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Factors Impacting High School Students' Behavioral Intention to Use Mobile Learning in Liupanshui, China

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Abstract

Purpose: This research investigates the factors impacting high school students' behavioral intention to use mobile learning in Chinese high schools, considering effort expectancy, social influence, facilitating condition, performance expectancy, attitude, behavioral intention, and use behavior. **Research design, data, and methodology:** The research uses a quantitative, survey-based research design, employing online data collection for Confirmation Factor Analysis (CFA) and structural equation modeling (SEM). The study applied a purposive sampling method that draws on Liupanshui Minzu High School. The quota sampling method is used to calculate the proportion from the total number of students in each grade. Last, the target sample size of 500 students is collected through convenience sampling by distributing it online. **Result:** The results show that the six hypotheses are supported. Use behavior is strongly influenced by behavioral intention. The behavioral intention was significantly driven by effort expectation, social influence, facilitating condition, performance expectancy, and attitude. **Conclusions:** The findings underscore the importance of creating a conducive environment where mobile learning is user-friendly, supported by peers, and equipped with the necessary resources. Additionally, highlighting the benefits of mobile learning and promoting a positive attitude can enhance students' willingness to engage with this technology.

Keywords: Facilitating Condition, Performance Expectancy, Behavioral Intention, Use Behavior, Mobile Learning

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The future of the Internet lies in the "Internet Plus" era, and the next step in educational technology will be to make full use of the web, thereby revolutionizing our teaching. The history of technology has been taught in schools from ancient to modern times. Technology has come a long way, from personal computers and multimedia software to smartphones and electronic bags to the now-ubiquitous Internet and Internet-enabled TVS, as well as artificial intelligence, virtual reality, and the cloud. Today, hardware technologies are increasing in convenience, efficiency, creativity, and inspiration. When applied to relevant conditions or teaching scenarios, they provide a solid foundation for building new forms of teaching (Little, 2012).

Mobile learning played a supporting role compared to other kinds of online education. The proliferation of mobile devices has resulted in their quick ascent to prominence as a primary channel for disseminating instructional and performance-aid content. In today's technologically advanced world, every respectable training or education professional must pay attention to mobile learning (Little, 2012). The use of mobile devices in the classroom is one of the most noticeable developments in education and training in recent years. This is a crucial issue since mobile education has become more popular after the COVID-19 pandemic. (Bahadur, 2022).

The effort expectations describe an individual's concept

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of ease of use with the system (Jambulingam, 2013). Expectation of effort is crucial to people's propensity to adopt new forms of technology. Effort expectancy, or the perceived difficulty of using a technology, strongly predicts whether or not a user will go through with their intended course of action (Wong et al., 2015). Effort expectancy is also contextual, and the degree of familiarity with similar technologies will affect it (Aavakare & Nikou, 2020).

Social influence refers to how people influence each other's behavior (Rice & Shook, 1990). Social influence plays a crucial role in shaping users' behavioral intentions. According to the definition (Venkatesh et al., 2008), social influence measures how much a person values the approval of the most important people in his or her life.

The facilitating conditions describe the extent to which the environmental, instrumental, and social enhancements consumers perceive as necessary to carry out desired activities are readily available. (Venkatesh et al., 2003) Formally defines facilitating conditions as "the degree to which individuals believe that an organizational and technical infrastructure exists to support the use of the system." This definition is widely used by other authors whose research has been reviewed.

As defined by Brown and Green (2016), performance expectations refer to the extent to which a customer expects to gain a performance advantage by adopting a technology. "The degree to which an individual believes that the use of the system will help him or her obtain the benefits of job performance" (Venkatesh et al., 2003) is the official definition of performance expectancy. The term "performance expectancy" (PE) refers to the hope that access to new information or tools will improve a person's efficiency and productivity (Aavakare & Nikou, 2020). Venkatesh et al. (2012) indicate that PE strongly indicates consumer attitudes and behaviors toward adopting new technologies. The term "performance expectancy" refers to the idea that the system should assist in achieving job-related goals (Venkatesh et al., 2003).

Attitude is "a psychological tendency manifested by subjectively evaluating an object's liking or disliking to a certain extent." Giles and Coupland (1991) define attitude as "a person's outlook, state of mind, and spontaneous beliefs about service." The four primary functions of attitudes are social acceptance seeking (the social adjustive function), product benefit seeking (the utilitarian function), decision-making aid (the knowledge function), and self-expression (the value expression function) (Grewal et al., 2004; Shavitt, 1992).

