Investigating the Predictability of Factors Affecting the Adoption of Mobile Learning and the Intention to Mobile Learning Acceptance Among Users

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The Paris Conference on Education 2026
Official Conference Proceedings

Abstract

The rapid proliferation of mobile devices has prompted educational systems worldwide to explore mobile learning (m-learning) as a means to enable anytime, anywhere individualized education. Understanding the factors influencing the acceptance of such technologies is critical for successful implementation. This study examines the determinants of m-learning acceptance among high school students in Iran, extending the Theory of Planned Behavior (TPB). Data were collected from 318 Iranian high school students and analyzed using structural equation modeling (SEM) in LISREL software. The findings confirmed the significant impact of attitude, subjective norms, and perceived behavioral control on behavioral intention to use m-learning. Contrary to expectations derived from the Technology Acceptance Model (TAM), perceived ease of use and perceived usefulness did not significantly influence attitude toward m-learning. Additionally, the hypothesized effect of learning autonomy on perceived behavioral control was not supported. These results highlight context-specific variations in technology acceptance within non-Western educational settings and suggest that cultural and infrastructural factors may moderate classic acceptance models. The study contributes to the literature on educational technology adoption in developing countries and offers practical implications for policymakers and educators aiming to integrate mobile learning effectively.

Keywords: TPB model, behavioral intention, attitude, mental norms

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Introduction

The education industry has experienced significant growth in the last decades and now has a unique opportunity to create effective learning using mobile learning (M-learning) (Eskandari & Valente, 2022). Researchers concluded that the efficiency of education in the traditional way reaches the highest quantitative and qualitative level when mobile communication technology is used as a supplement or part of combined education (Liu et al., 2022). Also, the high potential of M-learning as an educational tool is seen as the basis for creating a revolution in education (Mohd Razali Abd Samad et al., 2021). Recent advances in the field of communication and wireless technologies have made mobile devices accessible to everyone, facilitating their use and reducing their price.

It is important to note that having mobile devices does not necessarily mean using them in educational fields, as research shows that most students use their mobile phones for communication and pleasure-seeking purposes (Leung, 2020). However, the research has shown that students are interested in using new technologies in education and the reason for this is the diversity and flexibility of M-learning in education (Criollo-C et al., 2021). Therefore, educational institutions should be able to show the advantages of mobile devices for learning to students and provide the necessary conditions for the implementation of M-learning. Of course, the implementation of any system and technology requires knowing the factors influencing its acceptance in the new environment, therefore, to use M-learning as a new stage of electronic learning, the factors influencing its acceptance must be known in order to fully understand it. Its use in educational environments of the country took a step. In this regard, this research question can be raised, which are these factors, and more importantly, what is the degree of predictability of these factors on the intention to accept M-learning?

Literature Review

Basics and Conceptual Framework of Research

Due to insufficient integration of information and communication technologies (ICT) in education, educational systems have not progressed in line with broader technological and social transformations, creating a risk of learner disengagement from formal education (Adekunle Oke & Fernandes, 2020). As a result, education has increasingly incorporated ICT-based approaches such as distance learning, e-learning, and mobile learning (M-learning) to bridge this gap.

M-learning has been defined in multiple ways, reflecting its still-developing nature and the lack of consensus on the concept of "mobile." Early definitions emphasized mobile technologies, whereas more recent perspectives focus on learner mobility and contextual flexibility in using any available technology (Abdalwali Lutfi et al., 2022). In general, M-learning refers to the use of mobile or wireless devices for learning while learners are mobile (Yang et al., 2021). Broader definitions also include any learning occurring in mobile-supported environments, considering the mobility of both technology and learners (Oliveira et al., 2021). Accordingly, M-learning enables access to educational resources through devices such as smartphones, tablets, and PDAs, allowing learning across time and space (Criollo-C et al., 2021). In this sense, M-learning is often regarded as a subset and extension of e-learning, offering anytime-anywhere learning through mobile communication technologies (Eskandari & Tabibi, 2026).

