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Factors Influencing the Behavioral Intention to Use Mobile Learning Platform in Higher Education of Changsha, China

Juan Fan[1] and Changhan Li[2]
[1]Ph.D. Candidate, Graduate School of Business and Advanced Technology Management, Assumption University, Thailand
[2]Ph.D., Associate Program Director, Art, Music, Sports and Entertainment Management, Graduate School of Business and Advanced Technology Management, Assumption University, Thailand
[1]E-mail: 18483940@qq.com, ORCID ID: https://orcid.org/0009-0004-1045-5903
[2]E-mail: lichanghan@au.edu, ORCID ID: https://orcid.org/0000-0002-3706-605X

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Abstract
Background and Aim: This study explored the factors that influenced student behavioral intention regarding mobile learning platforms. The latent variables investigated in the study include system quality (SQ), service quality (SVQ), information quality (IQ), perceived usefulness (PU), satisfaction (SA), attitude (ATT), and behavioral intention (BI). The objective of the research is to determine the extent to which each variable influences the use of mobile learning platforms.
Materials and Methods: This study surveyed 500 undergraduate students at a public university in Changsha, China, about their views on mobile learning platforms. The data were analyzed using structural equation modeling (SEM) and confirmatory factor analysis (CFA).
Results: The results of the data analysis revealed that each hypothesized path was statistically significant, indicating strong direct relationships between the variables in the model. Notably, information quality exerted the greatest influence on perceived usefulness. The findings underscore the importance of these factors in enhancing the effective use of mobile learning platforms in higher education, boosting student satisfaction and behavioral intentions. This study's strengths include its robust sample size and the use of advanced statistical techniques like SEM and CFA, which provide a rigorous assessment of the model's validity. However, limitations include the study's focus on a single university, which may not fully represent the diverse experiences of students across different institutions. Additionally, while the study highlights critical factors influencing mobile learning, it does not address potential barriers or challenges students might face, such as technological issues or varying levels of digital literacy. Future research could explore these aspects to provide a more comprehensive understanding of mobile learning platforms' effectiveness.
Keywords: Mobile Learning Platform (MLP); Perceived usefulness; Attitude; Satisfaction; Behavioral intention

Introduction

The incorporation of Mobile Learning Platforms (MLPs) within higher education has garnered significant attention, reflecting a broader evolution in educational technology. As the education system increasingly embraces digital solutions, M-learning has emerged as a key approach, offering learners the flexibility to access educational content and services anytime and anywhere, thereby removing traditional temporal and spatial barriers (Althunibat et al., 2021). Understanding the factors that influence students' behavioral intentions to use MLPs has become essential for optimizing these platforms and improving educational outcomes.

MLPs leverage advanced technologies such as mobile communication networks, cloud computing, and big data analytics to provide flexible, accessible, and interactive learning experiences. To understand the determinants of students' behavioral intentions toward MLPs, this research applies two theoretical models: the Technology Acceptance Model (TAM) and the Information Systems Success Model (ISSM). TAM, developed by Davis (1989), posits that perceived ease of use and perceived usefulness are fundamental predictors of technology adoption. In the context of MLPs, perceived usefulness—the degree to which a student believes that using the platform will enhance their learning—is critical in influencing their intention to use the technology (Althunibat et al., 2021). ISSM, introduced by DeLone and McLean (2003), expands on TAM by emphasizing the roles of system quality, service quality, and information

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quality. These dimensions are crucial for determining user satisfaction, which in turn influences their attitudes toward MLPs and their overall behavioral intentions (Drwish et al., 2023).

Recent studies highlight the significance of quality factors in shaping user satisfaction and behavioral intention. For example, system quality has been shown to significantly enhance user satisfaction in e-learning environments, underscoring its importance for the efficiency of MLPs (Drwish et al., 2023). Similarly, service quality has been identified as a key determinant of successful mobile learning implementations, directly influencing learner satisfaction and the overall effectiveness of MLPs (Althunibat et al., 2021). Information quality, while important, may have a more nuanced role depending on the context, with some studies indicating a lesser impact on actual usage (Drwish et al., 2023).

The interplay of these factors—system quality, service quality, information quality, and perceived usefulness—significantly impacts students' satisfaction and their behavioral intention to adopt MLPs (Almaiah & Alismaiel, 2019).

In summary, this research aims to examine the factors influencing the behavioral intention to use MLPs in higher education in Changsha by applying TAM and ISSM. By investigating the interplay between system quality, service quality, information quality, perceived usefulness, satisfaction, attitude, and behavioral intention, the study seeks to offer valuable insights for optimizing MLPs and enhancing the overall learning experience. Understanding these factors will provide actionable recommendations for educators, policymakers, and technology developers working to improve the effectiveness and adoption of mobile learning technologies.

Objectives

1. Enhancing Mobile Learning Platform Design and Implementation

Research on the factors influencing college students' behavioral intentions to use mobile learning platforms aims to provide valuable insights for the design and implementation of these platforms. By examining elements such as system quality, information quality, and perceived usefulness, the study seeks to offer practical recommendations for improving platform design and functionality. This will help in creating more effective and user-friendly mobile learning environments that cater to the needs and preferences of students, thereby optimizing the overall learning experience in higher education.

