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Determinants of Graduate Students' Behavioral Intention to Use Mobile Learning Platforms at Hunan Normal University

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Abstract

Background and Aim: This research examined the factors affecting graduate students' behavioral intentions toward using a mobile learning platform. The study focused on several latent variables, including system quality (SQ), service quality (SVQ), information quality (IQ), perceived usefulness (PU), satisfaction (SA), attitude (ATT), and behavioral intention (BI). The goal of the study was to assess the degree to which each of these variables impacts the utilization of the mobile learning platform.

Materials and Methods: This research collected survey responses from 500 graduate students at a public university in Hunan, China, regarding their perspectives on using mobile learning platforms. Structural equation modeling (SEM) and confirmatory factor analysis (CFA) were employed to analyze the data.

Results: The data analysis results indicated that all hypothesized paths were statistically significant, demonstrating strong direct relationships between the variables in the model. Information quality, in particular, had the most substantial impact on perceived usefulness. These findings highlight the critical role of these factors in enhancing the effective use of mobile learning platforms in higher education, leading to increased student satisfaction and behavioral intentions. The study's strengths include a large sample size and the application of advanced statistical methods like SEM and CFA, offering a thorough evaluation of the model's validity. However, the study is limited by its focus on a single university, which may not capture the diverse experiences of students at other institutions. Moreover, while the study emphasizes key factors influencing mobile learning, it does not explore potential barriers or challenges students might encounter, such as technological issues or varying levels of digital literacy. Future research could address these aspects to gain a more comprehensive understanding of the effectiveness of mobile learning platforms.

Keywords: Mobile Learning Platform (MLP); Perceived Usefulness; Attitude; Satisfaction; Behavioral Intention

Introduction

In the tide of information technology in the 21st century, mobile learning, as a profound change in the field of education, is developing at an unprecedented speed and reshaping the face of higher education. Mobile learning, as the product of the deep integration of information technology and traditional education mode, can be traced back to the emergence of early handheld learning devices, but it entered the rapid development stage under the background of the popularity of mobile terminals such as smartphones and tablet computers and the increasing maturity of wireless network technology. This change not only greatly enriches the access to learning resources, but also becomes an important supplement and extension of contemporary graduate student group learning with its features of convenience, personalization, and instant feedback.

In the past, learning management systems were primarily built around non-mobile application models, limiting their accessibility and interactivity to fixed parameters Wang et al. (2020). However, as people's digital literacy increases and their understanding of learning and teaching methods evolves, LMS mobile apps are gradually gaining parity with non-mobile apps, closing the once-huge gap. The current evolution of the education system is moving towards mobile learning as a way to free users from time and space constraints, allowing users to interact seamlessly with educational content and services on mobile devices (Alzaza & Yaakub, 2011). Globally, mobile learning has become a trend that cannot be ignored in the field of higher education. With the continuous innovation of educational technology, mobile learning platforms continue to iterate and upgrade, and their functions are increasingly perfect. From simple course materials to complex online interaction, collaborative learning, and even learning behavior analysis based on big data, it has become possible. These advances not only improve learning efficiency but also promote

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the diversification and personalization of learning styles, providing a more flexible and autonomous learning environment for graduate students. It fosters an environment conducive to a myriad of informal and personalized learning approaches, thereby facilitating individual lifelong learning efforts (Sun, 2019). In addition, Sisouvong & Pasanchay (2024) claim that mobile learning revolutionized education by allowing students to access content at any time and tailor their studies to suit their own needs. Mobile learning significantly improved participation and access to resources globally, even in the face of problems like the digital divide. This approach encouraged self-directed, lifelong learning, which was crucial for adapting to the changing needs of education. Students were successful using MosoTeach, despite the study's findings indicating that affective and cognitive engagement did not significantly contribute to the improvement of learning outcomes. The outcome confirms that interactive learning environments fostered by mobile learning applications allow students to learn through both firsthand experience and observation (Xia & Phongsatha, 2025).

In Hunan Normal University, as an institution of higher learning with a profound academic heritage and distinct characteristics of The Times, the acceptance degree and demand of its graduate students for mobile learning also show a rapid growth trend. However, although the mobile learning platform has great potential to improve the learning effect, the actual use of it by graduate students is complicated by a variety of factors. These factors include not only the characteristics of the platform itself, such as interface friendliness and functional practicability but also the individual characteristics, learning habits, and learning environment of graduate students. Therefore, it is of great significance to explore how these factors affect the behavior intention of graduate students in using mobile learning platforms to optimize the construction of mobile learning platforms and improve the learning effect of graduate students.

In this context, this study aims to reveal the key factors affecting the behavior intention of Hunan Normal University graduate students using mobile learning platforms through systematic theoretical analysis and empirical research. Through an in-depth analysis of the interaction mechanism between these factors, this study will provide a scientific basis for universities to optimize the construction of mobile learning platforms and contribute academic wisdom to improving the quality of postgraduate education. At the same time, this study will further enrich and improve the relevant theories in the field of mobile learning, and promote the in-depth development of research in this field.

