing a solid basis for the analysis. With 500 valid responses in hand, advanced statistical tools such as Jamovi 2.3.28 and Amos 24.0 were employed to conduct Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). The CFA assessed the convergent validity of the constructs, ensuring that the theoretical framework aligned with the empirical data. The SEM then explored the causal relationships between the variables, offering a comprehensive understanding of the factors influencing students' attitudes and behavioral intentions. This methodical approach not only validated the model but also uncovered the underlying dynamics shaping students' engagement with mobile English learning.

Research Results

Demographic Information

A study conducted at Chengdu Medical College in China involved the collection of demographic data from first-year medical undergraduates enrolled in five different specialities. The data set comprised information on gender, age, and academic major. The majority of students were between 18 and 20 years of age, with a significant proportion of students enrolled in clinical medicine, paediatrics, anesthesiology, pharmacy, and preventive medicine specialities. The study revealed that 59.23% of students were enrolled in the clinical medicine program, 7.12% in paediatrics, 8.46% in anesthesiology, 17.69% in pharmacy, and 7.5% in preventive medicine (table 2).

Table 2 *Description of the distribution of sample features*

Demographic and General Data (N = 520)		Frequency	Percentage
Gender	Male	198	38.08%
	Female	322	61.92%
Age	18-20 years old	483	92.88%
	20-22 years old	33	6.35%
	22-24 years old	3	0.58%
	More than 24 years old	1	0.19%
Major Direction	Clinical Medicine	308	59.23%
	Paediatrics	37	7.12%
	Anesthesiology	44	8.46%
	Pharmacy	92	17.69%
	Preventive Medicine	39	7.5%

Source: Created by the author.

Confirmatory Factor Analysis (CFA)

This study employed a validated factor analysis to quantify each variable within its conceptual framework. The results demonstrated the presence of noteworthy scale items and acceptable factor loading values, thereby indicating an appropriate fit for the framework. The factor loading values exceeded 0.50 and the results were highly significant, including extracted mean squares greater than 0.50, p-values less than 0.05, and structural reliability exceeding 0.70(Table 3).

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

Variables	Source of Questionnaire (Measurement Indicator)	Item	Cronbach's Alpha	Factor Loading	CR > 0.7	AVE > 0.5
Performance Expectancy (PE)	Venkatesh et al. (2012)	5	0.950	0.884-0.922	0.953	0.801
Social Influence (SI)	Kaliisa et al. (2019)	4	0.902	0.722-0.906	0.906	0.708
Facilitating Condition (FC)	Venkatesh et al. (2003)	7	0.925	0.727-0.879	0.925	0.640
Perceive Playfulness (PP)	Moon et al. (2001)	5	0.954	0.852-0.950	0.954	0.808
Attitude (ATT)	Sun et al., (2023)	4	0.928	0.752-0.930	0.929	0.724
Behavioural Intention (BI)	Sung et al. (2015)	3	0.862	0.801-0.833	0.862	0.676
Perceived Usefulness (PU)	Requero et al. (2020)	4	0.929	0.827-0.919	0.929	0.766
Perceived Ease of Use (PEOU)	Davis (1989)	3	0.933	0.884-0.941	0.934	0.826

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

Source: Created by the author.

Discriminant Validity

Table 4 illustrates the discriminant validity of the model, with a maximum coefficient of 0.610 for any two latent variables. The standardized correlation coefficients between the two dimensions are less than the square root of the AVE values, indicating that the model exhibits good discriminant validity. This is demonstrated by the diagonal mean-variance.

Table 4 *Discriminant Validity*

Discriminant Validity	PE	SI	FC	PP	ATT	BI	PEOU	PU
PE	**0.895**							
SI	0.478	**0.841**						
FC	0.066	0.161	**0.800**					
PP	0.225	0.441	0.157	**0.899**				
ATT	0.310	0.321	0.173	0.326	**0.851**			

Discriminant Validity	PE	SI	FC	PP	ATT	BI	PEOU	PU
BI	0.395	0.450	0.238	0.304	0.349	**0.822**		
PEOU	0.426	0.436	0.078	0.445	0.094	0.276	**0.909**	
PU	0.457	0.362	0.099	0.324	0.406	0.610	0.268	**0.875**

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

Source: Created by the author

The study's variables demonstrate an appropriate correlation, and the CFI, TLI, GFI, AGFI, NFI, and RMSEA indicators align with the model. The study's discriminant and convergence validity have been confirmed, and the structural model is therefore deemed to be correct.in this investigation was confirmed by all of the measurements.

