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Research on Influencing Factors of Mobile Learning Behavior of Secondary Vocational Students

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Abstract

In recent years, with the continuous development of cognitive learning theory, research on learning behavior has been gradually discussed in the field of educational psychology. Among them, many scholars have explained the factors affecting learning behavior from different aspects. Taking secondary vocational students as the object, this paper intends to start from the internal and external factors affecting mobile learning behavior, integrate TAM model and TTF model, and combine quantitative and qualitative research methods to explore the influencing factors and generation paths of mobile learning behavior.

Keywords

Mobile learning, Technology acceptance model, Task technology matching model.

1. Introduction

Mobile learning is a new digital learning form with mobility, interaction, timeliness and personalization that utilizes wireless mobile communication technology to obtain educational information, educational resources and educational services through wireless mobile devices (mobile phones, tablets, etc.) [1].In the study of the influence factors of mobile learning, many researchers from the inside of the individual, the research on learners' individual psychological behavior research, this article refers to the internal factor is starting from the psychological characteristics of learners to research of mobile learning behavioral intention, Technology Acceptance Model (Technology Acceptance Model, TAM) can explore learners internal perception factors affect learning behavior. The external factor referred to in this paper is to study mobile learning based on the characteristics of mobile learning support system. Task Technology Fit (TTF) can explore the influence of users' use of new technologies on their external perception, that is, their mobile learning behavior.

2. Related research

2.1. Correlation Theory

2.1.1. Technology Acceptance Model (TAM)

TAM is the theoretical relationship model proposed by Fred D. Davis in 1989, based on the Theory of Reasoned Action (TRA), which studies the way individuals receive information technology [2].The technology acceptance model includes several key variables: Perceived Usefulness (PU), Perceived ease of use, Behavioral Intention (BI), and Behavioral Attitude (BA).The model that the use of the target system is mainly decided by the use of the individual user behavioral intention to use the behavioral intention is determined by the use of attitude and perceived usefulness, perceived usefulness and perceived ease of use has decided to use the attitude, external variables perceived usefulness and perceived ease of use decision, perceived ease of use is determined by the external variables [2].As shown in figure 1.

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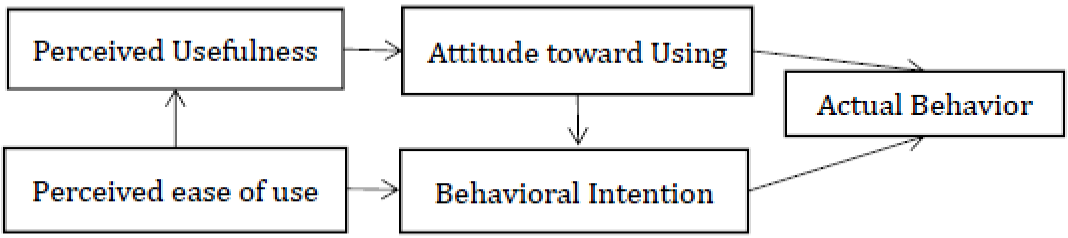

Fig 1. Technology Acceptance Model, TAM

2.1.2. Task Technology Matching Model (TTF)

Goodhue and Thompson in 1995 put forward the task technology matching model (the vera.ttf), used for explaining the new technology for the user to complete the task, the support degree of personal characteristics, task characteristics and technology characteristics of the three is the consistent degree between the task technology compatibility, personal characteristics is the user's own factors (such as age, gender, motivation, etc.) the extent of the use of information technology; Technical features refer to the hardware devices that the new technology can help the user to complete the task. Task characteristics are factors that encourage users to use new technologies to help them complete tasks [3]. According to Goodhue and Thompson, task characteristics, personal characteristics, and technical characteristics affect the technical matching degree of the task, thus affecting the usage behavior [3]. As shown in figure 2.