M-learning represents a significant opportunity for enhancing educational experiences in schools (Alfalah, 2023). Consequently, educational institutions aim to align with rapid ICT developments by adopting these technologies to improve teaching and learning processes. In this context, understanding factors influencing technology acceptance is essential for effective integration. However, research on M-learning adoption using information systems theories remains limited, prompting calls for further studies based on established models (Wang et al., 2022).

Most prior studies have applied the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). In contrast, this study employs the Theory of Planned Behavior (TPB) as its main framework, as it better captures individual-level adoption processes rather than organizational contexts (Dube et al., 2020). Unlike earlier models focusing mainly on system characteristics, TPB allows consideration of users' perceived capabilities, which is particularly relevant for M-learning adoption.

Accordingly, this study examines the relationships between attitude, subjective norms, and perceived behavioral control with behavioral intention toward M-learning. Additionally, perceived ease of use, perceived usefulness, and perceived playfulness are linked to attitude, while teachers' and students' readiness relate to subjective norms. Perceived self-efficacy and learning independence are also considered determinants of perceived behavioral control. The inclusion of perceived playfulness is justified by the inherently interactive and enjoyable nature of mobile devices, which can enhance user motivation and positive attitudes (Abdalwali Lutfi et al., 2022).

In this study, M-learning is defined as any learning activity conducted through mobile devices such as smartphones, tablets, and e-readers, enabling access, sharing, and creation of knowledge anytime and anywhere.

Attitude refers to an individual's positive or negative evaluation of performing a behavior and is influenced by beliefs about its outcomes (Ajzen, 2020). Perceived ease of use reflects the extent to which M-learning is considered effortless, while perceived usefulness refers to its value in facilitating timely access to information (Qashou, 2021). Perceived playfulness includes attention focus, curiosity, and enjoyment during interaction with M-learning systems (Wang et al., 2022).

Subjective norms represent perceived social pressure from important others regarding technology use and are known to significantly influence behavioral intentions (Bagheri et al., 2019; Bhutto et al., 2021). Perceived behavioral control reflects individuals' perceived ability to perform a behavior, including both control over resources and self-confidence (Dar et al., 2022).

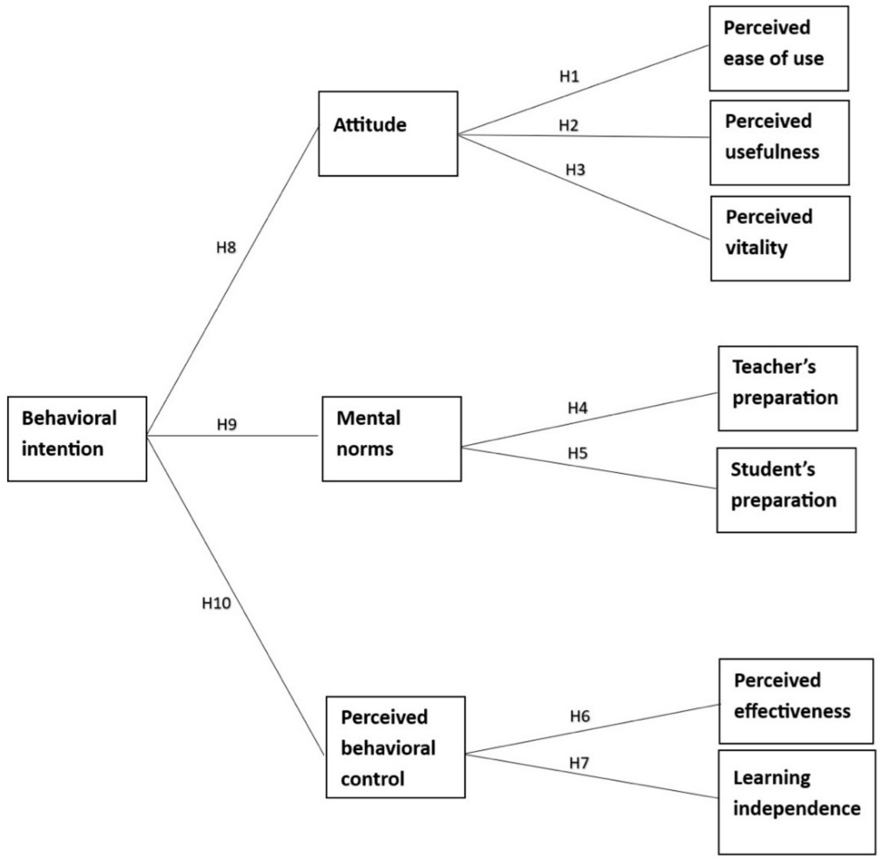
This construct is further explained through perceived self-efficacy and learning independence. Self-efficacy refers to confidence in one's ability to perform required actions and has been widely recognized as a predictor of technology adoption (Thongsri et al., 2020). Learning independence reflects self-discipline and responsibility in managing one's learning process (Orakci & Durnali, 2023). This is particularly important in M-learning contexts, where learners often operate independently from instructors and peers (Alamer & Al Khateeb, 2023).

