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Factors Influencing Private University Students' Behavioral Intention to Use Mobile Learning Tools

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Abstract
Background and Aim: Mobile learning is an emerging trend in education. Rain Classroom is a mobile learning tool and has a significant correlation with mobile learning. However, within the personal and informal learning environment, several research problems emerge. The study aims to explore the factors influencing private university students' behavioral intention to use Rain Classroom as a mobile learning tool, using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), extended with system quality, information quality, and perceived satisfaction.
Materials and Methods: A quantitative survey of 508 undergraduates was conducted, with data analyzed through Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) using SPSS 27 and AMOS 27.
Results: The findings indicated that factors including facilitating conditions, performance expectancy, social influence, effort expectancy, hedonic motivation, system quality, information quality, and perceived satisfaction all significantly influenced undergraduates' behavioral intention to use the rain classroom ($p < .001$). Furthermore, facilitating conditions, effort expectancy, social influence, and performance expectancy indirectly influenced behavioral intention via hedonic motivation. This is rarely paid attention to by previous studies.
Conclusion: This study enriches mobile learning research, particularly regarding Rain Classroom in private university settings, highlighting the importance of system reliability, content quality, and user satisfaction in promoting adoption. Notably, it also emphasizes the significant influence of social influence, effort expectancy, performance expectancy, and facilitating conditions on hedonic motivation, a facet underexplored in previous studies.
Keywords: Factors; Behavioral Intention; Mobile Learning Tool; UTAUT2; D & M Model

Introduction

Mobile learning is an emerging trend in education (Nikou & Economides, 2017). There are three ways which learning can be considered "mobile" at anywhere (Wang et al., 2018). Three basic elements of mobile learning: mobile learning devices, communication infrastructure, and learning activity models (Chang et al., 2003). Mobile learning devices include smartphones, laptops, tablet computers, and so on. The communication infrastructure uses mobile technology to connect mobile computing devices to relevant learning materials and learners. Learning activity models can be either in-class or out-of-class (Wang et al., 2018).

Based on mobile technology, mobile learning, as a form of e-learning, has become a relatively new field (Schuck et al., 2016). Mobile learning is a trend with great potential, providing new opportunities for education and learning assessment (Nikou & Economides, 2017). The m-learning is a complementary approach to face-to-face (F2F) learning and e-learning (Alowayr, 2021; Kumar Basak et al., 2018). It has the advantage for learners to engage with educational resources at any time and from any location (Kumar Basak et al., 2018). Some researchers asserted that mobile learning embodies the remarkable skill of harnessing mobile technology to enrich learning encounters (Ozuorcun & Tabak, 2012).

In many universities in China, mobile learning has been increasingly incorporated into formal classrooms (Schuck et al., 2016). Especially during the COVID-19 pandemic, with the nationwide internet course, mobile learning was rapidly rolled out and was practiced and strengthened. For example, smartphones, tablets and personal computers, and other mobile devices have been widely used in internet courses. The way students obtain learning materials and information, the form of submitting homework,

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and obtaining feedback are rehearsed and strengthened in an internet course, providing strong support for mobile learning.

In Mobile learning, technology is inseparable from the use of mobile learning tools. Mobile learning tools are the main medium and support of mobile learning. The use of mobile learning tools to promote the effects of education and learning has attracted widespread attention. The use of mobile learning tools potentially changes teaching and learning in the future (Kumar et al., 2020).

Mobile learning is achieved through communication, search, sharing, accumulation, and management of learning content (Grant, 2019). One of the challenges of mobile learning is that it often functions in informal learning environments, where the dynamics and effectiveness of learning can be difficult to assess and enhance (Viberg & Grönlund, 2015). Rain Classroom, a mobile learning tool developed by Tsinghua University in China in 2016 (Li & Song, 2017), is widely used in higher education in China. However, within the personal and informal learning environment, several research problems emerge: How does Rain Classroom effectively promote students' mobile learning? Such as the rain classroom's application of Chinese writing to undergraduates lacks relevant research. What specific factors influence students' behavioral intention to use Rain Classroom in such settings? Despite the significant correlation between Rain Classroom and mobile learning, there is a notable lack of research exploring these influencing factors. Clarifying these factors and further leveraging the effectiveness of Rain Classroom as a mobile learning tool is crucial for improving students' behavioral intention and engagement.

Sitar-Taut and Mican (2021) emphasized that mobile learning transcends traditional passive learning methods by facilitating direct interaction between students, educators, peers, and technical support through mobile learning tools. This interaction creates a collaborative and engaging learning environment, offering tailored educational content and activities designed to be interactive and immersive. By enhancing learning motivation, making learning more enjoyable, and promoting digital literacy and self-directed learning habits, mobile learning presents a transformative approach to education. Thus, understanding and addressing the research problems related to Rain Classroom's use in mobile learning, specifically focusing on Rain Classroom's application in Chinese writing, involve understanding how Rain Classroom promotes mobile learning in informal environments and identifying the key factors that influence students' behavioral intention to use this tool, is essential for realizing its full potential in fostering these positive educational outcomes. Addressing these problems is vital for enhancing the effectiveness of mobile learning and fostering improved educational outcomes among students.

Objectives

The research investigates the factors including performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), system quality (SQ), information quality (IQ) and perceived satisfaction (PS) contribute to influencing private university students' behavioral intention to use mobile learning tool like Rain Classroom.

Literature review

Theories Related to the Variables

The theories that are related to the variables utilized in this research are UTAUT2 and the D & M model.

UTAUT2

The unified theory of acceptance and use of technology (UTAUT) is a theoretical model widely used to explore users' behavioral intention to use technology. UTAUT provided a better understanding of the factors affecting acceptance and use of technology (Venkatesh et al., 2003). UTAUT contains four independent variables, including performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FS), and moderators include age, gender, experience, and voluntariness of use. Behavioral intention as an intermediate variable and use behavior as a dependent variable. Radovan and Kristl (2017) confirmed that the independent variables in the UTAUT were associated with behavioral

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intention. In 2012, Venkatesh et al. (2012) added hedonic motivation (HM), Price value (PV), and Habit (HT) variables to the model, which they named UTAUT2. The UATUT2 model contains seven exogenous variables and is used to explain the variables that predict an individual's behavior using a technological tool or application (Venkatesh et al., 2012). Venkatesh et al. (2012) called for the use of additional structures to improve its predictive power.

Moreover, Muangmee et al. (2021) added social distance to the UTAUT2 as an independent variable, expecting to increase the predictive ability of UTAUT2 in the case of measuring students' behavioral intention and actual use of e-learning tools (Muangmee et al., 2021).

D & M model

In 1992, DeLone and McLean introduced a model to measure the success of an information system. Ten years later, DeLone and McLean (2003) revised the model by considering the responses of the critics. They added an independent variable called "service quality", dividing the variable named "use" in the 1992 model into two variables, "use" and" intention to use ", turning "individual impact" and "organizational impact" into a variable called "net benefits". The D & M model has been applied and validated in many information system studies (Ojo, 2017).

Hassanzadeh et al. (2012) confirmed the accuracy of the D & M model on universities' e-learning platforms. Some researchers demonstrate that the D & M model can combine with the UTAUT model to predict the factors affecting students' online behavioral intention in using a discussion forum (Radovan & Kristl, 2017; Wut & Lee, 2021).

The research framework starts with UTAUT2, and the variables performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and behavioral intention are selected.

System quality (SQ) and Information quality (IQ) are two variables of the D & M model, which were used to measure behavioral intention (Wut & Lee, 2021). The researcher then adds them to the conceptual framework.

Perceived satisfaction (PS) has been suggested as a direct and pivotal antecedent of behavioral intention (Alowayr, 2021), encapsulating the essence of the students' fulfillment in achieving the myriad of benefits they aspire to reap from the learning journey (Wu et al., 2010). Then, it was added to the conceptual framework. Consequently, there are nine variables in this research.