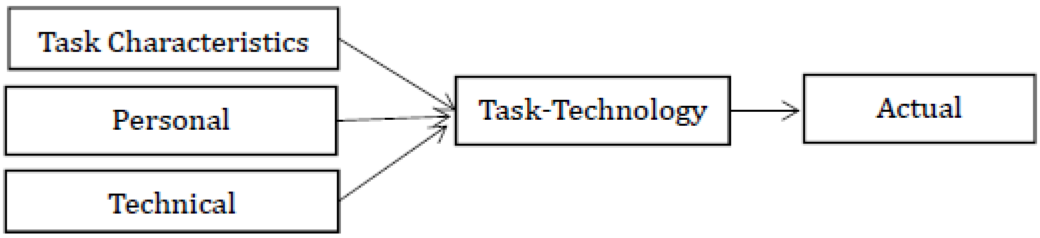

Fig. 2 Task Technology Fit, TTF

3. Model Construction and Hypothesis

In the research of technology acceptance behavior, some scholars have studied the combination construction of TAM and TTF model [4]. Taking normal colleges as an example, Wang Jintao constructed the theoretical relation models of eight latent variables, and found that the models had good adaptability [5]. The study found that TAM and TTF have a good binding degree [6].

On the basis of the existing literature, this research focuses on the external factors and internal factors that affect mobile learning behavior, technology acceptance model model of perceived usefulness and perceived ease of use is the learners intrinsic perception of their own cognition, attitude and emotion, the task of matching model model matching and task technology matching is for mobile learning behavior whether can achieve the goal of learning to perceive, is foreign in perception. This study combines intrinsic and extrinsic, and focuses on group differences in m-learning behaviors. Based on this, the structural equation model of M-learning behaviors is established, and hypotheses are proposed from the following aspects.

3.1. Perceived Usefulness

In mobile learning, perceived usefulness refers to the perception that students adopt mobile learning behaviors to improve their academic performance. Perceived usefulness is one of the key variables in TAM model, and Davis believes that it has a significant positive impact on behavioral intention [2].

H1: Perceived usefulness of learners' m-learning positively affects m-learning behavioral intention.

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3.2. Perceived Ease of Use

In mobile learning, perceived ease of use refers to the perception of the ease with which students adopt mobile learning behaviors. Perceived ease of use is also one of the key variables of TAM model. Davis believes that perceived ease of use has a significant positive impact on perceived usefulness, while perceived ease of use has a positive impact on behavioral intention [2].

H2: Perceived ease of use of m-learning positively affects m-learning behavioral intention.

H3: Perceived ease of use of learners' mobile learning positively affects perceived usefulness of mobile learning.

3.3. Behavioral Intention

In mobile learning, behavioral intention refers to students' perception of their willingness to adopt mobile learning behaviors. Numerous studies have confirmed the relationship between behavioral intention and actual behavior, such as teachers' information teaching behavior [7], children's online reading behavior [8], and villagers' emergency behavior [9]. Therefore, the following hypotheses emerge:

H4:m-learning behavioral intention positively affects learners' actual m-learning behavior.

3.4. Task Characteristics

In mobile learning, task characteristics refer to the tasks completed or learning effects achieved by students through mobile communication devices and mobile networks. Goodhue and Thompson believed that the task characteristics had a significant positive impact on the technical matching degree of the task [3].

H5: Task characteristics of learners' mobile learning positively affect task technology matching degree.

3.5. Technical Features

In mobile learning, technical features refer to the activity features of students' mobile learning by manipulating mobile communication devices. As with the task characteristics, it was believed by Goodhue and Thompson that it had a significant positive impact on the task technical matching [3].

H6: The technical characteristics of learners' mobile learning positively affect the task-technology matching degree.

3.6. Task Technology Matching Degree

In mobile learning, task technology matching refers to the extent to which students complete tasks through mobile learning behaviors [3]. Is one of the target variables for this study, which Goodhue and Thompson believe has important implications for the behavior of using the new technology.

H7: The task-technology matching degree of mobile learning positively affects the actual behavior of mobile learning. Based on the above assumptions, a research model of mobile learning behavior is established, as shown in Figure 3:

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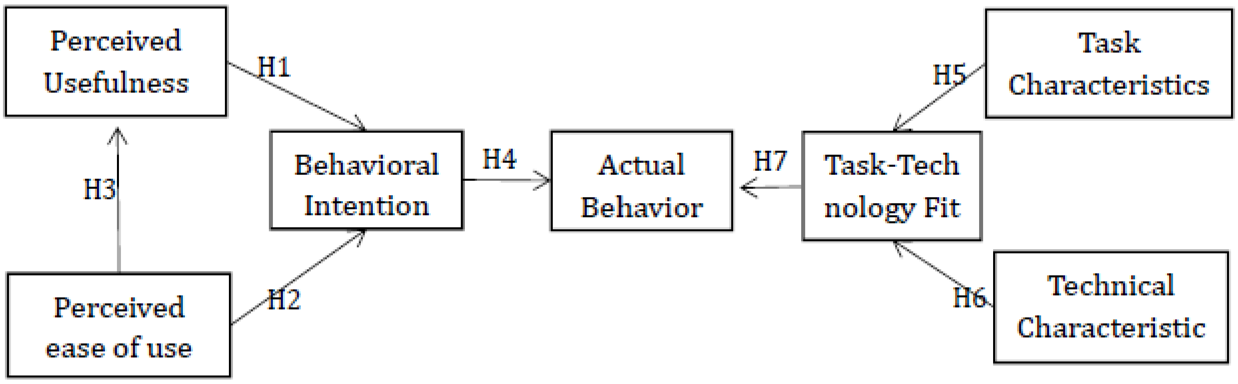

Fig 3. Mobile learning behavior research model

4. Empirical Research

4.1. Preparation of Questionnaires

This questionnaire is compiled according to the mature scale adopted by the existing research institute, combined with both Chinese and English, and then modified according to the characteristics of students. The questionnaire is divided into the following parts: perceived usefulness (PU), perceived ease of use (PEU), technical characteristics (TEC), task characteristics (TAC), technology-task matching (TTF), behavioral intention (BI), practical use behavior (AB) and demographic characteristics.

4.2. Questionnaire Distribution and Recovery

Due to the influence of COVID-19, all questionnaires were distributed online, that is, the star questionnaire was uploaded, the QR code was downloaded and sent to the class group to fill in. This sampling is to use a convenient way at home, a secondary vocational school students in Xinyang city issued a questionnaire. A total of 230 questionnaires were collected, of which 215 were valid. The effective rate is 93.47%. The questionnaire will be issued on May 05, 2020, and completed by May 10, 2019.

4.3. Data Statistics and Analysis

SPSS 20.0 and AMOS 20.0 were used for data analysis and model validation analysis. The data were input into SPSS for data initialization. The basic information of data source was analyzed for descriptive test of sample data, and the normal distribution of samples was tested. Then, Cronbach coefficient and CFA of the questionnaire were tested for analysis, and the convergent validity of the model was analyzed, so as to have a general judgment on the reliability and validity of the model. Finally, the structural equation model (SEM) analyzes the path of the model and tests the hypothesis.

4.3.1. Descriptive Statistical Analysis of Questionnaires

SPSS software was used to conduct descriptive statistics on the samples and analyze the demographic characteristics and basic information of the research objects:

4.3.2. Test of Measurement Model

In order to ensure the significance of structural model inspection, the measurement model inspection is carried out.

(1) Cronbach 'α values are commonly used to measure the reliability of the model. If Cronbach 'α value ≧ 0.7, measurement model has good reliability, Cronbach' α value between 0.5 to 0.7 show the reliability of the general measurement model. From table 2, Cronbach 'α value is greater than 0.7, better show the reliability of measurement model, the data consistency of measurement model to reach standard, as shown in table 2.

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Table 1. Descriptive analysis table of demographic Statistics

The basic information	category	The number of people	The percentage
gender	male	53	24.70%
	female	162	75.30%
grade	In grade one	67	31.20%
	Second grade	52	24.20%
	The third grade	96	44.60%
When using the Internet on a mobile phone	Less than 2 hours a day	32	14.90%
	Two to four hours a day	107	49.70%
	Four to six hours a day	64	29.80%
	More than 6 hours a day	12	5.60%
Mobile learning frequency	Every day,	43	20%
	3 to 4 times a week	117	54.40%
	1 to 2 times per week	43	20%
	Less than once a week	12	5.60%