2. Advancing Understanding of Behavioral Intentions in Mobile Learning

There is a need for a deeper understanding of how various factors influence students' behavioral intentions to engage with mobile learning platforms. This research intends to quantitatively analyze these influencing factors, such as attitudes toward technology and satisfaction with mobile learning experiences. By exploring these dimensions, the study aims to fill gaps in existing research and provide a foundation for further investigation into students' engagement with mobile learning tools. The findings will contribute to a more nuanced understanding of student behavior in the context of mobile learning.

3. Promoting Effective Mobile Learning Strategies and Policies

Investigating the factors that affect students' intentions to use mobile learning platforms is crucial for developing effective educational strategies and policies. The research aims to uncover insights into how perceived usefulness, system quality, and user satisfaction influence students' engagement with mobile learning. These insights will be instrumental in formulating targeted strategies and policies to enhance mobile learning adoption and effectiveness. Additionally, the study will support the development of best practices for integrating mobile learning into higher education curricula, thereby fostering a more responsive and adaptive educational environment.

Review of Literature

Overview of Foreign Research

The research on mobile learning platforms has been extensive, with scholars examining various aspects of M-learning across different educational contexts. A significant body of literature has focused

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on the application of the Technology Acceptance Model (TAM) and the Information Systems Success Model (ISSM) in understanding the factors that influence students' behavioral intentions to use MLPs.

Davis (1989) originally developed TAM to explain the relationship between perceived ease of use, perceived usefulness, and users' intention to adopt new technologies. This model has been widely applied in mobile learning studies to assess how these factors influence students' adoption of MLPs. Venkatesh and Davis (2000) extended the original TAM to include additional factors such as subjective norms and facilitating conditions that further explain technology adoption behaviors.

The ISSM, proposed by DeLone and McLean (2003), has also been instrumental in understanding the success of mobile learning platforms. According to DeLone and McLean, system quality, service quality, and information quality are critical determinants of user satisfaction and behavioral intention. Research by Wang et al. (2009) applied the ISSM in the context of mobile learning and found that these quality factors significantly influence students' satisfaction with MLPs, which in turn affects their continued use of the platforms.

Alzaza and Yaakub (2011) conducted a study on the awareness and requirements of mobile learning services among students in higher education, emphasizing the need for reliable and user-friendly platforms to ensure successful adoption. Their findings suggest that while students are generally positive about mobile learning, the quality of the system and the relevance of the content are critical factors that determine their satisfaction and willingness to engage with MLPs.

Finally, Vavoula et al. (2007) proposed a theory of learning for the mobile age, which underscores the importance of context-aware learning experiences that mobile platforms can provide. Their research has been influential in shaping the understanding of how mobile learning can be designed to support personalized and adaptive learning environments, thereby enhancing the overall educational experience.

Overview of Domestic Research

In China, the adoption and integration of mobile learning platforms in higher education have been the focus of extensive research in recent years. Various studies have explored the factors that influence students' behavioral intentions to use these platforms, particularly in the context of bridging the rural-urban education gap. An important area of focus is the acceptance and perception of rural secondary school students using mobile technology for informal English learning during the COVID-19 pandemic. For example, Guo et al. (2020) found that the behavioral intention of rural middle school students was significantly affected by perceived usefulness, convenience, and mobile device usage attitude. These findings highlight the critical role that these factors play in shaping students' willingness to use mobile learning technologies in rural Settings.

In addition, Jin et al. (2021) investigated the impact of the COVID-19 pandemic on mobile learning adoption in China, highlighting how the pandemic has accelerated the integration of digital learning tools in higher education. Their research shows that both service quality and perceived usefulness significantly influence users' willingness to transition from offline to online learning platforms. This shift to digital learning is particularly important for higher education institutions seeking to maintain educational continuity amid disruptive events.

Finally, Hai et al. (2022) emphasize that perceived usefulness has a significant positive effect on behavioral intention when adopting online learning. Their research shows that students are more likely to engage with online learning platforms if they find them useful. This finding is consistent with the Technology Acceptance Model (TAM), which argues that perceived usefulness is a key predictor of users' attitudes and intentions to adopt new technologies.

Mobile Learning

Mobile learning (M-learning) refers to the process of accessing educational content and engaging in learning activities via mobile devices such as smartphones, tablets, and other handheld devices. This form of learning is characterized by its flexibility, accessibility, and ability to support learners in various environments outside traditional classroom settings. According to Crompton (2013), M-learning is a subset of e-learning that specifically takes advantage of the mobility of the learner, offering the possibility

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to learn “anytime, anywhere.” This definition is further expanded by Traxler (2007), who emphasizes that M-learning is not only about the devices but also about the shift in the learning paradigm that enables personalized, situated, and contextual learning experiences.

Ally (2009) argues that the unique affordances of mobile learning, such as real-time interaction and the ability to access content across different contexts, make it a powerful tool for enhancing educational outcomes. The flexibility offered by M-learning is particularly beneficial in higher education, where students often require access to educational resources on the go due to their diverse schedules and commitments (Kukulska-Hulme & Traxler, 2005). Thus, mobile learning platforms (MLPs) represent a significant evolution in the educational landscape, providing a more learner-centered approach that aligns with the needs of contemporary students.