The use behavior has been the focus of social media research in recent years (Omar & Dequan, 2020). Users' actions on social media have beneficial effects because they can add hedonistic value, provide streaming experiences, and distract them from real-life problems (Yildiz & Seferoğlu, 2019). Davis (1989) mentioned that behavioral intention is the level individuals tend to reach when participating in the behaviors prescribed by The Technology Acceptance Model or TAM.

2. Literature Review

2.1 Effort Expectancy

An individual’s conception of the system’s intuitiveness in meeting their needs is captured by their “effort expectations” (Jambulingam, 2013). Effort expectations describe an individual's concept of ease of use with the system (Jambulingam, 2013). Expectation of effort is crucial to people's propensity to adopt new forms of technology.

Davis (1993) pointed out that people's attitude was an important predictor of their behavior and intention to participate in a particular event. The factor of attitude toward using could predict customers’ behavioral intentions (Klobas, 1995).

Users' motivation to utilize technology largely depends on their expectations of how much effort it will need. E-learning (Chao, 2019), digital libraries (Hamzat & Mabawonku, 2018), and student usage of e-government services (Mensah, 2019) are all examples of social science literature. The results back up the theory that users would quickly adapt to a system if they perceive it to be simple. This is especially true with learning systems utilized in the education sector. The following hypothesis has emerged because of these studies:

H1: Effort expectancy has a significant impact on behavioral intention.

2.2 Social Influence

Impacting other people's thoughts, feelings, and actions is known as a social influence (Elango et al., 2018). Social influence directly affects usage intention due to individuals being dominated by their friends, family, and peers to use technology (Salganik et al., 2006).

Social influence directly impacts behavioral intent because friends, family, and peers lead individuals to use technology. The most important component in directly predicting behavior is a person’s behavioral intention, a plan to do a certain acceptable behavior (Hasan & Bao, 2020).

The TPB and UTAUT argue that social influence (or subjective norms) will positively affect the behavioral intention, in this case, usage intention for technology (Ajzen, 1991; Venkatesh et al., 2003). The theory of reasoned action (TRA), created by Ajzen and Fishbein (1969), defines behavioral intention as the outcome variable or how someone decides to behave in the future. A hypothesis has been constructed based on these data:

H2: Social influence has a significant impact on behavioral intention.

2.3 Facilitating Condition

Multiple research projects have shown a clear correlation between facilitating conditions and usage intention (Nikou & Economides, 2017; Tan, 2013; Venkatesh et al., 2003). One of the facilitating conditions of the UTAUT Model created by Venkatesh et al. (2003) is the presence of conducive situations. It indicates how confident a user is that the necessary human and technological resources are in place to use the system effectively (Xie et al., 2022).

Students' expectations that the university's existing technological infrastructure would help them take advantage of U-learning reflect the degree to which these are facilitating conditions. This new paradigm has a strong implication for the deployment of technological solutions and the development of trust to improve the quality of learning tools and services to provide users with a sustainable learning experience (Hamzat & Mabawonku, 2018).

Facilitating conditions are the fourth factor the UTAUT proposes to influence usage intentions directly (Venkatesh et al., 2003). Two studies also tested facilitating conditions directly on actual use, finding a significant effect (Salloum & Shaalan, 2019; Tan, 2013). This research has led to the following hypothesis:

H3: Facilitating condition has a significant impact on behavioral intention.

2.4 Performance Expectancy

Performance expectancy (PE) refers to users' hopes that a new tool will help them do their jobs better (Venkatesh et al., 2003). The intention to accept an information system is impacted by five different theories (Venkatesh & Davis, 2000): the technology acceptance model (perceived ease of use), the motivational model (external motivation), the personal computer utilization model (job fit), the innovation diffusion theory (relative advantage), and the social cognition theory (outcome expectancy).

Whether it is a digital library (Hamzat & Mabawonku, 2018), mobile learning (Ali & Arshad, 2016), or E-learning of data mining (Fernández-Delgado et al., 2014), many studies have attested that the factor performance expectancy significantly impacts behavioral intention. Meta-analysis supports the UTAUT's claim that high expectations for a technology's performance increase enthusiasm for adopting it. (Venkatesh et al., 2003). The investigations yielded the following findings:

H4: Performance expectancy has a significant impact on behavioral intention.