Performance Expectancy

Performance expectancy refers to the extent to which an individual holds the belief that using the system will facilitate achieving improvements in their job performance (Venkatesh et al., 2003). Performance expectancy can also be defined as the extent to which individuals perceive that adopting and using a particular technology will enhance their ability to accomplish specific tasks or activities effectively and efficiently (Venkatesh et al., 2012). In the research, performance expectancy is defined as a mobile technology tool that should offer some help in achieving goals related to study performance (Wut & Lee, 2021).

Performance expectancy has consistently emerged as the most influential predictor of behavioral intention, as demonstrated by Venkatesh et al (2003). Wang et al., (2009) found that performance expectancy was a significant determinant of behavioral intention to use m-learning. Muangmee et al. (2021) discovered that performance expectancy was positively and significantly influenced the students' behavioral intention to adopt e-learning tools.

H1: Performance expectancy (PE) has a significant influence on behavioral intention (BI) to use the Rain Classroom as a mobile learning tool.

Sitar-Taut & Mican (2021) emphasized that the most powerful relationship was between performance expectancy and hedonic motivation. It was said that performance expectancy was significantly influenced by students' online hedonic motivation in using the discussion forum ($\beta = 0.399$, $p = 0.000$).

H2: Performance expectancy (PE) has a significant influence on hedonic motivation (HM) to use the Rain Classroom as a mobile learning tool.

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Effort Expectancy

Effort expectancy is defined as the extent to which an individual perceives the use of the system to be effortless and convenient, reflecting the degree of ease associated with its operation (Venkatesh et al., 2003). Effort expectancy can also be defined as the degree of ease associated with consumers' use of technology (Venkatesh et al., 2012).In this research, effort expectancy is defined as the degree of difficulty in using a mobile technology tool (Wut & Lee, 2021). Muangmee et al. (2021) found that effort expectancy significantly influenced the students' behavioral intention to adopt e-learning tools.

H3: Effort expectancy (EE) has a significant influence on behavioral intention (BI) to use the Rain Classroom as a mobile learning tool.

Sitar-Taut & Mican (2021) found that social influence was significantly influential on students' online hedonic motivation in using the discussion forum.

H4: Effort expectancy (EE) has a significant influence on hedonic motivation (HM) to use the Rain Classroom as a mobile learning tool.

Social Influence

Social Influence is articulated as the extent to which an individual perceives the conviction held by significant others that he or she ought to adopt and utilize the new system (Venkatesh et al., 2003). This concept encapsulates the influence that the opinions and actions of others exert on an individual's decision to embrace a new system. Social influence can be articulated as the perception held by consumers that their significant others, such as family members and friends, hold the belief that they ought to adopt a specific technology (Venkatesh et al., 2012). In this research, social influence is defined as the degree to which someone perceives that important others believe he or she should use the specific technology (Venkatesh et al., 2012). According to the research (Muangmee et al., 2021), social influence positively and significantly influenced the students' behavioral intention to adopt e-learning tools.

H5: Social Influence (SI) has a significant influence on behavioral intention (BI) to use the Rain Classroom as a mobile learning tool.

Brandford Bervell et al. (2021) found that facilitating conditions had a significant influence on hedonic motivation, with a Standardized Coefficient (β) value is 0.591, t-value is 8.136, and P-value is .000.

H6: Social Influence (SI) has a significant influence on hedonic motivation (HM) to use the Rain Classroom as a mobile learning tool.

Facilitating Conditions

Facilitating conditions were defined as the extent to which an individual perceives the availability and adequacy of both organizational and technical infrastructures that serve as a foundation to support and enable the utilization of the system (Venkatesh et al., 2003). Facilitating conditions are defined as the support offered by the organization (Sitar-Taut & Mican, 2021).

Research has conclusively demonstrated that facilitating conditions exerted a profound influence on the behavioral intention to adopt mobile learning (Nikou & Economides, 2017). According to the research (Muangmee et al., 2021), facilitating conditions were positively and significantly influenced the students' behavioral intention to adopt e-learning tools.

H7: Facilitating conditions (FC) have a significant influence on behavioral intention (BI) to use the Rain Classroom as a mobile learning tool.

Sitar-Taut & Mican (2021) attempted to verify that effort expectancy was significantly influenced by students' online hedonic motivation in using the discussion forum, but they failed. While effort expectancy significantly influenced hedonic motivation was not supported in the research conducted by Sitar-Taut & Mican (2021), the researcher continues to explore effort expectancy's influence on hedonic motivation, because some researchers discovered that effort expectancy significantly influences attitude (Sumak & Sorgo, 2016).

H8: Facilitating conditions (FC) have a significant influence on hedonic motivation (HM) to use the Rain Classroom as a mobile learning tool.

System Quality

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System quality is characterized by the technical excellence of an information system, encompassing its reliability, adaptability, and responsiveness, along with other inherent system attributes (Petter et al., 2008). System quality pertains to the integration of hardware and software excellence within information systems. Its core emphasis lies in the system's efficacy, evaluating how effectively the combined capabilities of hardware, software, policies, and operational procedures of these systems cater to the informational requirements of users (Tajuddin, 2015). In this research, system quality is defined as the accuracy and efficiency of the mobile technology tool (Wut & Lee, 2021). System quality was one of the independent variables in the conceptual framework to predict whether it had a significant influence on behavioral intention. The results indicated that the standardized path coefficient between system quality and behavioral intention was significant, with a value of 0.348 (t-value = 6.502) and a p-value less than 0.05.

H9: System quality (SQ) has a significant influence on behavioral intention (BI) to use the Rain Classroom as a mobile learning tool.

Information Quality

Information quality can be broadly conceptualized as the content furnished by the system, which serves to augment and enrich the user's knowledge base (DeLone & McLean, 2003). Information quality explains the quality of a communication system, ensuring that the information it disseminates is comprehensive, precise, current, and valuable (Petter et al., 2008). In this research, information quality is defined as the ability of a mobile learning tool can convey the intended meaning. (Wut & Lee, 2021).

According to the research by DeLone & McLean (2003), information quality was examined in the information systems success model to positively influence behavioral intention. Much research supported the significant relationship between these two variables (Cao, 2022).

H10: Information quality (IQ) has a significant influence on behavioral intention (BI) to use the Rain Classroom as a mobile learning tool.

Perceived Satisfaction

Perceived satisfaction refers to the extent to which students are content with their learning experiences. The level of satisfaction serves as a measure of the success or failure of a system (Liaw, 2008). It was considered a standard for measuring enjoyment and meets consumers' expectations. Wu et al. (2010) defined it as the attainment of all intended advantages that students seek to achieve through the learning journey. In this research, perceived satisfaction is defined as the benefits students aim to gain from the learning process (Alowayr, 2021).

The research (Liaw, 2008) showed that learners' perceived satisfaction and perceived usefulness were significant contributors to their behavioral intention to utilize the e-learning system.

H11: Perceived satisfaction (PS) has a significant influence on behavioral intention (BI) to use the Rain Classroom as a mobile learning tool.

Hedonic Motivation

Hedonic motivation, defined as the experience of pleasure or enjoyment derived from technology usage, has been identified as a crucial factor influencing technology acceptance and usage behaviors, as evidenced by the findings of Brown & Venkatesh (2005). Venkatesh et al. (2012) emphasized that hedonic motivation was a predictor variable for assessing consumers' behavioral intentions towards technology adoption and utilization. In this research, hedonic motivation is defined as the degree of fun or pleasure related to using the mobile technology tool (Sitar-Taut & Mican, 2021).