Structural Equation Model (SEM)

Structural equation modelling (SEM) is a statistical technique that can be used to assess the relationship between independent and dependent variables. This relationship is often referred to as causal modelling or path analysis (Ullman & Bentler, 2012). The results detailed in Table 5 demonstrate that the model exhibits a strong fit with the data, as evidenced by the CMIN/DF value of 2.947 and the RMSEA of 0.061, both falling within the acceptable limits. The AGFI achieves a value of 0.800, and the CFI and TLI both surpass 0.900, indicating an exceptional fit. These findings collectively substantiate the efficacy of the SEM model as a suitable instrument for the examination of the factors that influence English learning through mobile phones.

Table 5 *Goodness of Fit for Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM)*

Fit Index	Acceptable Criterion	Practical Value (CFA)	Practical Value (SEM)
CMIN/DF	Jöreskog (1996) < 3.000	1.774	2.947
GFI	Yaşlioğlu & Yaşlioğlu (2020) ≥ 0.800	0.906	0.832
AGFI	Phogat, & Gupta, (2019) > 0.800	0.889	0.810
RMSEA	Afriani & Syah (2019) < 0.080	0.039	0.061
CFI	Bentler (1990) > 0.900	0.973	0.931
NFI	Bentler (1990 > 0.900	0.941	0.900
TLI	Afriani & Syah (2019) ≥ 0.900	0.970	0.926

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

Source: Created by the author.

Research Hypothesis Testing Result

The statistical significance of the research model was confirmed through regression analysis and R^2 variance evaluation (Table 6). Standardized path coefficients demonstrated significant effects: achievement expectations (β = 0.231, $p < 0.001$), social influence (β = 0.128, $p < 0.01$), convenience (β = 0.113, $p < 0.05$), and perceived playfulness (β = 0.216, $p < 0.001$) predicted attitudes toward mobile English learning. Perceived usefulness (β = 0.634) and ease of use (β = 0.132) significantly influenced behavioral intention (both $p < 0.001$). These results validate all hypotheses and highlight critical leverage points for optimizing mobile learning platforms in medical education.

Table 6 *Hypothesis Result of the Structural Model*

Hypotheses	Path			Standardized Path Coefficient (β)	T-Value	Tests Result
H1	ATT	⟵	PE	0.231	5.138 ***	Supported
H2	ATT	⟵	SI	0.128	2.849 **	Supported
H3	ATT	⟵	FC	0.113	2.543 *	Supported
H4	ATT	⟵	PP	0.216	4.830 ***	Supported
H5	BI	⟵	ATT	0.139	3.441***	Supported
H6	BI	⟵	PU	0.634	14.459 ***	Supported
H7	BI	⟵	PEOU	0.132	3.304 ***	Supported

Note: *** = p<0.001; ** = p<0.01; * = p<0.05.

Source: Created by the author.

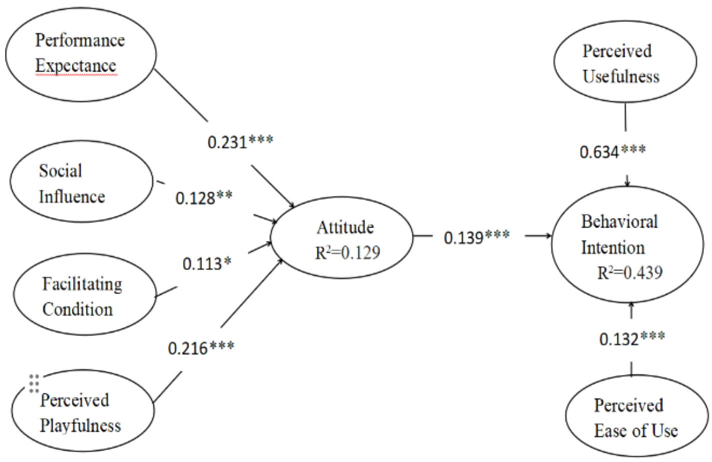

Figure 2: *Results of the pathway map analysis*

Note: *** = p<0.001; ** = p<0.01; * = p<0.05.