2.5 Attitude

According to Davis (1989), a person's attitude towards utilizing a system is impacted by their perceptions of its utility and its simplicity. Meanwhile, attitude toward using was a determinant of the behavioral intention, which would impact an individual's actual use behavior. According to Perry et al. (2017) research, according to the paradigm, one's perspective on use is the most important factor in shaping their desire to act.

According to Davis (1993), one's attitude may be used as a reliable indicator of one's future behavior intention and decisions about participation in a certain activity. Low self-monitor views are expected to be mostly utilitarian, emphasizing the practical. (Shavitt, 1992). Customers' future behavioral intentions may be predicted, at least in part, by their attitudes toward utilizing (Klobas, 1995). This finding is consistent with the prior research of Cheon et al. (2012) that mindset is one of the most significant predictors of future engagement with mobile learning services. Considering other elements alone, one's perspective on mobile learning could not be entirely explicable.

One's outlook on the job benefits from a genuine interest in what one does (Warren & Kelloway, 2010), and a person's desire to return to the workforce after retirement is heavily influenced by their outlook on employment. (Patrickson & Ranzijn, 2005). When predicting how people will use self-service technology, Michelle Bobbitt and Dabholkar (2001) found that attitude had a crucial role in shaping behavior intention and behaviors. According to the reasoned action theory (Ajzen & Fishbein, 1980), a person's attitude impacts their purpose and behavioral intention. This research has led to the following hypothesis:

H5: Attitude has a significant impact on behavioral intention.

2.6 Behavioral Intention

Behavioral intention describes a person's tendency and motivation to engage in desired behavior. Scholars believe that intentions represent various motivators encouraging a person to act a certain way. There is a strong link between behavioral intention and use behavior, yet most studies have failed to find such a link. Behavioral intent is an instance of planning to act a certain way (Abbasi et al., 2021). A person's behavioral intent is the degree to which they believe they will carry out the behavior that leads to their intent to use, as described (Yi et al., 2016).

According to Davis (1993), a person's attitude is the fundamental structure that predicts their behavior because it is directly related to their desire to engage in a particular behavior. In other words, a person's attitude can predict future behavior (Klobas, 1995). Individual behavioral tendencies based on emotional, thought, or experiential evaluations constitute "behavioral intent" (Spears & Singh, 2004). Positive and negative behavioral intentions belong to this trend (Ladhari, 2009). Positive behavioral intentions include plans to return to physical activity and recommend it to others (Zeithaml et al., 1996).

H6: Behavioral intention has a significant impact on use behavioral.

2.7 Use Behaviour

The most important component in directly predicting behavior is a person's behavioral intention, a plan to do a certain acceptable behavior (Hasan & Bao, 2020). In the study of social media, Usage behavior has recently emerged as a crucial factor. (Omar & Dequan, 2020). This is because social media usage has been shown to have several beneficial effects for its users, including increased hedonic value and flow experience and alleviating real-world problems. (Yildiz & Seferoğlu, 2019).

Media use also affects the quality of life of the elderly (Thompson & Heller, 1990). The so-called "user acceptance of information technology," there is no unified definition, generally refers to the user of a certain information technology or system of the internal behavioral willingness and the combination of external use behavior, that is, whether the user wants to use the system, the actual use of the system (Davis1989; Venkatesh et al., 2003).

Usage behavior refers to frequency of use, experience, and familiarity with information intermediaries. (Davis, 1989; Venkatesh et al., 2003). The theory of reasoned action (TRA), created by Ajzen and Fishbein (1969), defines behavioral intention as the outcome variable or how someone decides to behave in the future. Behavioral intention has been characterized as "a deliberate intent to engage in a behavior," the intensity of which may vary in response to contextual factors (Ingram et al., 2000). Intentional usage is the strongest predictor of actual use among students, followed by expected effort, conducive environment, and social influence. This research has led to the following hypothesis:

3. Research Methods and Materials

3.1 Research Framework

Conceptual frameworks are previous research frameworks developed from research. Adapted from three theoretical models, the Technology Acceptance Model (TAM) and the models in Planned Behavior Theory (TPB) are all part of the Unified Theory of Technology Acceptance and Use (UTAUT). This study adopts a six-element conceptual framework. Hair et al. (2013) identified independent factors, mediating variables, and dependent variables. The term "independent variable" refers to any factor outside the study that may potentially affect the "dependent variable" (Clark-Carter, 2010). The conceptual framework of this study is shown in Figure 1.