Objectives

The core objectives of this study are reconstructed as follows:

1. Identify key factors that influence the mindset and follow-up actions considered by graduate students when using mobile learning platforms.
2. Clarify strategic interventions from students, educators, teaching administrators, and higher education institutions to optimize the mobile learning experience for graduate students.
3. Develop recommendations that can positively influence these students' attitudes and behavioral intentions toward learning mobile platforms and foster a more favorable and effective learning environment.

Review of Literature

Mobile learning (M-learning) has emerged as a dominant trend in higher education, driven by ongoing innovations in educational technology. It transcends traditional constraints of time and space, allowing seamless interaction with educational content and services through mobile devices. (Alzaza & Yaakub, 2011). Mobile Learning Platforms (MLPs) are continually evolving, incorporating sophisticated features such as complex online interactions, collaborative learning, and data-driven learning analytics. These advancements enhance learning efficiency and support diverse and personalized learning experiences, creating a more flexible learning environment for students.

The Information Systems Success Model (ISSM), proposed by DeLone and McLean (2003), offers valuable insights into the success of MLPs. ISSM highlights system quality, service quality, and

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information quality as critical determinants of user satisfaction, which in turn influences behavioral intentions. Empirical research, such as that by Wang et al. (2009), confirms that these quality factors significantly affect students' satisfaction with MLPs, thereby impacting their continued use.

The Technology Acceptance Model (TAM), developed by Davis (1989), is another key framework for understanding technology adoption. TAM emphasizes perceived ease of use and perceived usefulness as crucial factors influencing technology acceptance. Recent extensions to TAM, including those by Dwivedi et al. (2019), incorporate additional variables such as subjective norms and facilitating conditions, providing a more comprehensive view of mobile learning adoption. Both ISSM and TAM offer valuable perspectives on how various factors affect user satisfaction and behavioral intentions.

Research demonstrates that well-designed MLPs can significantly improve academic performance and attitudes toward learning. (Demir & Akpinar, 2018). The integration of modern technologies, such as mobile internet, cloud computing, and big data, into educational contexts, enhances accessibility and diversity in learning, reflecting global trends toward universal education and lifelong learning. (Sun, 2019).

Weerasawainon and Ye (2019) Investigated the relationship between undergraduate students' use of mobile-assisted learning and their performance in learning Chinese as a foreign language. Their study shows that the use of mobile-assisted learning can significantly enhance students' learning outcomes, particularly in the context of foreign language acquisition. This provides additional evidence of the role of mobile learning platforms in improving educational results.

In China, mobile learning reflects these global trends, driven by rapid technological advancements and extensive content coverage. The widespread adoption and optimization of mobile learning platforms are facilitated by China's large mobile internet user base. As digital literacy improves, mobile LMS applications increasingly align with their non-mobile counterparts, narrowing the technological gap. (Wang et al., 2020). Additionally, the integration of wearable devices has further enhanced learning convenience and personalization. Recent Chinese research, such as that by Fang et al. (2023), underscores the significance of system and content quality in sustaining engagement with mobile learning platforms.

Despite the benefits, challenges persist, including varying levels of readiness and engagement among learners, as well as the tendency for some users to abandon mobile learning. Understanding the factors influencing students' behavioral intentions towards mobile learning is essential for addressing these challenges and improving the effectiveness of mobile learning platforms.

Technology Acceptance Model (TAM)

In 1989, Fred Davis proposed the technical acceptance model (TAM) (Davis, 1989; Davis et al., 1989). According to TAM, the ease of use of end users and their perception of technology usefulness are two fundamental factors driving the acceptance of new technology. (Davis, 1989; Pai & Huang, 2011). Davis et al. (1989) Argue that TAM has proven to be a well-known predictive framework because it is parsimonious and highly interpretable and can be used in a variety of environmental or research contexts. It is considered a powerful, simple, and influential model of innovation and acceptance behavior. So as you all know, TAM is considered the best framework for understanding technology adoption.

This assessment tool has been used to assess user acceptance of different technologies. (Almarashdeh, 2016; Chow et al., 2012; Teo et al., 2003; Wu, 2011). While TAM provides valuable insights into user acceptance of the technology, many scholars note that TAM has some limitations. In addition, Holden and Rada (2011) Make it clear that the lack of considering system features is a key weakness of TAM that can provide useful information to explain why users accept and adopt specific technical tools. To overcome these limitations, this study will use the Information System Success Model (ISSM), which has been used in the education field. (Almarashdeh, 2016; Mohammadi, 2015; Wang & Wang, 2009).

The DeLone and McLean information systems success model (ISSM)

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The ISSM developed by DeLone and McLean (1992,2003) is the product of an extensive literature review of the numerous variables associated with GIS success (Molla & Licker, 2001). ISSM has been identified as one of the most famous techniques for checking the effectiveness or failure of a given information system (Halawi et al., 2008; Wang & Wang, 2009).

In ISSM, the success of a given information system can be tested using eight interdependent variables: system quality, information quality, service quality, system use, use intention, user satisfaction, personal impact, and organizational impact, indicating that the DeLone and McLean (1992,2003) model considers the information system as a multiple and interrelated concept.