Finally, behavioral intention represents users' tendency to adopt and use technology and is commonly used as a proxy for actual usage in M-learning research (Alfalah, 2023; Qashou, 2021). Therefore, in the present study, due to the impossibility of investigating the actual use of the behavioral intention variable, it is used to predict the acceptance of M-learning.

Theoretical Framework and Research Hypotheses

In Figure 1, the conceptual model and the relationships between the research's variables have been made according to the definitions, the introduced variables and the background of the research are shown in the form of ten hypotheses with the symbols H1 to H10.

Figure 1
Conceptual Model of Research



Methodology

This research is applied in terms of purpose and descriptive-analytical in terms of method. The research was conducted through international collaboration: data collection took place in Iran via local researchers and schools, while data analysis was handled by the authors affiliated with institutions in Spain and the United States. To collect data, a questionnaire (Cheon et al., 2012) was used in the field of M-learning acceptance, and for the items related to perceived vitality variable, a questionnaire (Moon & Kim, 2001) was used. The final questionnaire includes 7 questions about demographic information and 37 main items in the form of a five-point Likert scale. The study population of this research was high school students in Iran, and high schools in Tehran were selected as available samples. Since the principles of determining the sample size in multivariate regression analysis are also true for determining the sample size in structural equation modeling, the following formula can be used to determine the minimum number of samples (1) (Wolf et al., 2016).

$$5q \leq n \leq 15q \quad (1)$$

(Where q is the number of observed variables [questionnaire items] and n is the sample size.)

Some other researchers suggest a minimum sample size of 200 to perform structural equations. According to the 37 items of the questionnaire and the minimum sample size of 200, in this research, 318 people were finally selected as the study sample, and in order to analyze the data, the structural equation modeling method was used with Lisrel 8.71 software.

In order to confirm validity, two methods of content validity and structure validity have been used. Obtaining the opinions of supervisors, advisors and four management experts confirmed content validity, and construct validity was used in the form of determining convergent and divergent validity. Convergent validity was confirmed by using confirmatory factor analysis in such a way that the factor loadings related to the questionnaire questions were higher than 0.5 and the average value of Average Variance Extracted (AVE) was higher than 0.5. Table 1 shows the results of convergent validity analysis.