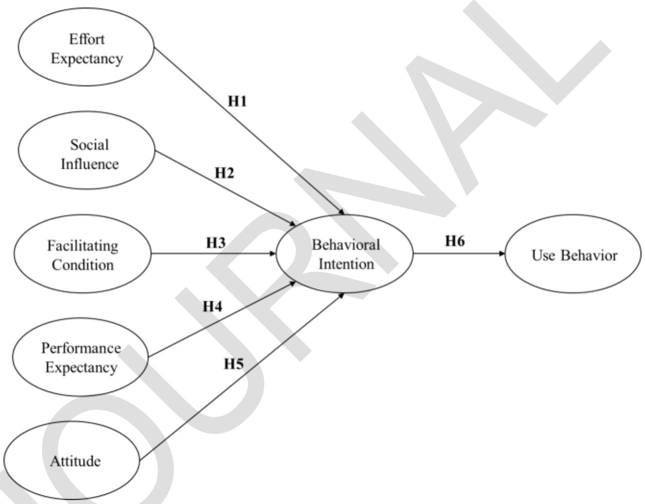

Figure 1: Conceptual Framework

H1: Effort expectancy has a significant impact on behavioral intention.

H2: Social influence has a significant impact on behavioral intention.

H3: Facilitating condition has a significant impact on behavioral intention.

H4: Performance expectancy has a significant impact on behavioral intention.

H5: Attitude has a significant impact on behavioral intention.

H6: Behavioral intention has a significant impact on use behavioral.

3.2 Research Methodology

This study uses quantitative research methodologies to examine the elements that impact Liupanshui City High School seniors' plans for using mobile devices for education. These statistics result from a poll administered using the user-friendly data-gathering platform Question Star.

The researcher conducted assessments for both reliability and validity. To assess the questionnaire's validity, three experts were invited to evaluate it using the Item Objective Congruence (IOC) method. For testing reliability, the Cronbach's alpha research technique was employed. In the pilot test, data were collected from a randomly selected sample of 30 respondents. The IOC results exceeded the 0.6 threshold, while the benchmark for acceptability in terms of

Cronbach's alpha values, following the criteria set by Nunnally and Bernstein in 1994, was set at surpassing 0.7

The analysis of the data was determined whether or not the proposed variables fit into the theoretical framework using a confirmatory factor analysis (CFA) and a structural equation model (SEM). The survey data was then double-checked and assessed. The study begins with an introduction, moves on to a review of the related literature and theoretical background, then sets forth a theoretical model and hypothesis before moving on to the development and administration of a questionnaire, followed by data collection and analysis, discussion, and disclosure, a conclusion, and finally, recommendations for future study.

3.3 Population and Sample Size

In this study, we will focus on participants in the subset of people who will be the recipients of the findings and conclusions of the study. The first, second, and third-grade students of Liupanshui Nationalities Middle School, who attend classes for more than one month, are the objects of this analysis. Compared to more conventional, regression-based statistical methods, a larger sample size is required for structured equation modeling (SEM) (Westland, 2010); hence, this factored into the determination of the sample size. The sample size was determined using an a priori sample size calculator for SEM research (Soper, 2020) using the following inputs: a modest effect size (0.2), a probability threshold of 0.05, the conceptual model, and the questionnaire. Based on these calculations, a sample size of at least 425 people is required. However, a sample size of 500 was employed in this investigation.

3.4 Sampling Technique

This study adopts the method of purposive sampling to select research objects. Participants were randomly selected from students at Liupanshui National Middle School. Use screening questions to ensure that the answers are appropriate for the target audience. Quota sampling calculates an appropriate sample size for each class after screening the entire population. The questionnaire is then sent to each grade based on the sample size predicted in the table. To ensure the reliability of sampling, the questionnaire was distributed to the most convenient target group by online and offline means. As part of the study, students at Liupanshui National High School who used mobile learning apps were asked to complete a questionnaire with a written consent by their parents due to the participants are under 18 years old.