The ISSM model has been widely used to explore and investigate users' intentions to reuse specific information systems in multiple research areas e.g. e-Commerce. (Wang, 2008), social network services (Lee & Kim, 2017), and knowledge management systems (Wang & Lai, 2014). Furthermore, ISSM clarified the faculty's intention to reuse LMS in the e-L environment. (Sharma et al., 2017).

System Quality

System quality has been widely recognized for its critical role across various contexts, particularly in information systems (IS) and online learning environments. Urbach and Müller (2012) Underscore that essential characteristics of information systems often prioritize usability and system performance, identifying these as key factors in evaluating system quality. Building on this, DeLone and McLean (2003) Integrated system quality is a technical communication construct within their IS Success Model, where it is considered a significant factor influencing organizational outcomes. Their work highlights the crucial role of system quality in driving business intelligence and organizational success.

Earlier studies by Teo et al. (2003) and Ahn et al. (2007) Also acknowledged is the importance of system quality, particularly in virtual communities and e-commerce environments, where it contributes to enhancing user satisfaction and trust. The importance of system quality in online learning environments has been further validated by research indicating its significant impact on student behavior and outcomes. For instance, studies by Lin (2007) and Thongsri et al. (2019) Emphasize the positive correlation between system quality and business intelligence, suggesting that high system quality is integral to successful online learning platforms.

In summary, system quality plays a crucial role in information systems and online learning environments, significantly influencing user perceptions, behaviors, and organizational outcomes.

Therefore, the following hypotheses are put forth:

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

Service Quality

The importance of service quality in information systems, especially in online learning environments, cannot be over-emphasized. Scholars have long recognized that service quality is a key factor affecting user satisfaction, system success, and organizational efficiency. This analysis aims to synthesize key insights from relevant literature and clarify the multifaceted dimensions and impacts of service quality in information systems.

The concept of service quality in information systems has evolved. Initially, Kettinger and Lee (1994) Introduced service quality as a basic function of system quality and information quality to measure the adoption and acceptance of information systems. This marked a paradigm shift, emphasizing the importance of user experience and satisfaction in system evaluation.

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.

Service quality has a higher significance in the context of e-Learning systems. Students' perception of technical support provided by universities through e-learning platforms reflects service quality. (J.-W.

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Lee, 2010; M.-C. Lee, 2010; Ozkan & Koseler, 2009). This emphasizes the importance of efficient technical support in ensuring a smooth user experience and improving overall system efficiency.

DeLone and McLean (2003) Define SEQ as the key characteristics of a system, including the latest hardware, software, and services provided by technical support personnel. Service quality includes factors such as reliability and technical knowledge, which significantly affect users' perception of SQ, especially in Mobile Learning environments where technical support plays a key role.

Asubonteng et al. (1996) Emphasize the importance of assessing service quality, emphasizing the need to meet established and expected needs to improve user satisfaction and organizational efficiency. Educational institutions can improve student satisfaction, usage trends, and organizational implementation by prioritizing the provision of high-quality services. (Lin & Hsieh, 2006).

In conclusion, service quality is the cornerstone of user satisfaction, system success, and organizational efficiency in information systems, especially in Mobile Learning environments. Understanding the multifaceted dimensions and impacts of service quality is critical for educators, administrators, and policymakers to optimize system performance and cultivate positive user experiences.

Therefore, the following hypotheses are put forth:

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

Information Quality

The concept of information quality is multifaceted and plays a crucial role in the effectiveness and success of information systems, as discussed by numerous researchers. DeLone and McLean (1992, 2003) originally proposed that information quality is a necessary construct for building successful information systems. They emphasized that factors such as service quality, system quality, and information quality are essential to the overall effectiveness of information systems.

Lin and Lu (2000) Identified information quality as one of the most influential factors affecting the effectiveness of user systems, highlighting its importance in shaping user perceptions and experiences. DeLone and McLean (2003) Further stressed the significance of information quality, noting that the content provided by the system enhances users’ knowledge levels.

Nelson et al. (2005) Defined information quality in the context of web services as the quality of the data provided, which includes elements such as determinability, completeness, usability, and format. They argued that the quality of content provided by web services can be measured through attributes like correctness, consistency, and speed. Additionally, Petter et al. (2008) Emphasized that information quality refers to the quality of communication systems, ensuring that the information conveyed is complete, accurate, timely, and useful.

Overall, information quality encompasses multiple dimensions and attributes, including completeness, accuracy, timeliness, usefulness, and value, all of which are critical for enhancing user experience and perception in information systems and online services.

Therefore, the following hypotheses are put forth:

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

Satisfaction

User satisfaction is a crucial component of the Information Systems Success Model. (DeLone & McLean, 2003), playing a key role in marketing by driving repeat purchases, generating positive public opinions, and fostering brand loyalty (Goode et al., 1996). Seddon (1997) Defines satisfaction as the positive feeling consumers have towards the use of online knowledge bases. Satisfaction represents a rational evaluation after using a product, reflecting the alignment between expectations and experience. (Nagy, 2018). It encompasses an overall assessment of one's experience with services and activities. (Wu et al., 2010)), typically based on immediate evaluations or psychological responses (Alshare & Lane, 2011; Oliver, 1993).