Table 1

The Results of Factor Loadings and Average Variance Extracted

Variable	AVE	Item	Factor loadings	Variable	AVE	Item	Factor loadings
Perceived ease of use	0.58	Q1	0.57	Perceived effectiveness	0.60	Q20	0.74
		Q2	0.54			Q21	0.77
		Q3	0.84			Q22	0.80
Perceived usefulness	0.61	Q4	0.72	Learning independence	0.60	Q23	0.63
		Q5	0.59			Q24	0.79
Perceived vitality	0.57	Q6	0.77			Q25	0.69
		Q7	0.54	Attitude	0.69	Q26	0.80
		Q8	0.55			Q27	0.80
		Q9	0.78			Q28	0.69
		Q10	0.57	Mental norms	0.64	Q29	0.75
		Q11	0.63			Q30	0.68
		Q12	0.57			Q31	0.76
Teacher's preparation	0.62	Q13	0.76	Perceived behavioral control	0.63	Q32	0.64
		Q14	0.78			Q33	0.71
		Q15	0.83			Q34	0.77
		Q16	0.56	Intention to acceptance M- learning	0.69	Q35	0.81
Student's preparation	0.63	Q17	0.76			Q36	0.79
		Q18	0.86			Q37	0.82
		Q19	0.58				

For divergent validity, the questions that measure one variable should have a high correlation with the target variable and a low correlation with the other variable. For this purpose, the root mean square of the extracted variance of the variable was compared with the correlation values that this variable has with other variable variables, and the root mean square of the extracted variance was greater than the correlation values, which confirms the divergent validity (Rönkkö & Cho, 2022). Table 2 shows the results of divergent validity analysis.

Table 2

The Pearson's Correlation Matrix and Root Mean Square Variance Extraction

Concept	1	2	3	4	5	6	7	8	9	10	11
Perceived ease of use	0.762										
Perceived usefulness	0.546**	0.781									
Perceived vitality	0.376**	0.472**	0.755								
Teacher's preparation	0.173**	0.194**	0.316**	0.787							
Student's preparation	0.348**	0.282**	0.294**	0.345**	0.794						
Perceived effectiveness	0.410**	0.487**	0.429**	0.189**	0.465**	0.812					
Learning independence	0.480**	0.535**	0.519**	0.330**	0.433**	0.568**	0.775				
Attitude	0.364**	0.497**	0.520**	0.374**	0.411**	0.628**	0.556**	0.831			
Mental norms	0.355**	0.421**	0.360**	0.364**	0.499**	0.405**	0.506**	0.529**	0.800		
Perceived behavioral control	0.334**	0.388**	0.392**	0.149**	0.410**	0.618**	0.479**	0.447**	0.392**	0.794	
Behavioral intention	0.394**	0.450**	0.394**	0.225**	0.426**	0.527**	0.458**	0.558**	0.433**	0.429**	0.831

Cronbach's alpha coefficient was also used to measure the reliability of the questionnaire. The results related to the reliability of each research variable are presented in Table 3. According to the results of the calculated coefficients, the reliability of the questionnaire was also confirmed.

Table 3

The Cronbach's Alpha Coefficient of Research Variables

Concept	*Item No.*	*Cronbach's alpha coefficient*
Perceived ease of use	3	0.655
Perceived usefulness	3	0.720
Perceived vitality	7	0.713
Teacher's preparation	3	0.713
Student's preparation	3	0.716
Perceived effectiveness	3	0.816
Learning independence	3	0.735
Attitude	3	0.803
Mental norms	3	0.771
Perceived behavioral control	3	0.752
Behavioral intention	3	0.854

Findings and Discussion

Tables 4 and 5 show descriptive findings related to demographic characteristics and research variables, respectively.

Table 4

The Descriptive Results of Demographic Findings

Demographic categories	*Range*	*Frequency*	*Percentage*
Gender	Female	168	52.8
	Male	150	47.2
Age	≥20	30	9.4
	21–25	176	55.3
	26–30	96	30.2
	≤31	16	5
Degree of study	Junior	168	52.8
	Senior	150	47.2
Discipline of study	Mathematical & physics	132	41.5
	Experimental science	36	11.3
	Humanities	150	47.2
Mobile devices	Cellular phone	107	32.7
	Smart phone	268	79.6
	Tablet	73	23
	Digital book reader	3	0.9
Mobile operators	MCI	219	68.9
	MTN Irancell	163	51.3
	RighTel	26	8.2
	Taliya	2	0.6
Using the Internet with a mobile device	Yes	275	86.5
	No	43	13.5
How to connect to the Internet	GPRS	53	16.7
	WiFi	222	69.8