Table 1: Sample Units and Sample Size

School Grade	Population Size	Proportional Sample Size
Grade 10	725	181
Grade 11	680	170
Grade 12	595	149
Total	**2000**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Demographic information collected from respondents was on gender and year of study. Questionnaires were distributed to 500 sets of students in Liupanshui Minzu High School. The respondents are 223 males and 277 females, representing 44.60 percent and 55.40 percent, respectively.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	223	44.60%
	Female	277	55.40%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

In this study, a validated factor analysis (CFA) was employed, utilizing the 'maximum fit estimation' parameter estimation method. According to the recommendations of Hair et al. (2006), factor loadings of 0.5 or higher were sought. The findings presented in Table 3 indicate that all individual factor loadings exceeded the 0.50 threshold. Additionally, the Composite Reliability (CR) values, with a benchmark of 0.7 or higher considered acceptable, and the Average Variance Extracted (AVE) values, with a benchmark of 0.4 or higher (Fornell & Larcker, 1981), were all well above these critical points.

Furthermore, the critical points for CRs and AVEs were both surpassed in Table 3, with CRs exceeding 0.7 and AVEs exceeding 0.4. Additionally, to establish acceptability, a threshold of Cronbach's alpha values surpassing 0.7 was used, in accordance with the criteria set by Nunnally and Bernstein in 1994.

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

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Effort Expectancy (EE)	Venkatesh et al. (2003)	4	0.812	0.797-1.769	0.851	0.588
Social Influence (SI)	Wut et al. (2022)	5	0.823	0.620-0.750	0.838	0.509
Facilitating Condition (FC)	Venkatesh et al. (2003)	4	0.829	0.809-0.820	0.868	0.621
Performance expectancy (PE)	Venkatesh et al. (2003)	4	0.908	0.807-0.773	0.866	0.618
Attitude (AT)	Gan (2017)	3	0.899	0.761-0.787	0.835	0.628
Behavioral intention (BI)	Gan (2017)	3	0.837	0.755-0.740	0.803	0.576
Use behavior (UB)	Wut et al. (2022)	4	0.939	0.758-0.756	0.844	0.575

The measurement model was evaluated using confirmatory factor analysis to confirm model fitness. Six latent variables are illustrated in Table 4 of the measurement model: effort expectancy, social influence, facilitating condition, performance expectancy, attitude, behavioral intention, and use behavior. Modification to the measurement model was optional for this study as the original measurement model has already presented a model fit. The acceptable values of goodness-of-fit indices presented the model fit in Table 4. The statistical values of indices were compared to the acceptable criteria. In which, the values were CMIN/DF =1.211, GFI = 0.950, AGFI =0.938, NFI=0.944, IFI = 0.990, TLI =0.988, CFI=0.990, and RMSEA = 0.021.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	1.211
GFI	≥ 0.90 (Sica & Ghisi, 2007)	0.950
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.938
NFI	≥ 0.90 (Wu & Wang, 2006)	0.944
IFI	≥ 0.90 (Hair et al., 2006)	0.990
CFI	≥ 0.90 (Hair et al., 2006)	0.988
TLI	≥ 0.90 (Hair et al., 2006)	0.990
RMSEA	< 0.08 (Pedroso et al., 2016)	0.021
Model Summary		**In harmony with empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, IFI = Incremental Fit Index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation

In Table 5, the discriminant validity was strong. The larger value of AVE square roots suggested that all variables were significant compared to the factor correlations.

Table 5: Discriminant Validity

	EE	SI	FC	PE	A	BI	UB
EE	**0.767**						
SI	0.375	**0.713**					
FC	0.225	0.291	**0.788**				
PE	0.397	0.391	0.305	**0.786**			
A	0.254	0.189	0.383	0.214	**0.792**		
BI	0.526	0.542	0.373	0.573	0.430	**0.759**	
UB	0.525	0.508	0.390	0.535	0.372	0.664	**0.758**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

The model fit of the structural model was evaluated by using maximum likelihood and goodness-of-fit indices. The fit indices comprise of chi-square statistics (CMIN/df), Root of the Mean Square Residual (RMR), the Goodness of Fit Index (GFI), the Adjusted Goodness of Fit Index (AGFI), Normed Fit Index (NFI), Comparative Fit Index (CFI), Incremental Fit Index (IFI), Tucker-Lewis Index (TLI), and the Root Mean Square Error of Approximation (RMSEA). The indices will evaluate seven latent variables: effort expectancy, social influence, facilitating condition, performance expectancy, attitude, behavioral intention, and use behavior.