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Furthermore, satisfaction is a critical indicator for assessing the effectiveness of technological advancements, reflecting the willingness of participants to continue using the technology. (Locke, 1969). Satisfaction is closely related to users' overall evaluation of the services provided by institutions. (Fornell, 1992), and there is a positive correlation between student satisfaction and behavioral intention (Athiyaman, 1997; Browne et al., 1998; Clemes et al., 2008; Machleit & Mantel, 2001; Zeithaml et al., 1996). Additionally, satisfaction reflects students' positive attitudes and optimistic expectations in their online educational experiences. (Nagy, 2018).

In general, satisfaction can be measured through repeat purchases, user access, and surveys, indicating users' perceptions of the system and their evaluation of the user experience. (Chiu et al., 2007; Petter et al., 2008). Research consistently shows a positive correlation between satisfaction and behavioral intention. (Chao, 2019), with high satisfaction promoting continued use of platforms in online learning environments (Chiu et al., 2007; Lin, 2007).

Therefore, the following hypotheses are put forth:

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

Perceived Usefulness

Perceived usefulness is a crucial concept in technology adoption, defined as the subjective belief in a system's ability to enhance job performance. (Davis et al., 1989). This belief is shaped by various factors, including the perceived benefits and advantages of using system technologies across different contexts. (Ndubisi et al., 2003). Numerous studies have underscored the importance of perceived usefulness in driving user attitudes and acceptance of technology. (Bhattacherjee & Sanford, 2006; Hsu & Lu, 2004; McKechnie et al., 2006). Specifically, perceived usefulness has been found to significantly influence users' intentions to adopt new technologies, including online learning platforms. (Davis, 1989).

In the realm of online learning, perceived usefulness extends to the extent to which it helps learners achieve their learning goals and improve their learning abilities. (Yang, 2013). This perception motivates students to engage in online learning activities, particularly when they perceive tangible benefits from the experience. (Venkatesh & Bala, 2008). During the COVID-19 pandemic, students viewed online education as a means to continue learning and maintain a positive attitude amidst lockdowns, further highlighting the importance of perceived usefulness in technology acceptance. (Singh et al., 2021).

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

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). Attitudes play a crucial role in the Technology Acceptance Model (TAM) as fundamental influencing factors of satisfaction. (Alshare & Lane, 2011). Studies have shown that attitudes are important predictors of behavioral intentions. (Golnaz et al., 2010; Hoi, 2020; Nagy, 2018). Kim et al. (2015) Emphasize the significant impact of attitudes on individuals' perceptions. Attitudes are psychological attributes that influence individual behavior, as indicated by Fishbein and Ajzen (1981). Positive attitudes directly influence the willingness to use online learning platforms, as supported by multiple scholars. (Liker & Sindi, 1997; Mathieson, 1991; O'cass & Fenech, 2003). Students' attitudes towards online learning systems significantly affect their intention to use them, particularly during and after the pandemic, influencing their motivation to engage in learning activities. (Al-Rahmi et al., 2020). Positive attitudes towards online learning consistently motivate students to enhance their learning efficiency, influencing their adoption of the system. (Ajzen, 2005).

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By considering the various perspectives and definitions of attitudes provided by scholars, it's evident that attitudes play a crucial role in shaping individuals' perceptions, motivations, and behavioral intentions toward utilizing technology, particularly in the context of mobile learning systems.

Therefore, the following hypotheses are put forth:

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

Conceptual Framework

The conceptual framework of this study is shown in Figure 1. The investigators devise a conceptual schema aimed at elucidating the determinants of Hunan normal university students' propensity towards adopting Mobile Learning Platforms (MLP). This inquiry delves into existing pertinent theories, subsequently enhancing them to formulate a theoretical framework tailored specifically for this research context. The conceptual schema is refined through the integration of two pivotal theories—Davis's Technology Acceptance Model (TAM) and DeLone and McLean's (2003) Information Systems Success Model (ISSM)—and three primary empirical insights, thereby contributing a nuanced understanding of the study's central focus. Previous research has provided studies of system quality (SQ), quality of service (SVQ), information quality (IQ), perceived usefulness (PU), satisfaction (SA), attitude (ATT), and behavioral intent (BI). Huang et al. (2007) Identified and established a link between individuals' perception of usefulness, their subsequent attitudes towards a particular entity or concept, and ultimately, their behavioral intentions about it. The satisfaction of customers is intimately tied to both the quality of the system and the level of service provided (Hussein et al., 2021). Legramante et al. (2023) Emphasize the pivotal significance of information quality within their framework, positing a clear correlation among individuals' perceived usefulness of information, their resultant satisfaction, and the subsequent behavioral intentions that emerge. 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).