Table 2. Reliability coefficient of measurement model

Latent variables	item	The mean	The standard deviation	Cronbach 'ɑ
Perceived ease of use	PEU1	4.524	1.22	0.806
	PEU2	4.662	1.212	
	PEU3	4.758	1.2	
Perceived usefulness	PU1	4.546	1.159	0.871
	PU2	4.594	1.117	
	PU3	4.382	1.105	
	PU4	4.854	1.112	
The technical features	TAC1	4.859	1.099	0.858
	TAC2	5.023	1.042	
	TAC3	5.259	1.075	
Task characteristics	TEC1	4.859	1.087	0.801
	TEC2	4.589	1.018	
	TEC3	4.687	1.056	
Task - skill matching	TTF1	5.159	1.012	0.758
	TTF2	5.023	1.128	
	TTF3	4.427	1.035	
Behavioral intention	BI1	5.239	1.005	0.861
	BI2	5.256	1.002	
	BI3	5.121	1.01	
Actual use behavior	AB1	4.649	1.039	0.820
	AB2	4.321	1.031	
	AB3	5.052	1.001	

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(2) To test the convergence validity of the measurement model, the following conditions should be met: factor load > 0.7, composite reliability > 0.7, and average variance extracted value >0.5.Only when these three conditions are met can the convergence validity of the measurement model be better, as shown in Table 3.The factor load of each measurement item is greater than 0.7, the compound reliability is greater than 0.7, and the extracted value of mean variance is greater than 0.5, indicating that the measurement model has a good convergence validity.

Table 3. Convergence validity of the measurement model

Latent variables	item	Factor loading	Composite reliability (CR)	Average variance extracted value (AVE)
Perceived ease of use	PEU1	0.721	0.816	0.616
	PEU2	0.816		
	PEU3	0.780		
Perceived usefulness	PU1	0.844	0.882	0.677
	PU2	0.884		
	PU3	0.780		
	PU4	0.729		
The technical features	TAC1	0.774	0.863	0.699
	TAC2	0.910		
	TAC3	0.783		
Task characteristics	TEC1	0.781	0.811	0.607
	TEC2	0.741		
	TEC3	0.781		
Task - skill matching	TTF1	0.812	0.768	0.544
	TTF2	0.741		
	TTF3	0.712		
Behavioral intention	BI1	0.808	0.861	0.695
	BI2	0.841		
	BI3	0.827		
Actual use behavior	AB1	0.822	0.822	0.625
	AB2	0.772		
	AB3	0.743		

(3) To test the discriminant validity of the measurement model, it is generally believed that if the square root value of AVE of each test variable is greater than the correlation value of this variable and other test variables, it means that there is a good discriminant validity among all test variables. As can be seen from Table 4, the square root of AVE of all latent variables is greater than its correlation coefficient with other latent variables, indicating that this measurement model can well meet the criterion of discriminant validity.

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Table 4. Discriminant validity of the measurement model

	AVE	AB	BI	TTF	TEC	TAC	PI	PEU	PU
AB	0.625	**0.791**							
BI	0.695	0.429	**0.834**						
The vera.ttf	0.544	0.535	0.348	**0.738**					
TEC	0.607	0.214	0.297	0.496	**0.779**				
TAC	0.699	0.437	0.515	0.368	0.244	**0.836**			
PI,	0.708	0.200	0.479	0.154	0.153	0.135	**0.841**		
PEU	0.616	0.267	0.352	0.256	0.134	0.148	0.258	**0.785**	
PU	0.677	0.248	0.424	0.114	0.021	0.287	0.233	0.078	**0.823**

4.3.3. Structural Model Test

Through AMOS 20.0 software using maximum likelihood estimation method to analyze the latent variable model adaptation degree, chi-square value is 349.017, the degrees of freedom for 263, chi-square/degrees of freedom is 1.327, GFI = 0.921, AGFI = 0.902, CFI = 0.978, NFI = 0.916, RMSEA = 0.032, each index reach the standard, excellent model adaptation degree, that model has good fitting, for further analysis of the path.

Table 5. Research hypothesis testing results

Assuming that	The path	Path coefficient	significant	The authentication
H1	Perceived usefulness → behavioral intention	0.34	* * *	Support the hypothesis
The H2	Perceived ease of use → behavioral intention	0.262	* * *	Support the hypothesis
H3	Perceived ease of use → perceived usefulness	0.097		Do not support hypothesis
H4	Behavior intention → actual use behavior	0.297	* * *	Support the hypothesis
H5	Task characteristics → task - technology matching	0.421	* * *	Support the hypothesis
H6	Technical features → task-technical matching	0.287	* * *	Support the hypothesis
H7	Task-technology matching → actual usage behavior	0.464	* * *	Support the hypothesis

Note: ** represents P<0.01 and *** represents P<0.001.