System Quality

System quality is defined as the technical quality of the information system, including its reliability, flexibility, response time, and other system features (Petter et al., 2008). DeLone and McLean (1992) emphasize the close relationship between system quality and system technical standards. They emphasize the importance of technical attributes in determining the quality of information systems. Lederer et al. (2000) support this concept by identifying system quality as a reliable predictor of perceived usefulness, emphasizing its importance in shaping user perception and behavior. Lee and Chung (2009) identify system quality as a key factor influencing user trust and technology adoption in different environments, emphasizing its role in shaping user attitudes and behavior. In the context of online learning, universities prioritize system quality when selecting online learning platforms to ensure ease of use, convenience, and reliability, as highlighted by Ho et al. (2010). Moreover, according to the Information System Model, system quality is a critical success attribute that influences user satisfaction and intention to use (DeLone & McLean, 2003).

Therefore, the following hypotheses are put forth:

H1: System quality significantly influences users’ satisfaction with the MLP.

Service Quality

Saeed et al. (2003) emphasize that service quality refers to the effectiveness of services provided by a service provider, indicating the degree to which services meet the needs and expectations of users. Santos (2003) extends this definition by highlighting that service quality also encompasses a comprehensive measure of high-quality services offered in the virtual market, reflecting the overall excellence and satisfaction experienced by customers. DeLone and McLean (2003) emphasized the key role of service quality in building successful information systems. They believed that service quality is the decisive factor affecting perceived usefulness and user satisfaction, thereby significantly impacting system adoption and effectiveness. Educational institutions can improve student satisfaction, usage trends, and organizational implementation by prioritizing the provision of high-quality services (Lin & Hsieh, 2006).

Therefore, the following hypotheses are put forth:

H2: Service quality significantly influences users’ satisfaction with the MLP.

Information Quality

Bailey and Pearson (1983) and Srinivasan (1985) define information quality as the quality of information generated and displayed by a system. This encompasses attributes like accuracy, authenticity, and responsiveness, highlighting the importance of the information's reliability and trustworthiness. Additionally, Petter et al. (2008) highlighted that information quality pertains to the effectiveness of communication systems, ensuring that the information delivered is comprehensive, accurate, timely, and useful. Wang and Lin (2012) further expand on this definition by highlighting that information quality refers to the ability of the system to convey information intentions. This suggests that information quality is not only about the accuracy of the information but also about how effectively it communicates the intended message or purpose. Lin and Lu (2000) emphasized that information quality is the most effective factor affecting the effectiveness of user systems, indicating its importance in shaping user perception and

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experience. Tella and Mutula (2010) concluded that students' evaluation of information quality depends on whether the institution provides valuable information that meets their needs and expectations, highlighting the importance of meeting user needs when evaluating information quality.

Therefore, the following hypotheses are put forth:

H3: Information quality significantly influences the Perceived usefulness of the MLP.

Satisfaction

Satisfaction, as a key component of the consumer experience, is defined as the sense of pleasure generated when a product or service meets consumer expectations (Oliver, 1999).To achieve customer satisfaction, suppliers not only understand but also strive to meet the needs of customers (Harris & Harrington, 2000). However, satisfaction is a multifaceted emotion with complex underlying causes and consequences that go beyond simple product or service performance (Mano & Oliver, 1993). Bhattacherjee (2000) proposed a causal relationship between user satisfaction and motivation to continue using information systems, which is influenced by previous experiences of use. In addition, satisfaction is a key indicator for evaluating the effectiveness of technological advances, indicating participants' willingness to continue using technologies (Locke, 1969).In addition, satisfaction reflects students' positive attitudes and optimistic expectations in the online education experience (Nagy, 2018).

Therefore, the following hypotheses are put forth:

H5: Satisfaction significantly influences users' behavioral intention to use the MLP.

Perceived Usefulness

Davis et al. (1989) define perceived usefulness as the degree to which a person has confidence in the system's ability to improve job performance. Specifically, perceived usefulness has been found to significantly influence users' intentions to adopt new technologies, including online learning platforms (Davis, 1989). Furthermore, individuals' perceived usefulness of technology is closely intertwined with their attitudes and intentions toward its use (Rahman & Sloan, 2015). Positive perceptions of usefulness enhance users' willingness to engage with technology and maintain their learning performance over time (Teo & Zhou, 2014). Additionally, perceived usefulness has been identified as a key determinant of satisfaction and attitudes towards online learning among university faculty and students (Cheong & Park, 2005; Renda dos Santos & Okazaki, 2016).

Therefore, the following hypotheses are put forth:

H4: Perceived usefulness significantly influences users' satisfaction with using the MLP.

H6: Perceived usefulness significantly influences users' behavioral intention to use the MLP.

H7: Perceived usefulness significantly influences users' attitudes to use the MLP.