The goodness-of-fit indices were calculated in Table 5.2 based on the structural model. The results of statistical values were CMIN/DF = 2.059, GFI = 0.904, AGFI = 0.884, NFI=0.901, IFI=0.947, TLI = 0.940, CFI = 0.946 and RMSEA=0.046.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	2.059
GFI	≥ 0.90 (Sica & Ghisi, 2007)	0.904
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.884
NFI	≥ 0.90 (Wu & Wang, 2006)	0.901
IFI	≥ 0.90 (Hair et al., 2006)	0.947
CFI	≥ 0.90 (Hair et al., 2006)	0.940
TLI	≥ 0.90 (Hair et al., 2006)	0.946
RMSEA	< 0.08 (Pedroso et al., 2016)	0.046
Model Summary		**In harmony with Empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, IFI = Incremental Fit Index, CFI = Comparative fit index, TLI = Tucker-Lewis index, and RMSEA = Root mean square error of approximation

4.4 Research Hypothesis Testing Result

The correlation magnitude among the independent and dependent variables proposed in the hypothesis is measured by regression coefficients or standardized path coefficients. As presented in Table 7, six proposed hypotheses were supported. Use behavior was strongly impacted by behavioral intention. effort expectancy, social influence, facilitating condition, performance expectancy, and attitude significantly drove behavioral intention.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: EE→BI	0.338	6.759*	Supported
H2: SI→BI	0.359	6.665*	Supported
H3: FC→BI	0.134	2.972*	Supported
H4: PE→BI	0.413	7.992*	Supported
H5: A→BI	0.287	5.811*	Supported
H6: BI→UB	0.694	10.074*	Supported

Note: * $p<0.05$
Source: Created by the author

H1 has shown a significant impact of effort expectancy on behavioral intention; this structural pathway results in a standard coefficient value of 0.338 and a t-value of 6.759. **H2** has shown a significant impact of social influence on behavioral intention. This structural pathway results in the standard coefficient value of 0.359 and t-value of 6.665. Facilitating conditions significantly impacted behavioral intention with a standardized path coefficient of 0.134 and a t-value at 2.972 in **H3.** Performance expectancy significantly impacted behavioral intention with a standardized path coefficient of 0.413 and a t-value of 7.992 in **H4** Attitude is a significant factor impacting behavioral intention, with a standardized path coefficient of 0.287 and a t-value of 5.811 in **H5.** The behavioral intention significantly impacted use behavior with a standardized path coefficient of 0.694 and a t-value of 10.074 in **H6.**

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

The research findings underscore the significance of several factors impacting high school students' behavioral intention to use mobile learning in Chinese high schools. Effort expectancy, social influence, facilitating conditions, performance expectancy, attitude, and behavioral intention were identified as influential determinants.

Effort expectancy, denoting the ease with which students can use mobile learning, is a key driver. When mobile learning is perceived as user-friendly and convenient, students are more inclined to adopt it (Chao, 2019; Hamzat & Mabawonku, 2018; Mensah, 2019).

Social influence plays a pivotal role, highlighting the impact of peer support and collaborative learning experiences. The presence of a supportive community can enhance students' motivation to engage with mobile learning (Elango et al., 2018; Salganik et al., 2006).

Facilitating conditions, encompassing access to necessary resources and support, are crucial. Schools must ensure that students have access to devices, internet connectivity, and technical assistance to overcome potential barriers (Nikou & Economides, 2017; Tan, 2013; Venkatesh et al., 2003).

Performance expectancy, related to the expected benefits of mobile learning, emerged as a significant factor. When students perceive that mobile learning can enhance their academic performance, they are more likely to embrace it (Ali & Arshad, 2016; Fernández-Delgado et al., 2014; Hamzat & Mabawonku, 2018).

Attitude, reflecting the overall sentiment towards mobile learning, was identified as an influential factor. A positive attitude, cultivated through demonstrating the value and relevance of mobile learning, positively impacts behavioral intention (Patrickson & Ranzijn, 2005; Warren & Kelloway, 2010).

The research confirms that behavioral intention strongly influences use behavior. When students express a genuine intention to use mobile learning, it is likely to translate into actual use (Ladhari, 2009; Spears & Singh, 2004).