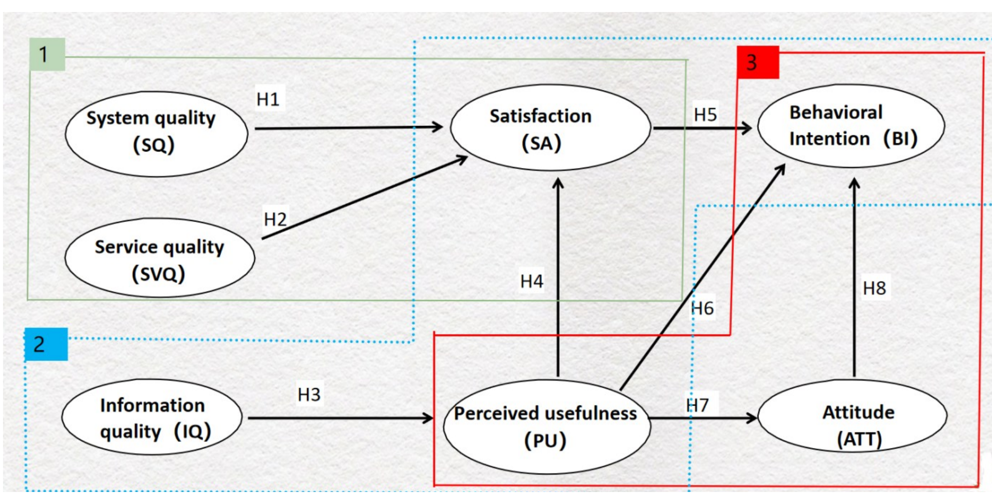

Figure 1 Conceptual Framework

Methodology

Research Instrument

In this study, a questionnaire survey was adopted as the core research method, and the postgraduate students of Hunan Normal University deeply explored their attitude tendencies and behavioral intentions of using mobile learning platforms. The questionnaire is carefully designed and consists of three sections: the screening questions aim to accurately locate the target group, the overview of the demographic characteristics of the participants provides rich background information for data analysis, and the core part

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focuses on seven potential variables closely linked to the theoretical framework, covering the multi-dimensional factors that affect the students' behavioral intention.

Before the questionnaire was officially released to the majority of graduate students, the research team took a rigorous pre-review process and invited three industry experts to evaluate the project-objective consistency (IOC) measure to ensure the scientific and valid content of the questionnaire. Subsequently, as a part of the pre-survey, 30 questionnaires were sent to some students for trial filling, aiming to test the reliability and applicability of the questionnaire through this small-scale practice.

After the data collection was completed, rigorous statistical analysis methods - confirmatory factor analysis (CFA) and structural equation model (SEM) were used to analyze the data in depth. This process not only systematically verified the internal structure of the data and the fit of the hypothetical model, but also presented the results of data analysis in a detailed way, which laid a solid foundation for the refining of subsequent research conclusions and the proposal of strategy suggestions.

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 enrollment of 42,000 students, including more than 13,000 graduate students. To ensure reliable and accurate research results, graduate 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 graduate 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	First-year graduate	653	251
	Second-year graduate	647	249
Total		1300	500

Data Collection and Analysis

According to the classic study of Krejcie and Morgan (1970), even in a small initial sample (such as 425 participants), the characteristics of a wider group (such as close to 50,000 people) can be effectively reflected through scientific methods, ensuring the representativeness of the study conclusions. Given that Hunan Normal University currently has a large population of more than 13,000 graduate students, this study cleverly combined the strategy of purpose sampling and stratified sampling to ensure that the sample can cover a wide range and truly reflect the diversity of the graduate student population of the university.

As a non-probabilistic sampling technique, the core of purpose sampling lies in the use of professional judgment and discretion of researchers. This covers a variety of methods such as judgmental sampling, selective sampling, and subjective sampling, all of which have the common feature of allowing

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researchers to select participants according to the specific needs, personal expertise, or perspective of the research question. (Rai & Thapa, 2015). Although this process deviates from the rigor of traditional random sampling, it can accurately focus on the characteristics of specific groups that are key to the research problem.

In this study, the researchers used this strategy and carefully selected a group of graduate students between the ages of 22 and 30 who had some knowledge and experience of mobile learning platforms as research objects. Such selection not only reflects the accurate grasp of the characteristics of the target group but also greatly enhances the explanatory power and depth of the research to explore the factors affecting the group's behavioral intention of mobile learning.

Specifically, by focusing on this specific age group and those with experience using mobile learning platforms, the researchers were able to more deeply analyze the internal mechanisms and external factors that influence their choices, preferences, and intentions for learning behavior. This targeted sampling method not only improves the relevance and effectiveness of the research but also lays a solid data foundation for subsequent analysis work -- the 500 effective responses finally collected constitute a rich and robust data set, providing strong support for revealing the behavior characteristics and trends of graduate students in the field of mobile learning. The specific sampling information is shown in Table 2.

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 276 males, constituting 55.2% of the total, and 224 females, making up 44.8% of the respondents. Regarding grades, there were 252 freshmen, constituting 50.4% of the total, and 248 Sophomores, making up 49.6% of the respondents.