Attitude

Attitude, according to Ajzen (1991) and Davis (1989), represents an individual's inclination or passive sentiment towards a particular object or behavior. Attitudes, as defined by Chennamaneni et al. (2012), refer to an individual's positive or negative evaluations of an object or behavior. These evaluations are shaped by previous life experiences or feelings, influencing a person's tendency to respond positively or negatively to behavior (Ajzen, 1987; Kuehn, 2008). Giles and Coupland (2014) further elaborate that attitudes encompass an individual's opinions, mental state, and spontaneous beliefs about the service, reflecting responses to experiences related to the service. Attitudes are assessed based on accessibility, applicability, reliability, and appearance, and are considered in information comparability assessment (Ozgen & Kurt, 2013). Attitudes are psychological attributes that influence individual behavior, as indicated by Ajzen (1980). They are evaluations of specific objects or behaviors by individuals and are integral to reactions to online technology (Agarwal & Prasad, 1998).

Empirical evidence strongly supports the correlation between attitude and behavioral intention, extensively reviewed in existing literature (Chuttur, 2009; King & He, 2006; Marangunić & Granić, 2015; Yousafzai et al., 2007). Intentional behavior is statistically influenced by attitude factors, as demonstrated in previous research (Gurban & Almogren, 2022; Teo et al., 2019). There's a significant correlation

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between attitudes and acquisition intentions, as observed in various studies (Amos et al., 2008; Hoi, 2020).

Therefore, the following hypotheses are put forth:

H8: Users' attitude significantly influences users' behavioral intention to use the MLP.

Conceptual Framework

The researchers propose a conceptual framework to uncover the factors that influence the willingness of Changsha College students to use MLP. This study examines the existing relevant theories makes improvements on this basis, and puts forward a theoretical framework suitable for this study. The researchers revised the conceptual framework based on two core theories and three main findings. The conceptual framework for these two core research theories is Davis' (1989) Technology acceptance model (TAM) and DeLone and McLean's (2003) Information Systems Success Model (ISSM). Hussein et al. (2021) explored the effects of system quality, service quality, information quality, perceived ease of use, and perceived usefulness on teacher satisfaction. Legramante et al. (2023) argue that information quality plays a key role in their model and establish a relationship between perceived usefulness, satisfaction, and behavioral intent. Huang et al. (2007) established the relationship between perceived usefulness, attitude, and behavioral intention. Therefore, Figure 1 shows the conceptual framework formed in this study based on previous theories (Davis, 1989; DeLone & McLean, 2003; Huang et al., 2007; Hussein et al., 2021; Legramante et al., 2023).

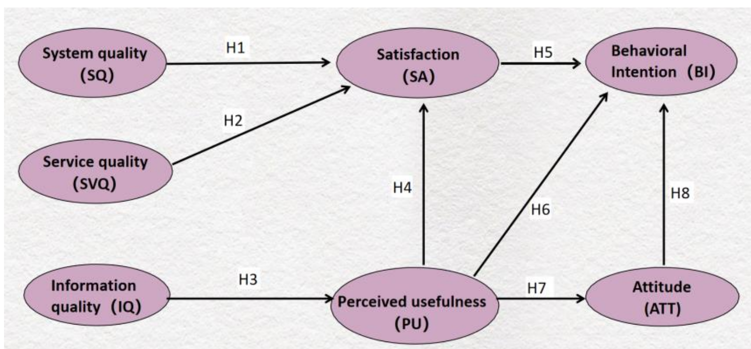

Figure 1 Conceptual Framework

Methodology

Research Instrument

The researcher distributed online surveys using a quantitative approach to reach the target populations. 27 scale items, derived from earlier studies, were employed to assess the latent variables. This included 5 items for system quality (SQ), 4 items for service quality (SVQ), 3 items for information quality (IQ), 6 items for perceived usefulness (PU), 3 items for satisfaction (SA), and 3 items for attitude(ATT), 3 items for behavior intention (BI). Seven independent variables were gauged using a 5-point Likert scale, where 1 represented "strongly disagree" and 5 denoted "strongly agree".

The researchers engaged three domain experts for a comprehensive evaluation of survey validity before its dissemination. This validation process relied on the item-objective congruence (IOC) index, with all items scoring a threshold of at least 0.6, confirming their validity. Subsequently, a pilot study involving 50 participants verified the instrument's validity and stability through Cronbach's alpha, yielding coefficients ranging from 0.767 to 0.923, which conformed to the reliability standards established by George and Mallery (2003). To further safeguard the survey's validity and reliability beyond the pilot phase, iterative refinements were made, incorporating feedback to address ambiguities and inconsistencies. Additionally, rigorous attention was paid to enhancing the clarity and comprehensibility of survey instructions and items, aiming to minimize respondent confusion and optimize data quality.

Population and Sample

According to Krejcie and Morgan (1970), a sample size of 425 was identified, suitable for a population approaching 50,000. Statistics show that China's Hunan Normal University has a total

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enrollment of 42,000 students, including more than 13,000 graduate students. To ensure reliable and accurate research results, undergraduate students from different majors were selected and all studied in the university. This sample selection ensures representation from diverse student groups, improving the generality of research findings to learners in similar academic contexts. A total of 500 valid responses were obtained, providing sufficient data for further analysis.