Hedonic motivation has consistently served as a pivotal predictor in the realm of consumer technology utilization (Venkatesh et al., 2012). According to the research (Muangmee et al., 2021), hedonic motivation was positively and significantly influenced the students' behavioral intention to adopt e-learning tools. Avcı (2022) used hedonic motivation as an independent variable to predict whether it had a significant influence on behavioral intention for using digital learning resources. The results indicated that it was a significant predictor of behavioral intention ($t=5.055$, $p<.05$).

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H12: Hedonic motivation (HM) has a significant influence on behavioral intention (BI) to use the Rain Classroom as a mobile learning tool.

Behavioral intention

Behavioral intention represents the robustness of the purpose forged to accomplish a defined task or engage in a particular behavior (Davis, 1989). Behavioral propensity clarifies students' readiness to adopt an online learning system or the prospect of a student engaging in the action of utilizing an online platform (Venkatesh & Davis, 2000; Cao, 2022). In this research, it is defined as someone who intends to use a mobile learning tool (Wut & Lee, 2021).

According to the research (Muangmee et al., 2021), the students' behavioral intention to adopt e-learning tools was positively and significantly influenced by facilitating condition ($\beta=0.50$, $p<0.05$), hedonic motivation ($\beta=0.35$, $p<0.05$), performance expectancy ($\beta=0.22$, $p<0.05$), social influence ($\beta=0.20$, $p<0.05$), effort expectancy ($\beta=0.14$, $p<0.05$).

Conceptual Framework

The conceptual framework for this research is constructed based on UTAUT2 and combined with the D & M model. Variables include performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, behavioral intention, system quality, and information quality are retained. External variable perceived satisfaction is added to the model.

The conceptual framework of the study is presented in Figure 1.

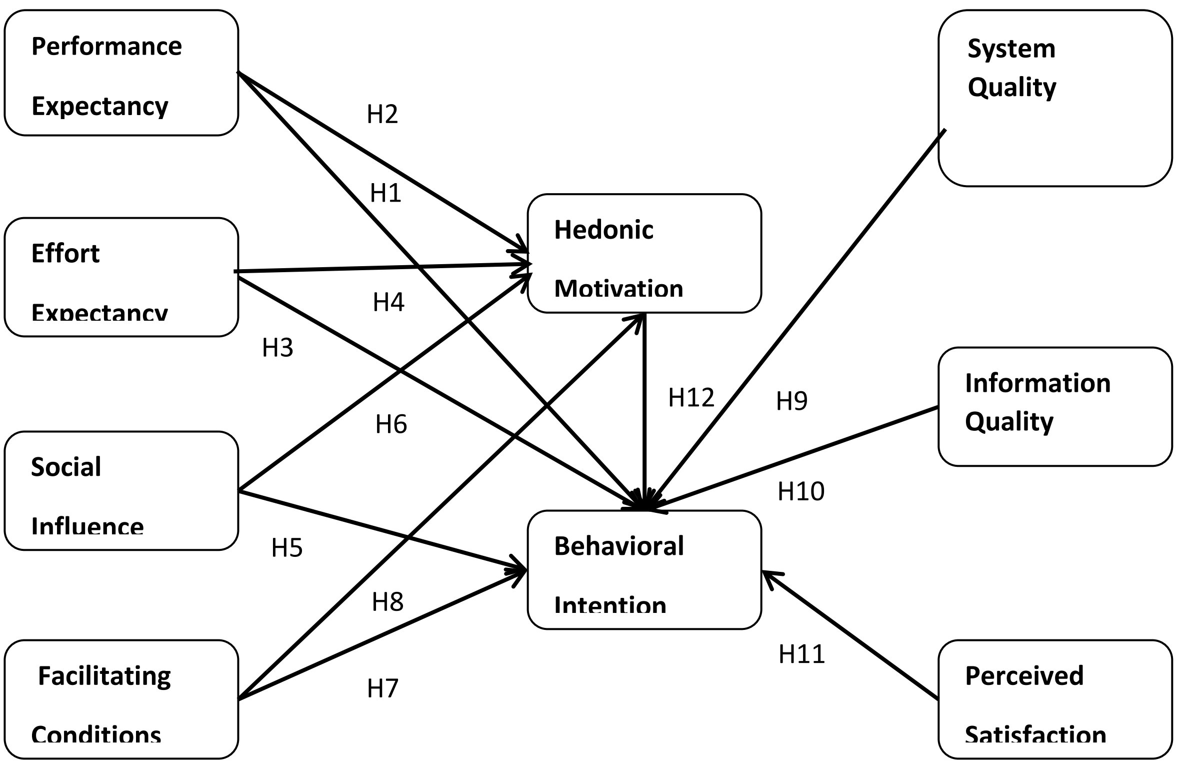

Figure 1 Conceptual framework

Methodology

Research Instrument

This is a quantitative survey research, uses the questionnaire as a research instrument to collect data. A descriptive technique to establish the relation between independent variables and dependent variables,

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students' behavioral intention to use the Rain Classroom as a mobile learning tool. To effectively generalize results, an online questionnaire was employed to gather data. Questions originated from 9 variables and 34 items. Variables performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating condition (FC), information quality (IQ), perceived satisfaction (PS), and behavioral intention (BI) are all four items. System quality (SQ) and hedonic motivation (HM) both have three items. All 34 items are supported by previous research literature. Each item in the study was assessed using a 5-point Likert scale, which spanned from 1 = "Strongly Disagree" to 5 = "Strongly Agree". The researchers invited three professionals in related fields to evaluate the validity of the questionnaire. The evaluation process uses project-objective consistency (IOC) indices. After the evaluation of the three experts, the score of each item is above 0.67, which meets the requirement of questionnaire validity. In addition, 40 students were invited to participate in the pilot study to assess the internal consistency reliability of the questionnaire. Cronbach's alpha coefficient was used in the measurement scale. After reliability evaluation, all values of each variable are more than 0.80 (see Table 3), indicating that the reliability of the questionnaire is satisfactory.

Population and Sample: The population of the research is undergraduates from the School of Culture and Media at a private university in Zhanjiang city, Guangdong province, China. The numbers are 5107 in September 2024. The researcher used CALCULATOR: A-priori Sample Size Calculator for Structural Equation Models (https://www.danielsoper.com/statcalc) to calculate the sample size. The Conceptual framework contains 9 variables and 34 items. Anticipated effect size is 0.2, Desired statistical power level is 0.8, probability level is 0.05, according to CALCULATOR, the minimum sample size is 460. The purposive sampling method has been utilized to select the samples for this study. The samples had used Rain Classroom for their mobile learning, taught by the researcher. They are aged between 18 and 30.

Data Collection Process: When the questionnaire was sent to the students (samples), the researcher sent a questionnaire filling instruction first. It included that the respondents should be over 18 years old and informed them that the purpose of this questionnaire was only for research. The questionnaire was completed anonymously to protect the privacy of the respondents. In the process of filling in the questionnaire, respondents could terminate their answers at any time if they did not want to continue. The questionnaire was sent to students by Wenjuanxing and successfully gathered 508 valid questionnaires.

Data Analysis: The researcher employs the IBM SPSS version 27 and IBM AMOS version 27 to analyze the data. The Confirmatory factor analysis (CFA) and Structural equation model (SEM) were implemented to analyze complex relationships between multiple variables and test all hypotheses in the study.

Results

Demographic Information

The students in the sample were in total of 508, and came from two majors, including 317 Chinese language and literature, accounting for 62.4%, and 191 Chinese language international education students, accounting for 37.6%. Of the total number of students in the sample, 202 students were 18-19 years old, which accounted for 39.8%, 314 students were between the ages of 20-25, which accounted for 57.6% and 8 students were between the ages of 26-30, which accounted for 1.6%. There were 72 male students, which accounted for 14.2% and there were 436 female students, which accounted for 85.8% of the total number of students. There were 168 students who were freshmen, which accounted for 33.1%. 85 students were sophomores, which accounted for 16.7%. 124 students were junior and 131 students were senior, accounting for 24.4% and 25.8%.