In conclusion, this research provides valuable insights into the factors influencing high school students' behavioral intention to use mobile learning in Chinese high schools. The findings underscore the importance of creating a conducive environment where mobile learning is user-friendly, supported by peers, and equipped with the necessary resources. Additionally, highlighting the benefits of mobile learning and promoting a positive attitude can enhance students' willingness to engage with this technology.

The study has practical implications for educators, schools, and policymakers in China, as it suggests strategies for optimizing mobile learning initiatives. By addressing the identified factors, schools can foster a more engaging and effective learning environment, capitalizing on the growing potential of mobile technology.

However, it's important to acknowledge that the mobile learning landscape is dynamic, and students' preferences and needs may evolve. Further research is warranted to continually assess the impact of mobile learning on students' academic performance and to adapt strategies to align with changing trends and technologies. This research serves as a foundation for ongoing exploration of the topic and the development of future educational practices in Chinese high schools.

5.2 Recommendation

Based on the findings of this research, several recommendations can be made. Chinese high schools should actively incorporate mobile learning into their educational practices, recognizing that students have a positive intention to use this technology. This integration should be executed with careful attention to factors that influence behavioral intention.

Educators and policymakers should emphasize the importance of making mobile learning user-friendly and ensuring that students perceive it as easy to use. Reducing barriers to use, such as technical difficulties, can positively impact students' intentions to use mobile learning. Schools can harness the power of social influence by encouraging peer support and collaborative learning experiences. Creating a supportive community around mobile learning can enhance students' behavioral intention and overall engagement.

Schools should ensure that necessary resources and support are readily available to students. This may include access to devices, internet connectivity, and technical support to facilitate the smooth use of mobile learning. To boost students' behavioral intention, educators should highlight the potential benefits of mobile learning, such as improved academic performance and enhanced learning outcomes.

Schools and teachers should promote a positive attitude toward mobile learning by demonstrating its value and relevance in the educational process. A favorable attitude can drive students' intention to engage with this technology. High schools should regularly assess the effectiveness of their mobile learning initiatives and make necessary adjustments based on student feedback and changing technological trends.

Teachers and instructors should receive training to effectively utilize mobile learning tools in their teaching methods. This training can help in aligning their teaching strategies with students' behavioral intentions. Schools can involve students in decision-making processes regarding the implementation and improvement of mobile learning initiatives. Their input and feedback can lead to more student-centric solutions.

Encourage further research to explore the evolving landscape of mobile learning and its impact on students' academic performance and learning experiences, with a focus on any emerging factors that may influence behavioral intention. These recommendations should assist Chinese high schools in optimizing their mobile learning strategies, ensuring that they align with students' behavioral intentions, and ultimately fostering a more effective and engaging learning environment.

5.3 Limitation and Further Study

Although this study's contribution and utility have been verified, the factors that impact students' use of a mobile learning behavior model have yet to be empirically tested. This is because the study does not suggest any practical applications or verification of these findings, such as locating and considering some cutting-edge software to encourage students' mobile learning willingness and learning performance improvement through experimentation. Discussions sometimes degenerate into sloppy use of language, superficial explanations, and potentially biased judgments.

The growth of mobile learning is aided by researchers' investigations into its theoretical underpinnings, which focus primarily on questions ranging from conceptual definition and theoretical study to application mode. Learning on the go is not only about using gadgets; it also considers real-world context. Blending it with other approaches to learning will increase the effectiveness of instruction, and teachers will be able to focus on each student's unique growth and nurture their innovative potential. Overall, the theory and practice of mobile learning have yielded rewarding results throughout their lengthy evolution, and there is still a vast amount of untapped potential for future growth, so further research is required. However, the impact of specific factors impacts the willingness of high school students to use mobile learning. This study aims to address this vacuum in the literature by determining the impact of effort expectation, social influence, facilitation conditions, performance expectancy, attitudes, and other factors on high school students in Liupanshui, China, and the impact of these characteristics on students' intentions towards mobile learning behaviors. The study has verified some conclusions of the existing research on the impacting factors of college students' mobile learning behavior intention and obtained the role path of individual characteristics factors on the learning behavior willingness of high school students. The main conclusions are: In the effect of core variables, the effect of impacting factors is social influence, effort expectation, and performance expectancy. Consideration should be given to promoting students' mobile learning willingness by creating a good atmosphere for mobile learning, optimizing the mobile learning experience, and guiding students to clarify their learning goals.

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