Purpose sampling refers to a variety of non-probabilistic sampling methods, including judgmental sampling, selective sampling, or subjective sampling, and researchers exercise discretion in selecting research units (Rai & Thapa, 2015). Guided by the researcher's judgment rather than randomness, purposeful sampling underscores the deliberate selection of individuals based on specific characteristics pertinent to the research inquiry. This approach aims to deepen the exploration of key themes or phenomena by zeroing in on attributes relevant to resolving the research question. In the present study's context, the researchers adopted purposeful sampling to target undergraduate students from a university, who possess shared demographic traits (18-22 years old) and a common experience with mobile learning platforms. This selective sampling strategy facilitates an in-depth analysis of the factors influencing these students' behavioral intentions toward utilizing mobile learning platforms.

Table 1 Population and Sample Size

School Name		Number of Students	Sample Size
Hunan Normal University	Freshman	1366	253
	Sophomore	1334	247
Total		**2700**	**500**

Data Collection and Analysis

In adherence to ethical principles, all study participants received comprehensive informed consent, encompassing detailed explanations of the study's nature, objectives, and potential risks, with their voluntary participation duly recorded. Furthermore, to safeguard participants' privacy, all personally identifiable information (e.g., names, and ID numbers) was anonymized throughout the experimental process. To attain an adequate sample size, questionnaires assessing college students' perceptions of mobile learning platforms were disseminated to a total of 520 participants, facilitated by an email invitation targeting potential students. This email explicitly outlined the study's rationale, assured the confidentiality of responses, and provided contact details for any inquiries, thereby ensuring transparency and participant protection.

Utilizing Amos software, the researcher eventually collected 500 questionnaires with useful answers and performed confirmatory factor analysis (CFA) to evaluate discriminant validity, average variance extracted (AVE), composite reliability (CR), factor loading, and t-values, followed by employing a structural equation model (SEM) to investigate the hypotheses and effects of interrelationships among the variables.

Results

Demographic Information

The researcher collected 500 valid data for this study. The main selection process had a high response rate and was precise and of excellent quality. Among the survey participants, there were 266 males, constituting 53.2% of the total, and 234 females, making up 46.8% of the respondents. Regarding grades, there were 251 freshmen, constituting 50.2% of the total, and 249 Sophomores, making up 49.8% of the respondents.

Table 2 Demographic Information

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	266	53.2%
	Female	234	46.8%
Grade	Freshman	251	50.2%
	Sophomore	249	49.8%

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Confirmatory Factor Analysis (CFA)

The findings from the research indicated favorable goodness-of-fit indices for the measurement model. Specifically, the CMIN/DF stood at 1.043, below the threshold of 5.00 (Awang, 2012), while the GFI reached 0.957, surpassing the 0.85 criterion (Sica & Ghisi, 2007). Furthermore, the AGFI achieved a value of 0.946, exceeding the 0.80 benchmark post-adjustment through Amos statistical software. These collective indices signified acceptability for the measurement model.

The statistical summary in Table 3 revealed Cronbach's alpha value exceeding 0.70, comprehensive reliability (CR) surpassing 0.60, and average variance extracted (AVE) exceeding 0.50. Consequently, these outcomes validated both the convergent and discriminant validity of the CFA results.

Table 3 Goodness of Fit for Confirmatory Factor Analysis

Latent Variables	Source of Questionnaire	Factors Loading	Cronbach's Alpha	AVE	CR
System Quality	Hussein et al. (2021)	0.718-0.768	0.903	0.560	0.864
Service Quality	Hussein et al. (2021)	0.721-0.762	0.767	0.562	0.837
Information Quality	Legramante et al. (2023)	0.767-0.788	0.917	0.603	0.820
Perceived Usefulness	Legramante et al. (2023)	0.720-0.797	0.868	0.572	0.889
Satisfaction	Hussein et al. (2021)	0.748-0.783	0.862	0.585	0.809
Attitude	Huang et al. (2007)	0.765-0.867	0.871	0.648	0.847
Behavioral Intention	Huang et al. (2007)	0.774-0.798	0.932	0.599	0.817

According to this study, discriminant validity was in favor since its value was greater than the sum of all actor correlations. The data was enough to show construct validity because the convergent and discriminant validity were established.

Table 4 Discriminant Validity

	SQ	SVQ	IQ	PU	SA	ATT	BI
SQ	**0.748**						
SVQ	0.308	**0.750**					
IQ	0.318	0.362	**0.776**				
PU	0.340	0.364	0.319	**0.756**			
SA	0.348	0.372	0.285	0.279	**0.765**		
ATT	0.280	0.401	0.366	0.314	0.379	**0.805**	
BI	0.374	0.459	0.396	0.348	0.345	0.404	**0.774**

Structural Equation Model (SEM)

Employing the Characteristic Function Analysis (CFA) framework, a discrete collection of linear equations underwent rigorous estimation and subsequent validation procedures within the context of a

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Structural Equation Model (SEM). The study by Erasmus et al. (2015) examined the causal connections among various constructs composed of independent and dependent variables. As a result, each robust fit index obtained from the SEM validation process adequately fulfilled the research objectives.