Table 5

The Descriptive Indices for Research Variables

Concept	*Mean*	*Standard Deviation*	*Skewness*	*Kurtosis*
Perceived ease of use	4.0199	0.62707	-0.478	0.723
Perceived usefulness	4.0136	0.63942	-0.504	0.289
Perceived vitality	3.7062	0.5792	-0.171	0.117
Teacher's preparation	3.2369	0.77495	-0.338	-0.077
Student's preparation	3.7182	0.68009	-0.339	0.353
Perceived effectiveness	3.8623	0.81797	-0.765	0.374
Learning independence	3.6898	0.72247	-0.309	0.342
Attitude	3.6751	0.7893	-0.531	0.393
Mental norms	3.6088	0.71489	-0.362	0.105
Perceived behavioral control	4.0999	0.64809	-0.313	-0.428
Behavioral intention	4.0221	0.75929	-0.803	0.975

Fit of the Research Model

In the confirmatory factor analysis, the measurement tool was confirmed according to the obtained coefficients. In this part, the results of fitting the research model, as shown in Figure 2 and Table 6, indicate the approval of the model in terms of fit indices. Therefore, it is possible to depict the results of hypothesis testing according to the findings obtained through path analysis.

Figure 2

The Research Model in the Estimation Mode of Standard Coefficients and the Significance Mode of T Coefficients