Source: Created by the author

Path analysis was conducted to elucidate the influence of the variables. Performance expectations, social influences, facilitating conditions, and perceived playfulness collectively explained 12% of the variance in attitudes toward mobile English learning ($R^2 = 0.129$). Perceived usefulness, perceived ease of use, and attitudes accounted for 43% of the variance in behavioral intentions to use mobile English ($R^2 = 0.439$). (see Figure 2). These findings highlight the multifaceted nature of technology adoption in educational contexts, consistent with the complexities observed in similar studies across diverse fields (Harter, 1960).

Conclusions

Our research findings indicate that perceived usefulness is the most significant predictor of behavioral intention, a conclusion consistent with Davis's (1989) original Technology Acceptance Model (TAM). The TAM posits that perceived usefulness is a key determinant of users' intention to adopt technology. This perspective is further supported by numerous studies in the field of educational technology. For instance, Scherer et al. (2019) conducted a meta-analytic structural equation modeling study and found that perceived usefulness significantly influences teachers' adoption of digital technology in education.

Additionally, Sharma et al. (2023) explored the factors influencing e-learning technology adoption among youth in India using an extended TAM model, highlighting the importance of perceived usefulness. However, our study also emphasizes the significance of attitude, which is shaped by performance expectations, social influence, facilitating conditions, and perceived playfulness. This extends the traditional TAM by incorporating additional factors relevant to the context of mobile English learning for medical students. The inclusion of these factors provides a more comprehensive understanding of the determinants of medical students' attitudes and behavioral intentions toward mobile English learning. For example, social influence has been identified as a significant predictor of students' intention to use mobile learning in collectivist cultures, such as South Korea (Kang et al., 2015).

Similarly, facilitating conditions, such as technological infrastructure, have been shown to impact mobile learning adoption in regions with varying levels of technological development (Khan et al., 2015). The concept of perceived playfulness is also recognized as an important factor in enhancing user engagement and learning outcomes in mobile learning environments.

Limitations

This study acknowledges four principal methodological limitations. First, the exclusive reliance on self-reported measures introduces potential response biases, particularly social desirability effects, despite the implementation of anonymity protocols. Second, the sample is limited to first-year medical students from five specialties at a single Chinese institution, which restricts the generalizability of the findings to broader populations due to geographic and disciplinary homogeneity. Third, the cross-sectional design precludes causal inference and longitudinal observation of behavioral dynamics. Fourth, while the questionnaire incorporated validated scales, its cultural specificity to the Chinese context and potential linguistic barriers, such as English proficiency requirements, may constrain its cross-cultural applicability.

Recommendations

1. **Recommendation on the research application**

1.1 Optimizing personal factors, it is essential to encourage medical students to set clear learning goals, manage their time effectively, and fully utilize available resources. This approach will enhance their medical expertise and English proficiency, maximizing the benefits of mobile learning tools and leading to improved language skills and academic performance.

1.2 Enhance perceived playfulness, developers should create interactive and enjoyable learning content. For example, incorporating gamification elements and multimedia resources can make the learning process more engaging.

1.3 Designing suitable learning platforms, hardware designers and software developers must consider the specific needs of medical students. The platforms should be user-friendly, interactive, and aligned with their learning objectives.

1.4 Enhance perceived usefulness, educators and developers should ensure that the learning content is relevant to the medical profession and meets the actual needs of learners. For instance, providing English learning materials related to clinical practice can help students apply what they have learned in real-life situations.

2. **Recommendation on further research**

2.1 Enhancing technological infrastructure, educational institutions should invest in improving infrastructure and providing adequate support, including access to reliable internet, modern mobile devices, and technical assistance. This will ensure smooth and effective mobile learning experiences.

2.2 Optimize facilitating conditions, it is essential to offer necessary technical support and resources to enable learners to utilize mobile learning platforms seamlessly. For instance, providing technical training and help documents can address the challenges learners face during usage.

2.3 Promoting social support， encouraging positive social interactions and support from peers, instructors, and family members can significantly enhance students' attitudes toward mobile English learning. Collaborative learning activities, feedback sessions, and family engagement programs can foster a supportive learning environment.

2.4 Emphasize social impact, establishing learning groups and discussion forums can promote communication and cooperation among students, thereby enhancing their motivation and behavioral intentions.

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