Mean Values of the Variables: Researchers typically use the mean and standard deviation (SD) of the data to measure the dispersion or divergence of survey data. Table 1 shows the participants' opinions regarding the attribute of relative advantage associated with the mobile learning tool. The total mean was 3.627, which represented "agree" (Norman, G., 2010). The average value of all items was larger than the midpoint, ranging from 3.520 to 3.770. According to Norman (2010), the mean value of the item from 3.51 - 4.50, represented "agree".

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Table 1 Descriptive Analysis of Each Variable

Variables	Items	Mean	Std. Deviation	Interpretation
Performance Expectancy	PE1	3.540	1.197	Agree
	PE2	3.600	1.196	Agree
	PE3	3.530	1.291	Agree
	PE4	3.530	1.349	Agree
Effort Expectancy	EE1	3.630	1.182	Agree
	EE2	3.710	1.131	Agree
	EE3	3.690	1.163	Agree
	EE4	3.640	1.177	Agree
Social Influence	SI1	3.520	1.196	Agree
	SI2	3.530	1.157	Agree
	SI3	3.570	1.138	Agree
	SI4	3.530	1.159	Agree
Facilitating Conditions	FC1	3.670	1.198	Agree
	FC2	3.610	1.181	Agree
	FC3	3.650	1.161	Agree
	FC4	3.610	1.263	Agree
System Quality	SQ1	3.590	1.098	Agree
	SQ2	3.770	1.059	Agree
	SQ3	3.720	1.100	Agree
Information Quality	IQ1	3.680	1.050	Agree
	IQ2	3.720	1.080	Agree
	IQ3	3.750	1.048	Agree
	IQ4	3.550	1.107	Agree
Perceived Satisfaction	PS1	3.550	1.086	Agree
	PS2	3.620	1.114	Agree
	PS3	3.520	1.201	Agree
	PS4	3.560	1.094	Agree
Hedonic Motivation	HM1	3.620	0.985	Agree
	HM2	3.720	0.959	Agree
	HM3	3.650	1.007	Agree
Behavioral Intention	BI1	3.670	1.079	Agree
	BI2	3.710	1.141	Agree
	BI3	3.670	1.180	Agree
	BI4	3.700	1.034	Agree
Total		**3.627**	**1.134**	**Agre**

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Confirmatory Factor Analysis (CFA)

The research findings demonstrated a satisfactory goodness-of-fit for the measurement model. CFA Model Fit Indices include the ratio of the chi-square value to the degree of freedom (CMIN/DF), estimated root mean square error (RMSEA), goodness of fit index (GFI), adjusted Goodness of Fit index (AGFI), normalized goodness of fit index (NFI), Comparative Goodness of Fit Index (CFI), Tuck-Lewis Index (TLI). The statistical values of each index in this study were CMIN/DF = 1.403, GFI = 0.926, AGFI = 0.911, NFI = 0.944, CFI = 0.983, TLI = 0.981, and RMSEA = 0.028. See Table 2. Therefore, the structural model seems to be a satisfactory fit.

Table 2 Confirmatory Factor Analysis Fit Indices and Adjustments

Fit Index	Acceptable Criteria	Source	Statistical Values
CMIN/DF	≤5.0	Wheaton et al.,1977	1.403
RMSEA	≤ 0.08	Pedroso et. al., 2016	0.028
GFI	≥ 0.90	Sica & Ghisi, 2007	0.926
AGFI	≥ 0.85	Sica & Ghisi, 2007	0.911
CFI	≥ 0.90	Sharma et al., 2005	0.983
TLI	≥ 0.90	Wu & Wang, 2006	0.981
NFI	≥ 0.90	Bentler, 1990	0.944
Model Summary			In harmony with empirical data

The results of the CFA model fit indices showed that the results passed all of the acceptable criteria.

In order to test the construct validity, a convergence validity test was carried out. Convergent validity confirms the consistency of the relationship between constructs (Churchill, 1979). The usual method used to measure convergent validity was Cronbach's Alpha reliability (CA), factor loading, composite or construct reliability (CR), and average variance extracted (AVE). The results were summarized in Table 3.

Factor loading measures the coefficient among construct groups. The greater the factor load value, the higher the reliability of the project (Hair et al., 2010). The acceptable threshold for factor load is 0.5 or higher (Hair et al.1998). In this study, factor loading for all individual items was greater than 0.70, ranging from 0.729 to 0.903.

The Composite Reliability (CR) values provide a measure of the internal consistency among the indicators used to measure each construct. A CR value above 0.7 is generally considered acceptable. The CR values for the variables are greater than 0.7, suggesting that the indicators used in the study are reliable and consistent in measuring the construct. See Table 3.

AVE value above 0.5 is considered acceptable, and the AVE value of each variable is more than 0.5, suggesting that the indicators are effective in measuring the underlying construct.

Table 3 Descriptive Statistics of Factor Loading, AVE, and CR

Variables	Items	CA	t-value	Factors Loading	CR (> .7)	AVE (>.5)
Performance Expectancy	PE1	0.937	29.820***	0.884	0.938	0.791
	PE2		29.390***	0.878		
	PE3		30.497***	0.893		

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Variables	Items	CA	t-value	Factors Loading	CR (> .7)	AVE (>.5)
	PE4			0.903		
Effort Expectancy	EE1	0.905	20.644***	0.835	0.906	0.707
	EE2		21.371***	0.859		
	EE3		21.791***	0.874		
	EE4			0.792		
Social Influence	SI1	0.891	18.430***	0.848	0.890	0.671
	SI2		19.083***	0.884		
	SI3		17.570***	0.807		
	SI4			0.729		
Facilitating Conditions	FC1	0.902	21.594***	0.804	0.903	0.699
	FC2		23.295***	0.858		
	FC3		22.760***	0.840		
	FC4			0.841		
System Quality	SQ1	0.836		0.774	0.837	0.632
	SQ2		16.707***	0.840		
	SQ3		16.257***	0.769		
Information Quality	IQ1	0.873		0.778	0.873	0.633
	IQ2		18.882***	0.833		
	IQ3		18.204***	0.801		
	IQ4		17.418***	0.769		
Perceived Satisfaction	PS1	0.874		0.762	0.876	0.639
	PS2		18.982***	0.848		
	PS3		16.938***	0.757		
	PS4		18.560***	0.827		
Hedonic Motivation	HM1	0.864	20.967***	0.817	0.849	0.653
	HM2		20.134***	0.785		
	HM3			0.821		

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Variables	Items	CA	t-value	Factors Loading	CR (> .7)	AVE (>.5)
Behavioral Intention	BI1	0.922	20.794***	0.798	0.889	0.668
	BI2		20.924***	0.801		
	BI3		22.222***	0.835		
	BI4			0.834		

Note: CA = Cronbach's Alpha, *** = P<.001

Before the structural equation model analysis, the discriminant validity of each construct is also tested. According to Fornell & Larcker (1981), discriminant validity can be based on comparing the correlation coefficient of each structure with the square root of the AVE. The result of the square root of AVE needs to be greater than the correlation coefficient of the construct to ensure the discriminant validity. Table 4 shows the results. The square root of AVE values is higher than the correlation coefficient among constructs.

Table 4 Discriminant Validity

Variables	PE	EE	SI	FC	SQ	IQ	PS	HM	BI
PE	**0.889**								
EE	0.287	**0.841**							
SI	0.052	0.004	**0.819**						
FC	0.383	0.072	0.030	**0.836**					
SQ	0.077	0.017	0.093	0.227	**0.795**				
IQ	0.031	0.126	0.020	0.132	0.395	**0.796**			
PS	0.144	0.053	0.080	0.176	0.281	0.219	**0.799**		
HM	0.480	0.378	0.236	0.425	0.314	0.363	0.353	**0.808**	
BI	0.621	0.368	0.204	0.642	0.380	0.361	0.463	0.738	**0.817**

Structural Equation Model (SEM)

To test the hypotheses of causal relationship among the variables proposed, the Structural Equation Model (SEM) was employed in the model. In this section, the goodness of fit of the SEM model was evaluated through the assessment of six indices: CMIN/DF, GFI, AGFI, CFI, NFI, and RMSEA. These fitting indices provide a comprehensive evaluation of model fitting and enable to understanding of the adequacy of their structural model. Table 5 shows the Fit Indices Results of the Structural Equation Model. The current model fit analysis is in harmony with the empirical data.