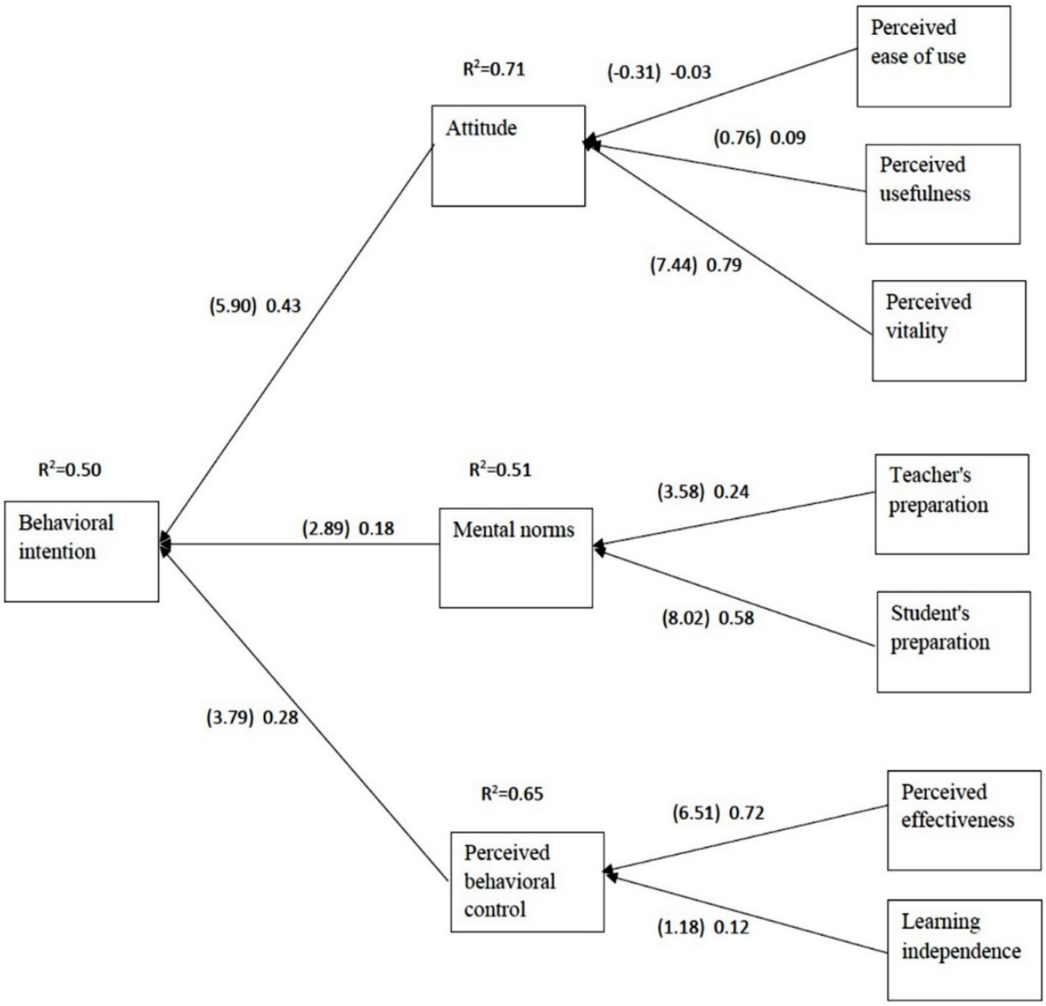


Table 6

The Model Fit Indices and Obtained Values

Indices	*Model estimates*	*Allowed limit*
Chi-square distribution	2.048	> 3
GFI	0.83	< 0.80
AGFI	0.81	< 0.80
RMSEA	0.057	> 0.090
CFI	0.96	< 0.90
NFI	0.92	< 0.90
NNFI	0.95	< 0.90
IFI	0.95	< 0.90

In figure number 2, the outputs of the path analysis show the research model in two modes of estimation of standard coefficients and significance mode. The research model shows the factor loadings and path coefficients in the estimation mode of the standard coefficients, and in the t coefficients or significance mode, it shows the values of the t statistic, which are used to judge the significance of the relationships.

Table 7 shows the results of the test of ten hypotheses in a summary form.

Table 7
The Path Coefficient, T-Statistic, Coefficient of Determination (COD) and the Result of Research Hypotheses

Research hypotheses	path coefficient	T-statistic	COD	Sig.	Result
Perceived ease of use→ Attitude	-0.03	-0.31	0.71	P > 0 .05	Reject
Perceived usefulness→ Attitude	0.09	0.76		P > 0 .05	Reject
Perceived vitality→ Attitude	0.79	7.44		P < 0.01	Confirm
Teacher's preparation→ Mental norms	0.24	3.58	0.51	P < 0.01	Confirm
Student's preparation→ Mental norms	0.58	8.02		P < 0.01	Confirm
Perceived effectiveness→ Perceived usefulness	0.72	6.51	0.65	P < 0.01	Confirm
Learning independence→ Perceived usefulness	0.12	1.18		P > 0.05	Reject
Attitude→ Intention to acceptance mobile learning	0.43	5.90	0.50	P < 0.01	Confirm
Mental norms→ Behavioral intention	0.18	2.89		P < 0.01	Confirm
Perceived behavioral control→ Behavioral intention	0.28	3.79		P < 0 .01	Confirm

As shown, seven of the ten hypotheses were supported, while three were rejected. The results indicated that perceived ease of use and perceived usefulness did not have a significant effect on attitude toward M-learning (H1 and H2 rejected). In contrast, perceived vitality had a significant positive impact on attitude. Both teachers' preparation and students' preparation showed significant positive effects on mental norms. Perceived effectiveness was found to positively influence perceived behavioral control, whereas learning independence did not show a significant effect. Finally, attitude, mental norms, and perceived behavioral control all demonstrated significant positive relationships with behavioral intention to use M-learning.

Conclusion

The purpose of this research was to introduce and determine the intensity of factors influencing the acceptance of M-learning and identify the type of relationships between these factors. Data analysis showed that the three main variables of the TPB model (attitude, mental norms and perceived behavioral control) have a positive and significant relationship with students' behavioral intention to accept M-learning and are considered suitable predictors for it. Meanwhile, attitude has the most effect with a path coefficient of 0.43, followed by perceived behavioral control with a path coefficient of 0.28 and mental norms with a path coefficient of 0.18. The reason for this could be the reduction of the influence of others' views on students' performance/non-performance of certain behavior. Also, the model used in this research showed that 50% of the variance of behavioral intention to accept M-learning ($R^2 = 0.50$) was influenced by three factors of attitude, mental norms and perceived behavioral control. This shows the high predictability of the model in the studied society.