Table 2 Demographic Information

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	276	55.2%
	Female	224	44.8%
Grade	First-year graduate	252	50.4%
	Second-year graduate	248	49.6%

Confirmatory Factor Analysis (CFA)

The researchers used AMOS software to tweak the measurement model repeatedly, eventually achieving indicators that matched the acceptable range. The adjusted indicators are as follows: CMIN/DF=1.139 (<5.00), GFI=0.952 (≥0.85), AGFI=0.941 (≥0.80), CFI=0.993 (≥0.80), NFI=0.947 (≥0.80), TLI=0.992 (≥0.80), RMSEA=0.017 (<0.08). All indexes meet the requirements, indicating that the measurement model has good fitting indexes, which can lay a good foundation for the subsequent structural equation model.

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Table 3 Goodness of Fit for Confirmatory Factor Analysis

Index	Acceptable Values	Source	Fitting Result
CMIN/DF	< 5.00	Awang (2012);Al-Mamary and Shamsuddin (2015)	1.139
GFI	≥ 0.85	Sica and Ghisi (2007)	0.952
AGFI	≥ 0.80	Sica and Ghisi (2007)	0.941
CFI	≥ 0.80	Bentler (1990)	0.993
NFI	≥ 0.80	Wu and Wang (2006)	0.947
TAG	≥ 0.80	Sharma et al. (2005)	0.992
RMSEA	<0.08	Pedroso et al. (2016)	0.017

The statistical summary in Table 4 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 4 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)	0.720- 0.765	0.903	0.551	0.860
Service Quality	Hussein et al. (2021)	0.729- 0.795	0.767	0.566	0.839
Information Quality	Legramante et al. (2023)	0.724- 0.779	0.917	0.561	0.793
Perceived Usefulness	Legramante et al. (2023)	0.735- 0.773	0.868	0.560	0.884
Satisfaction	Hussein et al. (2021)	0.730- 0.763	0.862	0.564	0.795
Attitude	Huang et al. (2007)	0.780- 0.807	0.871	0.628	0.835

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Latent Variables	Source of Questionnaire	Factors Loading	Cronbach's Alpha	AVE	CR
Behavioral Intention	Huang et al. (2007)	0.790- 0.809	0.932	0.640	0.842

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 5 Discriminant Validity

	SQ	SVQ	IQ	PU	SA	ATT	BI
SQ	0.742						
SVQ	0.405	0.752					
IQ	0.423	0.427	0.749				
PU	0.368	0.297	0.392	0.748			
SA	0.349	0.351	0.372	0.357	0.751		
ATT	0.427	0.400	0.393	0.397	0.391	0.792	
BI	0.422	0.460	0.499	0.377	0.395	0.455	0.800

Structural Equation Model (SEM)

Using the CFA methodology, a specific set of linear equations underwent estimation and validation through the structural equation model (SEM). The study by Erasmus et al. (2015) Examined the causal connections among various constructs composed of independent and dependent variables. Consequently, each strong fit indicator within the SEM validation sufficed for the research's objectives. The specific results are shown in Table 6.

Table 6 Goodness of Fit for Structural Equation Modeling

Index	Criterion	Source	After Adjustment Values
CMIN\DF	<5.00	Awang (2012); Al-Mamary and Shamsuddin (2015)	1.729
GFI	≥ 0.85	Sica and Ghisi (2007)	0.930
AGFI	≥ 0.80	Sica and Ghisi (2007)	0.916
CFI	≥ 0.80	Bentler (1990)	0.963
NFI	≥ 0.80	Wu and Wang (2006)	0.917
TLI	≥ 0.80	Sharma et al. (2005)	0.959
RMSEA	< 0.08	Pedroso et al. (2016)	0.038

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Research Hypothesis Testing Result

Table 7 shows the calculation results for each structure path. The standardized path coefficient β of system quality has a significant effect on satisfaction at 0.212 (T-value= 3.616). Similarly, service quality also had a significant impact on satisfaction, with a beta of 0.263 (t=4.407), and it is worth noting that information quality had the most significant impact on perceived usefulness, recording a beta of 0.534 (t=9.300). In addition, perceived usefulness had significant effects on satisfaction (β=0.272, T-value=5.119), attitude (β=0.303, T-value=5.454), and behavioral intention (β=0.177, T-value=2.980), among which the effect on attitude was the most significant. Satisfaction has a significant effect on behavioral intention, with a β of 0.494 (t=9.113). The behavioral intention was also significantly affected by attitude, showing a β of 0.333 (t=5.817).