Table 5 Goodness of Fit for Structural Equation Modeling

Index	Criterion	Source	After Adjustment Values
CMIN\DF	<5.00	Awang (2012)	1.707
GFI	≥ 0.85	Sica and Ghisi(2007)	0.933
AGFI	≥ 0.80	Sica and Ghisi (2007)	0.920
NFI	≥ 0.80	Sica and Ghisi (2007)	0.918
CFI	≥ 0.80	Bentler (1990)	0.964
TLI	≥ 0.80	Sharma et al. (2005)	0.960
RMSEA	< 0.08	Pedroso et al. (2016)	0.038

Research Hypothesis Testing Result

Table 6 shows the calculation results for each structure path. The standardized path coefficient β of system quality has a significant effect on satisfaction at 0.277 (T-value= 6.010***). Similarly, service quality also had a significant impact on satisfaction, with a beta of 0.331 (t=7.423*), and it is worth noting that information quality had the most significant impact on perceived usefulness, recording a beta of 0.438 (t=12.392***). In addition, perceived usefulness had significant effects on satisfaction (β=0.116, T-value=5.448***), attitude (β= 0.384, T-value=11.804***), and behavioral intention (β=0.226, T-value=5.051***), among which the effect on attitude was the most significant. Satisfaction has a significant effect on behavioral intention, with a β of 0.270 (t=7.439***). Behavioral intention was also significantly affected by attitude, showing a β of 0.301 (t=8.037***).

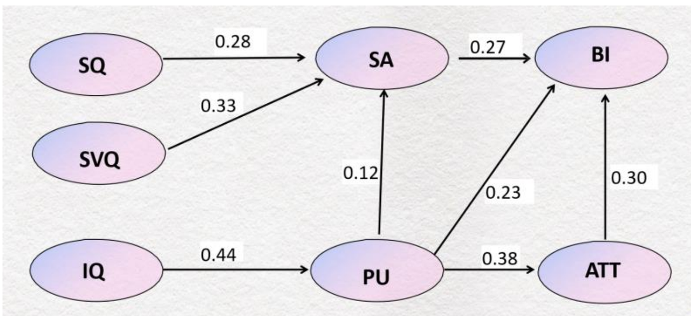

Figure 2 Structural Equation Model (SEM)

Table 6 Hypothesis Results

Hypothesis	Paths	Standardized Path Coefficient (β)	t-Value	Tests Result
H1	SQ --->SA	0.277	6.010	Supported
H2	SVQ --->SA	0.331	7.423	Supported
H3	IQ --->PU	0.438	12.392	Supported
H4	PU --->SA	0.116	5.448	Supported
H5	SA --->BI	0.270	7.439	Supported
H6	PU --->BI	0.226	5.051	Supported
H7	PU --->ATT	0.384	11.804	Supported
H8	ATT --->BI	0.301	8.037	Supported

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Subsequent extensions are derived from the information shown in Table 6 and Figure 2. In the structural path, H1 shows a standardized path coefficient value of 0.277, indicating that system quality is an important factor in students' satisfaction with mobile learning platforms. Moreover, according to the Information System Model, system quality is a critical success attribute that influences user satisfaction and intention to use (DeLone & McLean, 2003).

The coefficient value of H2 is 0.331, indicating that the relevant data support the hypothesis of the impact of service quality on satisfaction. Educational institutions can improve student satisfaction, usage trends, and organizational implementation by prioritizing the provision of high-quality services (Lin & Hsieh, 2006).

The standardized path coefficient value of H3 is 0.438, providing evidence to support the view that students' perceived usefulness to mobile learning platforms is significantly affected by information quality. Lin and Lu (2000) emphasized that information quality is the most effective factor affecting the effectiveness of user systems, indicating its importance in shaping user perception and experience.

In addition, the coefficient value of H4 is 0.116, suggesting that perceived usefulness is an influential factor in the satisfaction of the students in this study. Additionally, perceived usefulness has been identified as a key determinant of satisfaction and attitudes towards online learning among university faculty and students (Cheong & Park, 2005; Renda dos Santos & Okazaki, 2016).

Hypothesis 5 has a coefficient value of 0.270, which supports the following concepts:

There is a close relationship between students' satisfaction and behavioral intention. Bhattacherjee (2000) proposed a causal relationship between user satisfaction and motivation to continue using information systems, which is influenced by previous experiences of use.

The standard coefficient value of H6 is 0.226, indicating that perceived usefulness affects students' behavioral intention. Positive perceptions of usefulness enhance users' willingness to engage with technology and maintain their learning performance over time (Teo & Zhou, 2014)

The statistical coefficient of H7 is 0.384, indicating that perceived usefulness affects students' attitudes. Furthermore, individuals' perceived usefulness of technology is closely intertwined with their attitudes and intentions toward its use (Rahman & Sloan, 2015).

The standard coefficient value of H8 is 0.301, indicating that students' attitude toward mobile learning platforms significantly affects students' behavioral intentions. Empirical evidence strongly supports the correlation between attitude and behavioral intention, extensively reviewed in existing literature (Chuttur, 2009; King & He, 2006; Marangunić & Granić, 2015; Yousafzai et al., 2007)

Discussions

This study investigates the factors influencing college students' behavioral intentions to use mobile learning platforms within the context of higher education in China. The research identifies critical paths that link system quality, service quality, and information quality to perceived usefulness, satisfaction, attitude, and ultimately behavioral intention. By analyzing the standardized path coefficients, this study highlights the intricate relationships among these variables and underscores the importance of each in shaping students' engagement with mobile learning technologies.