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Table 5 Fit Indices Results of the Structural Equation Model

Fit Index	**ptable Criteria**	**stical Values**
CMIN/DF		[illegible]
GFI	5	[illegible]
SRMR	8	[illegible]
RMSEA	0	[illegible]
CFI	0	[illegible]
TLI	0	[illegible]
Model Summary		rmony with empirical data

Research Hypothesis Testing Result

The correlation among the independent and dependent variables proposed in the hypothesis is measured by regression coefficients or standardized path coefficients. The Hypothesis Testing Results of the Structural Equation Model (Table 6) show the hypothesis testing for each of the hypotheses stated in the study.

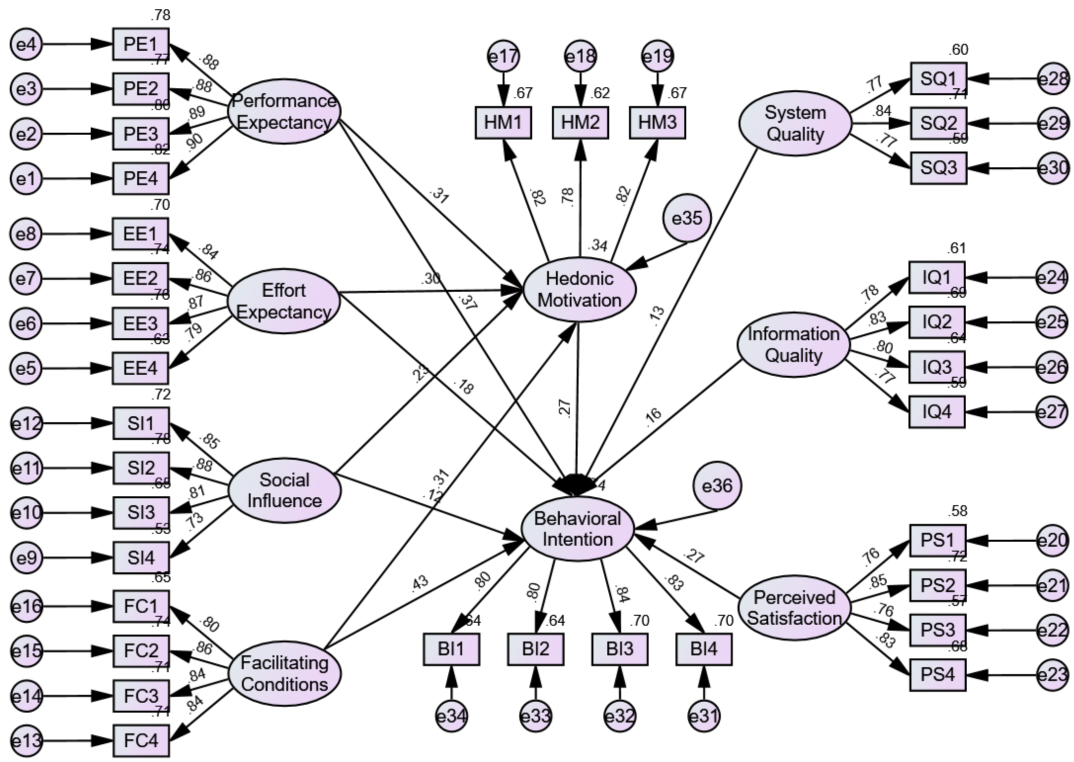

Figure 2 The Structural Equation Model (SEM) Path Diagram of the Study

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According to Table 6, all 12 hypotheses are supported with the P-values < .001. PE, EE, SI, FC, SQ, IQ, PS, and HM have a significant influence on BI. Meanwhile, PE, EE, SI, and FC have a significant influence on HM, are supported, with all the P-values < .001.

Table 6 Hypothesis Testing Results of the Structural Equation Model

Hypothesis	**Standardized Coefficients (β)**	**t-value**	**Testing result**
H1: BI ← PE	0.373	10.415***	Supported
H2: HM ← PE	0.313	7.080***	Supported
H3: BI ← EE	0.121	5.194***	Supported
H4: HM ← EE	0.298	6.556***	Supported
H5:BI ← SI	0.180	3.620***	Supported
H6: HM ← SI	0.228	5.042***	Supported
H7:BI ← FC	0.427	11.217***	Supported
H8: HM ← FC	0.314	6.909***	Supported
H9: BI ← SQ	0.129	3.924***	Supported
H10:BI ← IQ	0.163	5.024***	Supported
H11: BI ← PS	0.273	8.009***	Supported
H12:BI ← HM	0.268	6.172***	Supported

Note: *** = P<.001

Direct, Indirect, and Total Effects of Relationship

The relationship among the variables can be influenced directly or indirectly, and AMOS can help to calculate and determine the influences. The direct effect (DE) of a relationship means that the two variables are correlated without the influence of the intermediate variable. Indirect effects (IE) relationships are correlations between variables that exist through at least one moderating variable. Total effect (TE) is the sum of the direct and indirect effects of a relational path. (Raykov & Marcoulides, 2000). R-squared (R2) value represents the proportion of the change in the dependent variable, showing the proportion of that variable that can be explained by another variable. (Henseler & Sarstedt, 2012). The acceptable level of R2 is at least 0.1 (Falk & Miller, 1992).

Table 7 shows the results of the direct, indirect, and total effects of the relationship among the variables based on the hypotheses proposed. The R2 value of 0.337 and 0.735, which are both greater than the commonly accepted minimum (at least 0.1) threshold for adequate model fit, indicates that the model explains a significant portion of the variance in the dependent variables. It means that the independent variables have a substantial influence on the dependent variables, as measured by the proportion of variance explained (R^2).

Specifically, an R^2value of 0.337 suggests that approximately 33.7% of the variability in HM can be attributed to the independent variables (PE, EE, SI, FC) in the model. Similarly, an R^2value of 0.735 implies that 73.5% of the variability in BI is explained by the model. These values demonstrate that the model has a good fit and is capturing a meaningful amount of the relationship between the variables.

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Table 7 Direct, Indirect, and Total Effects of Relationships

Independent Variables	**Independent Variables**							
	Hedonic Motivation (HM)				**Behavioral Intention (BI)**			
	DE	**IE**	**TE**	**R^2**	**DE**	**IE**	**TE**	**R^2**
performance expectancy	.313	-	.313	.337	.371	.085	.456	.735
effort expectancy	.298	-	.298		.180	.080	.260	
social influence	.228	-	.228		.121	.061	.182	
facilitating conditions	.314	-	.314		.380	.131	.511	
system quality	-	-	-		.129	-	.129	
information quality	-	-	-		.163	-	.163	
perceived satisfaction	-	-	-		.273	-	.273	
hedonic motivation	-	-	-		.268	-	.268	

According to Table 7, performance expectancy (.085), effort expectancy (.080), social influence (.061), and facilitating conditions (.131) have an indirect influence on behavioral intention. This indirect influence is based on hedonic motivation as the intermediate variable.

Discussion

First of all, the study determines the factors that influence the behavioral intention of private university students in using a mobile learning tool.

The research aims to determine the factors influencing private university students' behavioral intention to use mobile learning tools like Rain Classroom. The samples come from private university undergraduates who had used a rain classroom as a mobile learning tool for their Chinese writing course learning. The research results can be used as a reference for other courses and other private universities to use the rain classroom as a mobile learning tool.