4.3.4. Hypothesis Testing

Table 5 shows the test results of the research hypothesis. The perceived usefulness of learners' m-learning positively affects m-learning behavior. The verification results support hypothesis H1 with a path coefficient of 0.340 (P <0.001).The perceived ease of use of mLEARNING positively affects mLEARNING behavioral intention, and the verification results support hypothesis H2 with a path coefficient of 0.262 (P <0.001).The perceived ease of use of mobile learning positively affects the perceived usefulness of learners, and the verification results do not support hypothesis H3, that is, the perceived use of mobile learning has no significant influence on the perceived ease of use. The behavioral intention of mLEARNING learners positively influences the actual use behavior of MLEARNING. The verification results support

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hypothesis H4 with a path coefficient of 0.297 (P <0.001).The task characteristics of learners' mobile learning positively affect the task technology matching degree, and the verification results support hypothesis H5 with a path coefficient of 0.421 (P <0.001).The technical characteristics of learners' mobile learning positively affect the task-technology matching degree, and the verification results support hypothesis H6 with a path coefficient of 0.287 (P <0.001).The task-technology matching degree of mLEARNING positively affects mlearning behavior, that is, the data results support hypothesis H7 with a path coefficient of 0.464 (P <0.001).

5. Research Conclusion and Thinking

5.1. The Influencing Mechanism of Secondary Vocational Students' Mobile Learning Behavior

5.1.1. Internal Factors of Mobile Learning Behavior

(1) Perceived usefulness positively affects learners' behavioral intention of mobile learning.

It can be seen from the above data table that the path coefficient of perceived usefulness (=0.340) is greater than the influence of perceived ease of use (=0.262), indicating that students have great expectations on whether mobile learning behavior can truly improve their learning outcomes and is more conducive to their attention retention.

(2) Perceived ease of use positively influences m-learning behavioral intention.

According to the above data table, perceived usefulness of mobile learning behavioral intention beta = 0.262, P < 0.001 data shows that the degree of hardware and software is easy to use for mobile learning behavioral intention plays an important role, for learners to provide a simple and easy to operate, strong accessibility of equipment and learning platform for mobile learning behavior and has an important role.

(3) The data results show that the path coefficient between m-learning behavioral intention and actual learning behavior is =0.297, P<0.05, that is, the stronger the m-learning behavioral intention is, the higher the mlearning actual behavior execution will be.

5.1.2. External Factors of Mobile Learning Behavior

(1) Task technology matching degree, task characteristics and technical characteristics

The path coefficient of m-learning task characteristics and task technology matching degree is =0.421, P<0.05, indicating that task characteristics have a positive influence on task technology matching degree. In other words, the stronger mlearning task characteristics are, the higher the task technology matching degree will be. The path coefficient of technical characteristics and task technology matching degree is =0.287, P<0.05, indicating that technical characteristics positively affect task technology matching degree, that is, the stronger the technical characteristics of mobile learning, the higher the task technology matching degree will be.

(2) Task technology matching degree and actual mobile learning behavior

The path coefficient between the task-technology matching degree and the actual use behavior of m-learning was =0.463, P<0.05, indicating that the task-technology matching degree positively affected the actual behavior of m-learning. In other words, the higher the task-technology matching degree is, the higher the occurrence rate of learners' actual mobile learning behaviors will be.

5.2. Research Limitations

Although this study has gone through a lot of literature search and rigorous research design, it still has certain limitations due to the limitations of the researcher's own ability, mainly reflected in the limitations of sample data and research content.

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On the one hand, due to the limitations of time and financial resources, the number of samples in this study is not enough, and the source of samples is mainly limited to a vocational school in my city, which makes the study have certain limitations. Though the other side, this research model has been on the TAM and the vera.ttf combination, formed the combination model of 7 latent variables, but failed to take into account many factors, many researchers in their study and explore the other influence factors of mobile learning behavior (technical support, trust, subjective norm, behavior, attitude), this study is limited to can achieve the result that the number of samples and model integrating variables that are not in too much, and in the later study, can put the relevant variables for further, just for the generation of mobile learning behavior path for further inquiry.

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