System Quality and Satisfaction

The finding that system quality significantly influences satisfaction (β=0.277, T-value=6.010***) aligns with the Information Systems Success Model proposed by DeLone and McLean (2003). According to this model, system quality is a crucial determinant of user satisfaction and the intention to continue using an information system. The result underscores the necessity for educational institutions to prioritize the reliability, accessibility, and overall quality of their mobile learning platforms. A system that is user-friendly, stable, and accessible is more likely to satisfy students, leading to increased engagement and sustained use.

This finding is consistent with previous research conducted in different contexts. For example, Petter et al. (2013) found that system quality significantly influences user satisfaction across various information systems, including educational technologies. Their study emphasized that system quality, particularly aspects such as ease of use and reliability, directly impacts users' experiences and their overall satisfaction with the system.

Service Quality and Satisfaction

Service quality also plays a significant role in influencing student satisfaction, as evidenced by a standardized path coefficient of 0.331 (T-value=7.423*). This result supports the hypothesis that the

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quality of support services provided by the researcher, such as technical assistance and customer support, directly impacts students' satisfaction with mobile learning platforms. This finding is corroborated by Lin and Hsieh (2006), who argued that high-quality service is essential in enhancing user satisfaction and ensuring the successful implementation of technology within educational institutions.

The significance of service quality in educational settings is further supported by the work of Holsapple and Lee-Post (2006), who investigated the role of service quality in e-learning systems. Their study found that timely and effective support services significantly contribute to user satisfaction and the perceived effectiveness of the learning platform. This indicates that educational institutions must invest in robust support systems to ensure that students can effectively utilize mobile learning platforms, thus enhancing their overall learning experience.

Information Quality and Perceived Usefulness

Information quality was found to have the most significant impact on perceived usefulness, with a standardized path coefficient of 0.438 (T-value=12.392***). This finding suggests that the accuracy, relevance, and timeliness of information provided by the mobile learning platform are critical in shaping students' perceptions of the platform's usefulness. This result aligns with the research of Lin and Lu (2000), who emphasized that information quality is a key factor in determining the effectiveness of user systems. High-quality information enhances users' ability to achieve their goals, thereby increasing the perceived usefulness of the system.

This conclusion is further supported by Nelson et al. (2005), who highlighted the importance of information quality in user satisfaction and system success. Their study found that users are more likely to find a system useful when the information provided is accurate, complete, and relevant to their needs. In the context of mobile learning, this means that students are more likely to perceive the platform as valuable if it provides high-quality educational content that is directly applicable to their studies.

The strong relationship between information quality and perceived usefulness also echoes the findings of Wixom and Todd (2005), who found that information quality is a primary determinant of perceived usefulness in technology acceptance models. Their research suggests that when users perceive the information provided by a system as reliable and relevant, they are more likely to view the system as useful and be motivated to continue using it. This highlights the need for educational institutions to ensure that the content delivered through mobile learning platforms is of high quality and meets the specific needs of students.

Perceived Usefulness and Satisfaction

The study also found that perceived usefulness significantly influences satisfaction (β=0.116, T-value=5.448***). This result is consistent with the Technology Acceptance Model (TAM) proposed by Davis (1989), which posits that perceived usefulness is a key determinant of user satisfaction. When students find a mobile learning platform useful in achieving their academic goals, they are more likely to be satisfied with the platform, leading to increased engagement and continued use.

This finding is supported by Roca et al. (2006), who investigated the role of perceived usefulness in user satisfaction with e-learning systems. Their study found that perceived usefulness is a significant predictor of satisfaction, indicating that when students perceive a learning platform as beneficial to their studies, they are more likely to be satisfied with the platform. This suggests that educational institutions should focus on enhancing the perceived usefulness of mobile learning platforms by ensuring that they provide valuable and relevant content that meets the needs of students.

Perceived Usefulness, Attitude, and Behavioral Intention

Perceived usefulness was also found to have significant effects on both attitude (β=0.384, T-value=11.804***) and behavioral intention (β=0.226, T-value=5.051***). The strong influence of perceived usefulness on attitude supports the findings of Rahman and Sloan (2015), who argued that individuals' perceptions of the usefulness of technology are closely linked to their attitudes toward its use. When students perceive a mobile learning platform as useful, they are more likely to have a positive attitude towards using the platform, which in turn influences their intention to use it.

This relationship between perceived usefulness, attitude, and behavioral intention is well-documented in the literature. For example, Venkatesh and Davis (2000) found that perceived usefulness is a significant predictor of both attitude and behavioral intention in their extended TAM model. Their research suggests that when users perceive a technology as useful, they develop a positive attitude toward it, which increases their intention to use the technology. This highlights the importance of perceived usefulness in shaping students' attitudes and intentions towards mobile learning platforms.