In order to establish the conceptual framework for the study, previous literatures were studied and the relevant theories and research papers on the topic. Previous studies had found the potential factors influencing behavioral intention, given great inspiration for this study. Potential influencing factors of behavioral intention to use a mobile learning tool were based on the UTAUT2 model and the DeLone & McLean model. The final selection determines performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, system quality, information quality, and perceived satisfaction are the influencing factors of behavioral intention. In the conceptual framework, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, system quality, information quality, and perceived satisfaction directly influence behavioral intention, and they have significant influence on behavioral intention is confirmed in the study. This study also attempts to prove that performance expectancy, facilitating conditions, effort expectancy, and social influence have an indirect influence on behavioral intention, with hedonic motivation as an intermediate variable. In the research, this idea is confirmed, although it does not show a significant influence. This is rarely paid attention to by previous studies. Although Sitar-Taut & Mican (2021) established a relationship with hedonic motivation as an intermediate variable, they ultimately failed to elucidate how performance expectancy, facilitating

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conditions, effort expectancy, and social influence indirectly influence behavioral intention, with hedonic motivation serving as the intermediary.

Secondly, the study confirms and supplements the research theories.

Several theories and theoretical models have been utilized to elucidate the acceptance and utilization of techniques and were used in this study, including the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003; Thomas et al., 2013; Alghazi et al., 2021), and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012; Arain et al., 2019). Additionally, the DeLone and McLean (D & M) model, which has been applied and validated in numerous information system studies, has been employed to measure behavioral intention (DeLone & McLean, 2003; Ojo, 2017; Wu & Lee, 2021).

In UTAUT, independent variables performance expectancy, effort expectancy, and social influence, and the dependent variable behavioral intention establish a path relationship. The path relationship from facilitating conditions to behavioral intention is not established. This is changed in UTAUT2, establishing a direct path relationship between facilitating conditions and behavioral intention. The direct path relationships among independent variables, performance expectancy, effort expectancy, social influence, facilitating conditions, and the dependent variable behavioral intention are demonstrated in this study. These four independent variables have a significant influence on behavioral intention.

Hedonic motivation is also an independent variable added by UTAUT2, which establishes the direct path relationship from hedonic motivation to behavioral intention. This study confirmed that hedonic motivation has a significant influence on behavioral intention. UTAUT2 did not establish the path relationship among performance expectancy, effort expectancy, social influence, facilitating conditions, and dependent variable hedonic motivation, but these four independent variables have a significant influence on hedonic motivation, as confirmed in this study.

UTAUT2 did not establish the path relationship among performance expectancy, effort expectancy, social influence, facilitating conditions, and the dependent variable behavioral intention with hedonic motivation as an intermediate variable. This study establishes this chain relationship and confirms that performance expectancy, effort expectancy, social influence, and facilitating conditions have an indirect influence on behavioral intention with hedonic motivation as the intermediate variable. The proportion of indirect influence reached 18.6%-33.8%.

A previous study had integrated UTAUT and D & M model to establish the conceptual framework (Wut & Lee, 2021). Therefore, in this study, two independent variables of the D & M model, system quality, information quality, were added to the conceptual framework and used to measure behavioral intention. D & M model failed to establish the path relationship between system quality, information quality among behavioral intention. This study established a direct path relationship among system quality, information quality, and the dependent variable behavioral intention, and confirmed that these two independent variables have a significant influence on behavioral intention.

Thirdly, the study establishes a conceptual framework integrating UTAUT2 and D & M mode, and proves that the conceptual framework has a good Model Fit.

The conceptual framework, six variables (PE, EE, SI, FC, HM, BI) from UTAUT2, two variables (SQ, IQ) from the D & M model, are selected, and an external variable, perceived satisfaction. The conceptual framework is composed of seven independent variables, one intermediate variable (HM), and one dependent variable (BI), see Figure 1.

The Model Fit for the Confirmatory Factor Analysis (CFA) and Structural Equation Model (SEM) is meticulously estimated to ascertain that the model is a good fit.

CFA Model Fit Indices include the ratio of the chi-square value to the degree of freedom (CMIN/DF), estimated root mean square error (RMSEA), goodness of fit index (GFI), adjusted Goodness of Fit index (AGFI), normalized goodness of fit index (NFI), Comparative Goodness of Fit Index (CFI), Tuck-Lewis Index (TLI).

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CMIN/DF is used to assess the fit of the model to the data, that is, the ability of the model to interpret the data. The value of CMIN/DF is 1-3 is excellent (Wheaton et al.,1977). In this conceptual framework, the value of CMIN/DF is 1403, indicating a good model fit.

RMSEA is employed to evaluate the fit of a statistical model to the observed data. It measures the discrepancy between the fitted model and the perfect fit, providing an estimate of the population discrepancy per degree of freedom. A value less than 0.05 is typically considered a good fit (Pedroso et. al., 2016), and in this conceptual framework, the value of RMSEA is 0.028, indicating a good model fit.

The GFI is a measure used to assess how well the proposed model replicates the observed variance-covariance matrix. A GFI value of 0.90 or above is generally considered indicative of an acceptable model fit (Sica & Ghisi, 2007). In this conceptual framework, the value of GFI is 0.926, indicating a good model fit.

The AGFI provides a more nuanced evaluation of model fit. A value of AGFI above 0.90 is typically considered good. (Sica & Ghisi, 2007). In this conceptual framework, the value of AGFI is 0.911, reflecting a well-fitting model that accounts for its complexity.

The NFI compares the chi-square value of the proposed model to the chi-square value of a null model. A value of NFI above 0.90 is generally considered indicative of a good model fit (Bentler, 1990). In this conceptual framework, the value of NFI is 0.944.

The CFI is a measure of model fit that corrects for sample size biases and is less sensitive to model misspecification than some other indices. CFI values of 0.90 or above are often considered indicative of an excellent fit (Sharma et al., 2005). In this conceptual framework, the value of CFI is 0.983.

The TLI is a measure of model fit that adjusts for sample size and model complexity. Values of TLI above 0.90 are typically considered indicative of a good model fit (Wu & Wang, 2006). In this conceptual framework, the value of TLI is 0.981.

Therefore, verified by CFA analysis, the conceptual framework in this study seems to be at a satisfactory fit.

The correlation among the independent and dependent variables proposed in the hypothesis is measured by regression coefficients or standardized path coefficients. The Hypothesis Testing Results of the Structural Equation Model show that all of the 12 hypotheses are supported in the study. Specifically, an R^2 value of 0.735 implies that 73.5% of the variability in the dependent variable BI is explained by the model. These values demonstrate that the model has a good fit and is capturing a meaningful amount of the relationship between the variables.

Conclusion

This study investigated the factors influencing private university students' behavioral intention to use Rain Classroom as a mobile learning tool by employing the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) extended with system quality, information quality, and perceived satisfaction. The findings confirmed that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, system quality, information quality, and perceived satisfaction all significantly influence students' behavioral intention. System quality was found to have the strongest influence, highlighting the importance of a reliable and user-friendly platform in promoting continuous use.

The study also revealed that hedonic motivation played a crucial mediating role in linking various factors, such as performance expectancy, effort expectancy, social influence, and facilitating conditions, to behavioral intention. Students who perceived the platform as enjoyable and engaging were more likely to adopt it for sustained learning. Similarly, the results showed that facilitating conditions, such as institutional support and resource availability, significantly contributed to both hedonic motivation and behavioral intention, underscoring the importance of creating an enabling environment for technology use.

Information quality and perceived satisfaction were also significant predictors of behavioral intention. High-quality content that conveyed the intended meaning effectively improved user satisfaction and encouraged continued use of Rain Classroom. These findings align with prior research, such as Liaw

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(2008), Wut & Lee (2021), and emphasize the need to maintain high standards in content delivery and user satisfaction to ensure the tool's effectiveness in mobile learning contexts.