Despite the non-significance of the two variables perceived ease of use and perceived usefulness, perceived vitality as a predictor of the attitude variable has the greatest effect on attitude with a path coefficient of 0.79. The studied sample shows that 79.6 percent of the students use smart phones and all of them use mobile devices, this shows that in their opinion the perceived ease of use is no longer considered as a predictor of attitude and behavioral intention. Also, due to the fun and enjoyable aspects of M-learning, perceived usefulness has lost its predictability in favor of perceived vitality. Of course, this issue does not hide the importance of these two factors, and for the implementation of M-learning, usefulness and ease of use should be considered as effective factors in the design and construction of software, interface and educational materials. Also, 71% of the attitude variance highlights the need to pay attention to the aforementioned variables.

On the other hand, it was found that the preparation of teachers and the preparation of students have a positive and significant effect on mental norms, with the explanation that the preparation of students with a path coefficient of 0.58 is more than the preparation of teachers with a path coefficient of 0.24. This shows that students are more influenced by their peers to use M-learning. This shows that students believe that teachers are less prepared than students to use M-learning. In addition, it should be noted that the two variables of teachers' and students' preparation explain 51% of the variance of mental norms.

Finally, the results of data analysis regarding the effect of the perceived self-efficacy variable on the perceived behavioral control variable were also positive and significant, but the effect of the learning independence variable on the perceived behavioral control variable was not confirmed. There is a belief that the traditional methods of teaching and teacher-centered in traditional curricula have caused students to have less choice in choosing learning resources and activities. Therefore, the lack of self-confidence necessary to create knowledge and control the speed of learning by students and relying on teachers' opinions and beliefs in each part of learning can be considered as among the inhibiting factors in predicting the behavioral control variable perceived by learning independence. It should be noted that the two variables of perceived self-efficacy and learning independence explain 65% of the variance of perceived behavioral control, which is a significant amount.

Suggestions

Although mental norms had the least effect on behavioral intention in this research. But this finding showed that from the perspective of students, teachers are less prepared to use M-learning. Since this issue shows the importance of the role of teachers in accepting M-learning by students; therefore, it is suggested that schools prepare teachers for the implementation of M-learning systems in schools with various organizational supports such as technical support and professional development.

The high percentage of using smart phones in the studied sample (close to 80%) and all of them using mobile devices can be considered as a sign of changing the teaching style and diversifying it by the teachers. Therefore, in addition to revising the programs and curriculum content, special attention should be paid to the diversification of teaching methods by the policy makers in the educational field. Considering the effect of perceived self-efficacy on perceived behavioral control by students, it is necessary for students to consider the use of mobile devices as an opportunity for learning and if there are no suitable conditions in the educational environment, such a task for define themselves.

In conclusion, it should be noted that the model used in this research was the developed TPB model and the results showed that based on this model, 50% of the variance of M-learning acceptance can be explained by the factors of this model. Future researches can examine other models of technology acceptance to examine the acceptance of M-learning and compare the results with the current research model so that the most suitable model is the basis for future researches. In addition, the data of this research has been collected cross-sectionally, while the perception of people changes with the passage of time, education and experience. As a result, it is better for future researches to use longitudinal methods to obtain data so that they can better understand the state of M-learning acceptance and identify the influencing variables more accurately.

Declaration of Generative AI and AI-Assisted Technologies in the Writing Process

The authors declare that ChatGPT (OpenAI), an AI-assisted writing tool, was used to support English language refinement and structural editing of the manuscript. The use was limited to improving clarity, coherence, and academic phrasing. The ideas, design, procedures, findings, analyses, and discussion are based on the authors' research activities and project documentation, and the authors reviewed and finalized all content.

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