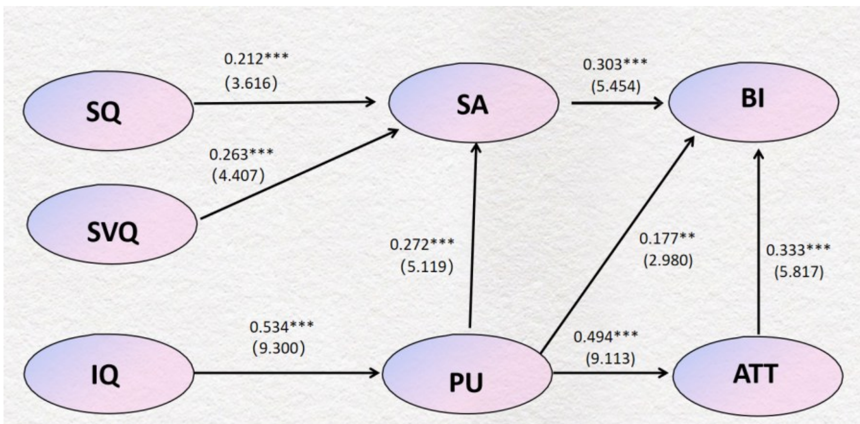

Figure 2 Structural Equation Model (SEM)

Table 7 Hypothesis Results

Hypothesis	Paths	Standardized Path Coefficient (β)	t-Value	Tests Result
H1	SQ --->SA	0.212	3.616	Supported
H2	SVQ --->SA	0.263	4.407	Supported
H3	IQ --->PU	0.534	9.300	Supported
H4	PU --->SA	0.272	5.119	Supported
H5	SA --->BI	0.303	5.454	Supported
H6	PU --->BI	0.177	2.980	Supported
H7	PU --->ATT	0.494	9.113	Supported
H8	ATT --->BI	0.333	5.817	Supported

In the structural path, H1 shows a standardized path coefficient value of 0.212, 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 0.263, 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).

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The standardized path coefficient value of H3 is 0.534, 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 0.272, suggesting that perceived usefulness is an influential factor in the satisfaction of graduate students in this study. Furthermore, perceived usefulness has been identified as a key determinant of satisfaction and attitudes toward online learning among university faculty and students.(Cheong & Park, 2005; Renda dos Santos & Okazaki, 2016)

Hypothesis 5 has a coefficient value of 0.303, 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 0.177, 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 0.494, 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 0.333, 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).

In summary, the direct path test results of the structural model show that all hypothesized paths are also statistically significant, which provides strong support for the interpretation of the research results.

Discussions

This study investigates the factors influencing college graduate 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=0.212, T-value=3.616) 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 recent research conducted in different contexts. For example, a study by Almaiah et al. (2020) Found that system quality significantly influences user satisfaction in mobile learning environments. Their research emphasizes that aspects such as ease of use, reliability, and the overall design of the system directly impact users' satisfaction and their intention to continue using the platform.

Service Quality and Satisfaction

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Service quality also plays a significant role in influencing student satisfaction, as evidenced by a standardized path coefficient of 0.263 (T-value=4.407). This result supports the hypothesis that the 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.

Al Mulhem (2020) Further supports the importance of service quality in educational settings by investigating its role in e-learning systems. Their study found that service quality has a positive and significant impact on enhancing user satisfaction with e-learning system quality. Therefore, educational institutions should pay special attention to these factors during the design and implementation process, recognizing their crucial role in improving the quality and effectiveness of e-learning systems to maximize the benefits derived from these platforms.

Information Quality and Perceived Usefulness

Information quality was found to have the most significant impact on perceived usefulness, with a standardized path coefficient of 0.534 (T-value=9.300). 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.

The close relationship between information quality and perceived usefulness also echoes the findings of Almaiah et al. (2020). They discovered that information quality, including accuracy and relevance, is crucial in determining students' perceived usefulness of e-learning platforms. It emphasizes the need for educational institutions to focus on delivering high-quality content to ensure the continued use of the platform.

Perceived Usefulness and Satisfaction

The study also found that perceived usefulness significantly influences satisfaction (β=0.272, T-value=5.119). 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 Al-Fraihat et al. (2020), who emphasized the role of perceived usefulness in driving satisfaction with e-learning platforms. Their research found that when students perceive the platform as useful, it directly contributes to their overall satisfaction and their willingness to continue using it. This suggests that educational institutions should focus on enhancing the perceived usefulness of mobile learning platforms by ensuring they provide valuable and relevant content that meets students' needs.

Satisfaction and Behavioral Intention

Satisfaction was found to have a significant effect on behavioral intention, with a standardized path coefficient of 0.303 (T-value=5.454). 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.

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This relationship between satisfaction and behavioral intention is also supported by the research of Al-Fraihat et al. (2020), who concluded that student satisfaction with e-learning systems is a key factor influencing their intention to continue using these systems, reinforcing the need for high-quality user experiences. This highlights the importance of ensuring that students have a positive experience with mobile learning platforms to encourage continued use.

Perceived Usefulness, Attitude, and Behavioral Intention

Perceived usefulness was also found to have significant effects on both attitude (β=0.494, T-value=9.113) and behavioral intention (β=0.177, T-value=2.980). 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.

The relationship between perceived usefulness, attitude, and behavioral intention is well-documented in the literature. For example, Nagy (2018) Found that in their extended TAM model, perceived usefulness is a significant predictor of both attitude and behavioral intention. Their research revealed that the perceived usefulness of online video content is a key factor influencing students' attitudes toward using these resources for learning, as well as their intention to do so.