Overall, the study provides robust empirical evidence supporting the adoption of Rain Classroom as a mobile learning tool in higher education. The integration of cognitive and technology acceptance variables in the theoretical model offers a comprehensive framework for understanding student behavior, and the results have significant implications for improving mobile learning strategies in private universities. The findings also point to the broader potential of leveraging digital tools to enhance learning outcomes and engagement.

Conclusion: Synthesis of contributions to knowledge is presented as a mind map.

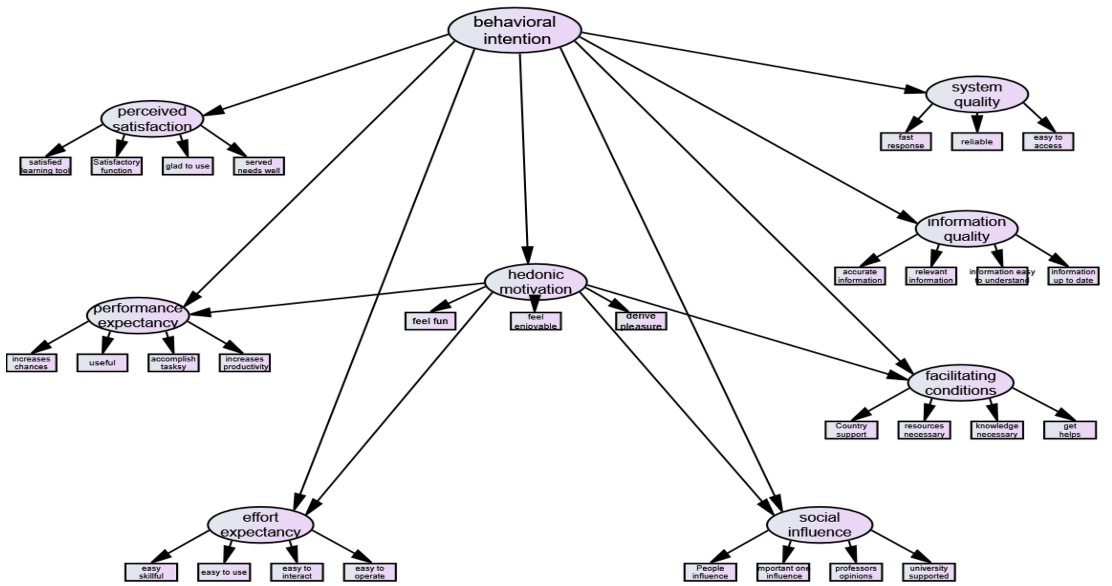

Figure 3 The factors that significantly influence private university students' behavioral intention to use the rain classroom as a mobile learning tool

Recommendation

In the future, the study should expand the population and sample scope to achieve broader generalizability of findings. This research was limited to students from the School of Culture and Media at a private university in Zhanjiang, Guangdong province. To ensure a more comprehensive understanding, future research should include students from multiple private universities across Guangdong province. This would provide a more diverse sample and offer insights into regional variations in the effectiveness of mobile learning tools like the Superstar Learning Platform.

Additionally, future research should incorporate more variables to enrich the research framework. Factors such as price value, habit, and service quality could offer deeper insights into the behavioral intentions and satisfaction of students using digital learning platforms. Moreover, applying qualitative or mixed methods, such as interviews and quasi-experimental designs, could enhance the depth of understanding by capturing nuanced perspectives and testing interventions in controlled environments.

Lastly, measures should be taken to minimize the influence of participant attitudes on data quality. Since individual differences in how participants approach questionnaires can affect the reliability of results, future studies could employ strategies such as clearer instructions, incentives for careful responses, or a combination of self-reported and observational data. These enhancements will ensure that future research is more robust, comprehensive, and reflective of real-world contexts.

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References

Alghazi, S. S., Kamsin, A., Almaiah, M. A., Wong, S. Y., & Shuib, L. (2021). For Sustainable Application of Mobile Learning: An Extended UTAUT Model to Examine the Effect of Technical Factors on the Usage of Mobile Devices as a Learning Tool. *Sustainability*. *13*(4), 1856. https://doi.org/10.3390/su13041856.

Alowayr, A. (2021). Determinants of mobile learning adoption: extending the unified theory of acceptance and use of technology (UTAUT). The International Journal of Information and Learning Technology. 39(1), 1–12. https://doi.org/10.1108/ijilt-05-2021-0070.

Arain, M., Tarraf, R., & Ahmad, A. (2019). Assessing staff awareness and effectiveness of educational training on IT security and privacy in a large healthcare organization. *Journal of Multidisciplinary Healthcare*. 12. 73-81. https://doi.org/10.2147/JMDH.S183275.

Avcı, S. (2022). Examining the factors affecting teachers' use of digital learning resources with UTAUT2. *Malaysian Online Journal of Educational Technology,* 10(3), 200–214. https://doi.org/10.52380/mojet.2022.10.3.399

Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin,* 107(2), 238–246. https://doi.org/10.1037/0033-2909.107.2.238

Brandford Bervell, B., Kumar, J. A., Arkorful, V., Agyapong, E. M., & Osman, S. (2021). Remodeling the role of facilitating conditions for Google Classroom acceptance: A revision of UTAUT2. *Australasian Journal of Educational Technology,* 38(1), 115–135. https://doi.org/10.14742/ajet.7178

Brown, S. A., & Venkatesh, V. (2005). Model of Adoption of Technology in Households: A Baseline Model Test and Extension Incorporating Household Life Cycle. *MIS Quarterly,* 29(3), 399-426. https://doi.org/10.2307/25148690

Cao, Y. (2022). Factors influencing online learning system usage among fourth-year students in higher education in Sichuan, China. *ABAC ODI Journal Vision. Action. Outcome,* 9(2), 123-143. https://doi.org/10.14456/abacodijournal.2022.9

Chang, C. Y., Sheu, J. P., & Chan, T. W. (2003). Concept and design of Ad Hoc and Mobile classrooms. *Journal of Computer Assisted Learning, 19*(3), 336–346. https://doi.org/10.1046/j.0266-4909.00035.x

Cho, G., Hwang, H., Sarstedt, M., & Ringle, C. M. (2020). Cutoff criteria for overall model fit indexes in generalized structured component analysis. *Journal of Marketing Analytics,* 8(4), 189–202. https://doi.org/10.1057/s41270-020-00089-1

Churchill, G. A. (1979). A Paradigm for Developing Better Measures of Marketing Constructs. *Journal of Marketing Research,* 16(1), 64–73. https://doi.org/10.1177/002224377901600110

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *Journal of Risk and Uncertainty,* 18(3), 321–325. https://doi.org/10.1023/a:1011156710779

Delone, W. H., & McLean, E. R. (2003). The DeLone and McLean Model of Information Systems Success: A Ten-Year Update. *Journal of Management Information Systems,* 19(4), 9–30. https://doi.org/10.1080/07421222.2003.11045748

Falk, R., & Miller, N. (1992). *A Primer for Soft Modeling*. University of Akron Press.

Fornell, C., & Larcker, D. F. (1981). Structural Equation Models with Unobservable Variables and Measurement Error: Algebra and Statistics. *Journal of Marketing Research*, 18, 382-388. http://dx.doi.org/10.2307/3150980

Grant, M. M. (2019). Difficulties in defining mobile learning: analysis, design characteristics, and implications. *Educational Technology Research and Development,* 67(2), 361–388. https://doi.org/10.1007/s11423-018-09641-4.

Hair, J.F., Anderson, R.E., Tatham, R.L., & Black, W.C. (1998). *Multivariate data analysis.* Prentice-Hall.