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The significant impact of perceived usefulness on behavioral intention is also consistent with the findings of Teo and Zhou (2014), who found that positive perceptions of usefulness enhance users' willingness to engage with technology and maintain their learning performance over time. This suggests that educational institutions should focus on enhancing the perceived usefulness of mobile learning platforms to encourage student engagement and sustained use.

Satisfaction and Behavioral Intention

Satisfaction was found to have a significant effect on behavioral intention, with a standardized path coefficient of 0.270 (T-value=7.439***). This finding supports the hypothesis that satisfied students are more likely to intend to continue using the mobile learning platform. This result is consistent with the work of Bhattacherjee (2000), who proposed a causal relationship between user satisfaction and the motivation to continue using information systems. According to Bhattacherjee, satisfaction is influenced by previous experiences of use, and satisfied users are more likely to have a positive intention to continue using the system.

This relationship between satisfaction and behavioral intention is also supported by the research of Chiu et al. (2005), who found that user satisfaction is a significant predictor of behavioral intention in the context of e-learning. Their study suggests that when students are satisfied with a learning platform, they are more likely to intend to continue using it, leading to sustained engagement and improved learning outcomes. This highlights the importance of ensuring that students have a positive experience with mobile learning platforms to encourage continued use.

Attitude and Behavioral Intention

Finally, the study found that attitude significantly affects behavioral intention, with a standardized path coefficient of 0.301 (T-value=8.037***). This result supports the hypothesis that students' attitudes towards mobile learning platforms are a key determinant of their behavioral intention to use the platform. This finding is consistent with the Theory of Planned Behavior (TPB) proposed by Ajzen (1991), which posits that attitude is a significant predictor of behavioral intention. When students have a positive attitude towards using a mobile learning platform, they are more likely to intend to use it, leading to increased engagement and sustained use.

The relationship between attitude and behavioral intention is also supported by the research of Chuttur (2009), who found that attitude is a significant predictor of behavioral intention in the context of technology adoption. Chuttur's study suggests that when users have a positive attitude towards technology, they are more likely to intend to use it, highlighting the importance of fostering positive attitudes towards mobile learning platforms among students.

This finding is further corroborated by the work of King and He (2006), who conducted a meta-analysis of TAM studies and found that attitude is a significant predictor of behavioral intention across various contexts. Their research suggests that when users have a positive attitude towards technology, they are more likely to intend to use it, which in turn leads to increased engagement and sustained use. This underscores the importance of fostering positive attitudes towards mobile learning platforms to encourage student engagement and continued use.

Limitations and Future Research

While this study provides valuable insights into the factors influencing college students' behavioral intentions to use mobile learning platforms, it is not without limitations. One significant limitation is the potential for data bias, as the sample may not be fully representative of the broader population of students in China. Additionally, the study may have overlooked the influence of contextual factors such as institutional policies, cultural differences, and the online learning environment, all of which could significantly impact students' behavioral intentions.

Future research should address these limitations by incorporating a more diverse sample and considering the influence of contextual factors. For example, future studies could examine the impact of different institutional policies on students' attitudes toward mobile learning platforms or explore how cultural differences influence students' perceptions of usefulness and satisfaction. Additionally, future research should consider the rapid advancements in technology.

Implications for Practice

This research first points out the direction for the design and development team of the mobile learning platform. By identifying and optimizing the core elements such as system quality, service quality, and information quality that affect the use behavior of college students, the user-friendliness and attractiveness of the platform can be significantly improved, to attract more college students to actively

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adopt mobile learning methods for learning. This not only enriches access to learning resources but also promotes the diversity and flexibility of learning styles so that learning is no longer limited by time and space.

At the same time, the research also has important practical value for higher education institutions. It helps educators understand the learning needs and preferences of college students, adjust teaching strategies, and make better use of mobile learning platforms to improve teaching results. By integrating online and offline teaching resources, personalized teaching and learning path customization can effectively stimulate students' learning interest and motivation, and cultivate their ability for independent learning and lifelong learning. These changes not only help enhance students' learning outcomes but also lay a solid foundation for their future career development and lifelong learning.

Recommendations for Future Research

First of all, the interaction mechanism among the influencing factors can be further refined, and through longitudinal tracking research or experimental design, how variables such as system quality, service quality, and information quality affect perceived usefulness, satisfaction and behavioral intention over time can be deeply discussed. This will help build more accurate and dynamic theoretical models and provide platform developers with more targeted optimization strategies.

Secondly, future research can be extended to college students with different disciplinary fields and cultural backgrounds to verify the universality and difference of this research. By comparing the use behavior intentions of students from different majors, grades, and cultural backgrounds, we can reveal the unique needs and preferences of specific groups for mobile learning platforms, and provide more diversified design ideas for platform developers.

In addition, with the continuous progress of technology, future research can also focus on the application of emerging technologies (such as artificial intelligence, virtual reality, etc.) in mobile learning platforms and their impact on college students' behavioral intentions. This will help to predict and lead the development trend in the field of mobile learning and promote the innovation and upgrading of educational technology.

In short, future research should continue to deepen the understanding of mobile learning platform users' behavioral intentions, explore more influencing factors and their interaction mechanisms, and provide solid theoretical support and practical guidance for the development of mobile learning.

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