The significant impact of perceived usefulness on behavioral intention is also consistent with the findings of Almaiah and Alismaiel (2019), who discovered that perceived usefulness has a notably strong effect on users' intention to use. This suggests that educational institutions should focus on enhancing the perceived usefulness of mobile learning platforms to encourage student engagement and sustained use.

Attitude and Behavioral Intention

Finally, the study found that attitude significantly affects behavioral intention, with a standardized path coefficient of 0.333 (T-value=5.817). 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 aligns with the views presented by Buabeng-Andoh (2021), which suggests that attitude significantly influences behavioral intention. When students hold a positive attitude towards using mobile learning platforms, they are more likely to intend to use them, leading to increased engagement and sustained use.

The relationship between attitude and behavioral intention is also supported by the research of Buabeng-Andoh (2021), who found that university students' intention to use mobile learning and found that attitudes, shaped by perceived usefulness and enjoyment, are crucial determinants of behavioral intention. Their research emphasizes that a favorable attitude towards mobile learning strongly influences the intention to use such platforms, reinforcing the importance of designing user-friendly and enjoyable learning environments.

This finding is further corroborated by the study of Buabeng-Andoh (2018), which also revealed that attitude towards use and subjective norms significantly influence students' behavioral intention to use mobile learning. Among the three endogenous variables examined, attitude had the most substantial impact on behavioral intention.

Limitations and Future Research

While this study offers valuable insights into the factors that shape college students' behavioral intentions to use mobile learning platforms, it is not without certain limitations. A key limitation lies in the possibility of data bias, as the sample may not fully capture the diversity of the broader student population in China. Furthermore, the study may have overlooked the role of contextual factors, such as institutional policies, cultural differences, and specific online learning environments, all of which could considerably influence students' behavioral intentions.

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To address these limitations, future research should include a more varied sample and take into account the impact of contextual factors. For instance, subsequent studies could investigate how different institutional policies affect students' attitudes toward mobile learning platforms or examine how cultural differences shape students' perceptions of usefulness and satisfaction. Additionally, future research needs to consider the rapid technological advancements in this field.

Implications for Practice

This study provides essential guidance for the design and development teams of mobile learning platforms. By pinpointing and refining key elements such as system quality, service quality, and information quality, which influence college students' usage behaviors, the platform's user-friendliness and appeal can be greatly enhanced. This, in turn, can encourage more college students to actively engage in mobile learning. The resulting improvements not only broaden access to educational resources but also foster a more diverse and flexible approach to learning, eliminating the constraints of time and space.

Additionally, this research holds significant practical value for higher education institutions. It aids educators in better understanding the learning needs and preferences of college students, enabling them to adjust teaching strategies accordingly and leverage mobile learning platforms to achieve better educational outcomes. By integrating online and offline teaching resources, educators can offer personalized instruction and customize learning pathways, effectively increasing students' interest and motivation in learning. This approach nurtures independent learning skills and supports lifelong learning, ultimately enhancing students' academic performance and laying a solid foundation for their future careers and continuous education.

Recommendations for Future Research

Based on the research findings, the researcher offers the following recommendations:

Recommendations for Applying Research Results

Regarding the results of the research objective, 1:The study found that system quality, service quality, and information quality are key factors influencing graduate students' attitudes and subsequent behaviors when using mobile learning platforms. Among these, information quality has the greatest impact on perceived usefulness, while system quality and service quality primarily affect satisfaction. Therefore, relevant agencies should take the following actions: improve the stability of the mobile learning platform, enhance the responsiveness of services, and provide more accurate and timely learning resources to optimize the student experience.

Regarding the results of the research objective, 2:The study found that students, teachers, educational administrators, and universities play critical roles in improving the experience of mobile learning platforms. By optimizing platform content, improving technical support, and adjusting teaching methods, student satisfaction and behavioral intentions can be enhanced. Therefore, relevant agencies should take the following actions: provide training for teachers and educational administrators to help them better utilize the platform's features, and strengthen technical support to ensure that students receive timely assistance during their usage.

Regarding the results of research objective 3: The study revealed that perceived usefulness, satisfaction, and attitude significantly impact behavioral intention. A positive attitude and high satisfaction among students strengthen their willingness to continue using the platform. Therefore, relevant agencies should take the following actions: promote the advantages of the platform, offer usage training, and provide incentives to encourage students to form a positive attitude toward the platform, thus increasing their intention to use it.

Recommendations for Future Research

This study has identified the significant influence of system quality, service quality, and information quality on students' behavioral intention to use mobile learning platforms. Importantly, these factors can serve as valuable insights for other types of online learning platforms. Future research should emphasize

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the relationship between these quality factors and students' long-term usage intentions and explore the applicability of these factors in different cultural contexts. For future research topics, it is recommended to investigate the diverse needs of students from different academic disciplines, examine the impact of technological advancements on mobile learning platform usage behavior, or assess the role of social interaction in online learning environments and its influence on behavioral intention.

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