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Hair, J.F., Black, W.C., Babin, B.J., & Anderson, R.E. (2010). *Multivariate Data Analysis.* 7th Edition, Pearson, New York.

Hassanzadeh, A., Kanaani, F., & Elahi, S. (2012). A model for measuring e-learning systems' success in universities. *Expert Systems with Applications*, 39(12), 10959–10966. https://doi.org/10.1016/j.eswa.2012.03.028

Henseler, J., & Sarstedt, M. (2012). Goodness-of-fit indices for partial least squares path modeling. *Computational Statistics*, 28(2), 565–580. https://doi.org/10.1007/s00180-012-0317-1

Kumar Basak, S., Wotto, M., & Bélanger, P. (2018). E-learning, M-learning and D-learning: Conceptual definition and comparative analysis. *E-Learning and Digital Media*, 15(4), 191–216. https://doi.org/10.1177/2042753018785180.

Kumar, J. A., Bervell, B., Annamalai, N., & Osman, S. (2020). Behavioral intention to use mobile learning: Evaluating the role of self-efficacy, subjective norm, and WhatsApp use habit. *IEEE Access*, 8, 208058–208074. https://doi.org/0.1109/ACCESS.2020.3037925

Li, X., & Song, S. (2017). Mobile technology affordance and its social implications: A case of "Rain Classroom." *British Journal of Educational Technology*, 49(2), 276–291. https://doi.org/10.1111/bjet.12586

Liaw, S.-S. (2008). Investigating students' perceived satisfaction, behavioral intention, and effectiveness of e-learning: A case study of the Blackboard system. *Computers & Education*, 51(2), 864–873. https://doi.org/10.1016/j.compedu.2007.09.005

Muangmee, C., Kot, S., Meekaewkunchorn, N., Kassakorn, N., Tiranawatananun, S., & Khalid, B. (2021). Students' use behavior towards e-learning tools during COVID- 19 pandemics: Case study of higher educational institutions of Thailand. *International Journal of Evaluation and Research in Education (IJERE)*, 10(4), 1166-1175. https://doi.org/10.11591/ijere.v10i4.21821

Nikou, S. A., & Economides, A. A. (2017). Mobile-based assessment: Investigating the factors that influence behavioral intention to use. *Computers & Education*, 109(1), 56–73. https://doi.org/10.1016/j.compedu.2017.02.005

Norman, G. (2010). Likert scales, levels of measurement and the "laws" of statistics. *Advances in Health Sciences Education*, 15(5), 625–632. https://doi.org/10.1007/s10459-010-9222-y

Ojo, Adebowale I. (2017). Validation of the DeLone and McLean Information Systems Success Model. *Healthcare Informatics Research*, 23 (1), 60–66. https://doi.org/10.4258/hir.2017.23.1.60.

O'rourke, N. & Hatcher, L. (2013). A Step-By-Step Approach to Using SAS for Factor Analysis and Structural Equation Modeling, Second Edition. SAS Institute.

Ozuorcun, N. C., & Tabak, F. (2012). Is M-learning Versus E-learning or are They Supporting Each Other? *Procedia - Social and Behavioral Sciences*, 46, 299–305. https://doi.org/10.1016/j.sbspro.2012.05.110

Pedroso, R., Zanetello, L., Guimaraes, L., Pettenon, M., Goncalves, V., Scherer, J., Kessler, F., & Pechansky, F. (2016). Confirmatory factor analysis (CFA) of the crack use relapse scale (CURS). *Archives of Clinical Psychiatry*, 43(3), 37-40.

Petter, S., DeLone, W., & McLean, E. (2008). Measuring information systems success: models, dimensions, measures, and interrelationships. *European Journal of Information Systems*, 17(3), 236–263. https://doi.org/10.1057/ejis.2008.15

Radovan, M., & Kristl, N. (2017). Acceptance of Technology and Its Impact on Teachers' Activities in Virtual Classroom: Integrating UTAUT and CoI into a Combined Model. *Turkish Online Journal of Educational Technology*, 16(3), 11–22.

Raykov, T., & Marcoulides, G. A. (2000). *A first course in structural equation modeling.* Lawrence Erlbaum Associates.

Schuck, S., Kearney, M., & Burden, K. (2016). Exploring mobile learning in the Third Space. *Technology, Pedagogy and Education*, 26(2), 121–137. https://doi.org/10.1080/1475939x.2016.1230555

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Sharma, G. P., Verma, R. C., & Pathare, P. (2005). Mathematical modeling of infrared radiation thin layer drying of onion slices. *Journal of Food Engineering*, 71(3), 282–286. https://doi.org/10.1016/j.jfoodeng.2005.02.010

Sica, C., & Ghisi, M. (2007). The Italian versions of the Beck Anxiety Inventory and the Beck Depression Inventory-II: Psychometric properties and discriminant power. In M. A. Lange (Ed.), *Leading-edge psychological tests and testing research* (pp. 27–50). Nova Science Publishers.

Sitar-Taut, D.-A., & Mican, D. (2021). Mobile learning acceptance and use in higher education during social distancing circumstances: an expansion and customization of UTAUT2. *Online Information Review*, 45(5), 1000–1019. https://doi.org/10.1108/oir-01-2021-0017.

Sumak, B., & Sorgo, A. (2016). The Acceptance and Use of Interactive Whiteboards among Teachers: Differences in UTAUT Determinants between Pre- and Post-Adopters. *Computers in Human Behavior*, 64, 602-620. https://doi.org/10.1016/j.chb.2016.07.037.

Tajuddin, M. (2015). Modification of DeLon and Mclean Model in the Success of Information System for Good University Governance. *The Turkish Online Journal of Educational Technology*, 14(4), 113–123.

Thomas, H., Smith, R., & Diez, F. (2013). *Human Capital and Global Business Strategy*. Cambridge University Press. https://doi.org/10.1017/CBO9781139519380.

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, 46(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, 36(1), 157–178. https://doi.org/10.2307/41410412

Viberg, O., & Grönlund, Å. (2015). Understanding students' learning practices: challenges for design and integration of mobile technology into distance education. *Learning, Media and Technology*, 42(3), 357–377. https://doi.org/10.1080/17439884.2016.1088869

Wang, Y.-S., Wu, M.-C., & Wang, H.-Y. (2009). Investigating the determinants and age and gender differences in the acceptance of mobile learning. *British Journal of Educational Technology*, 40(1), 92–118. https://doi.org/10.1111/j.1467-8535.2007.00809.x

Wang, Y.-Y., Wang, Y.-S., Lin, H.-H., & Tsai, T.-H. (2018). Developing and validating a model for assessing paid mobile learning app success. *Interactive Learning Environments*, 27(4), 458–477. https://doi.org/10.1080/10494820.2018.1484773

Wheaton, B., Muthen, B., Alwin, D., F., & Summers, G. (1977). Assessing Reliability and Stability in Panel Models. *Sociological Methodology*, 8 (1), 84-136. https://doi.org/10.2307/270754.

Wu, J.H., & Wang, Y.M. (2006). Measuring KMS success: A respecification of the DeLone and McLean's model. *Information and Management*, 43(6), 728–739. https://doi.org/10.1016/j.im.2006.05.002.

Wu, J.-H., Tennyson, R. D., & Hsia, T.-L. (2010). A study of student satisfaction in a blended e-learning system environment. *Computers & Education*, 55(1), 155–164. https://doi.org/10.1016/j.compedu.2009.12.012.

Wut, T. M., & Lee, S. W. (2021). Factors affecting students' online behavioral intention in using discussion forum. *Interactive Technology and Smart Education*, 19(3), 300–318. https://doi.org/10.1108/itse-02-2021-0034.

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Li, G., & Li, C. (2025). Factors Influencing Private University Students' Behavioral Intention to Use Mobile Learning Tools. International Journal of Sociologies and Anthropologies Science Reviews, 5 (4), 381-400;
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