DOI: 10.23977/appep.2023.040910
ISSN 2523-5842 Vol. 4 Num. 9

Factors Influencing Self-directed Learning Behavior of Higher Vocational Students in Guangdong, China, under Blended Teaching Mode

Junxiu Lin, Eugene P. Hontiveros*

School of Graduate Studies, La Consolacion University Philippines, Bulacan, 3000, Philippines
**Corresponding author*

Keywords: Self-directed Learning Behavior; Higher vocational students; Blended Teaching Mode; Structural Equation Modeling

Abstract: This paper investigates the influencing factors of self-directed learning behavior of higher vocational students under blended teaching mode. This study aims to analyze the influence of behavioral intention, attitude, perceived usefulness, perceived ease of use, compatibility, subjective norms, peer influence, supervisor influence, perceived behavioral control, self-efficacy, resource and technological conditions, past behavior, and preliminary knowledge on students' self-directed learning behavior. The study design consisted of collecting data through an online survey and applying structural equation modeling (SEM) for data analysis using SmartPLS 4.0 software. It was found that perceived behavioral control, past behavior, and preliminary knowledge have a significant impact on students' self-directed learning behavior. This study provides valuable insights for higher education faculty and institutions to optimize the implementation of blended learning and promote independent learning.

1. Introduction

In the era of the knowledge economy, there has been an increasing acceptance of lifelong learning, as noted by Hu[1]. Vocational courses have gained significant popularity as a universal public resource accessible to all individuals. Despite their evident benefits in fostering technical skills, vocational courses often lack adequate attention in terms of on-the-job training and post-career education. However, the inherent nature of the Internet as a platform for open and distance learning offers a solution to overcome spatial limitations and enhance the breadth of vocational courses. Additionally, it enables educators in vocational courses to stay aligned with technological advancements.

In the digital era, education has undergone significant changes with the integration of classroom and digital information. The application of digital technology in teaching has shifted from a special need to a necessary choice[2]. In 2020, the COVID-19 pandemic prompted Chinese universities and schools to adopt online teaching, leading to a surge in the popularity of the "online + offline" blended teaching mode. This trend has sparked discussions on curriculum reform, driven by the rise of Small Private Online Courses (SPOCs), Massive Open Online Courses (MOOCs), and other web-based educational platforms[3]. Blended teaching combines the advantages of online and offline education, addressing the limitations of traditional classroom teaching and offering flexibility, independent learning, and abundant resources. However, it is important to recognize that online education is not a universal solution. The blended teaching method aims to improve students' abilities and competencies by combining online and physical classroom learning, aligning with the Chinese government and Ministry of Education's requirements for high-quality courses that cater to personalized and independent learning needs.

In 2018, then-Chinese Minister of Education Chen Baosheng proposed at the National Conference on Undergraduate Education in Higher Education in a New Era that the curriculum of higher education institutions should be made more challenging, expand the difficulty of the curriculum, reasonably increase the difficulty of the curriculum, and expand the options of the curriculum. Colleges and universities should actively and effectively transform meaningless lessons (called "watery lessons") into difficult, challenging, and meaningful lessons (called "golden lessons"). Subsequently, the Ministry of Education [4] officially issued a document proposing to eliminate meaningless courses and create meaningful courses. Also in 2019, the Chinese Ministry of Education launched the “Double 10,000 Initiative”[5], which aims to create five types of high-quality courses, building quality education in five directions: online, offline, blended education, virtual simulation courses, and social practice. It can be seen that the blended teaching method is an important option in the construction of a quality curriculum.

The pursuit of high teaching quality not only affects undergraduate colleges, but also people pay more and more attention to the education quality and talent training mode of higher vocational education[6]. The application of modern educational technology can, to a certain extent, prevent the skills learned by the high-skilled talents trained in higher vocational colleges from being eliminated when they enter the society[7]. Therefore, promoting the application of modern teaching technology in higher vocational education and organically combining online resources with offline teaching will become a breakthrough in the reform and development of education and teaching in higher vocational institutions. In March 2022, China's Ministry of Education also launched the National Vocational Education Smart Education Platform, which covers four major sections: “Professional and Curriculum Service Center”, “Teaching Material Resource Center”, “Virtual Simulation Training Center” and “Teacher Service Center”[8].

The implementation of online educational resources and platforms presents challenges such as high participation rates but also high logout rates, delayed assessment of student learning outcomes, and limited interactivity[9]. These issues highlight the insufficient self-directed learning ability of higher vocational students to support a fully online teaching mode. There is a research gap in exploring the positive factors influencing self-directed learning behaviors in the blended teaching mode.

This study aims to fill the research gap by examining the factors influencing self-directed learning behavior of higher vocational students in a blended teaching environment. It integrates the Decomposed Theory of Planned Behavior (DTPB) and using two additional factors, past behavior and preliminary knowledge to enhance predictive power. Data was collected from 351 vocational students in Guangzhou, China, through a 5-point Likert self-designed questionnaire. The relationships among variables were analyzed using SEM, identifying factors impacting students' self-directed learning behavior. The proposed model provides insights into vocational students' self-directed learning behavior and offers recommendations for enhancing blended teaching and learning.

1.1 Hypotheses of the Study

H 1: There is no relationship that exists between and among the following influencing factors: Learning Intention, Blended Teaching Mode, Attitude, Perceived Usefulness, Perceived Ease of Use, Compatibility, Subjective Norms, Peer Influence, Superior Influence, Perceived Behavioral Control, Self-efficacy, Resource and Technology Facilitating Conditions, Past Behavior, and Preliminary Knowledge.

H 2: Past behavior is not correlated with self-directed behavior and learning.

H 3: Preliminary knowledge is not positively related to the respondents' self-directed behavior and learning intention.

Figure 1 below shows the detailed information on the hypotheses of the study.

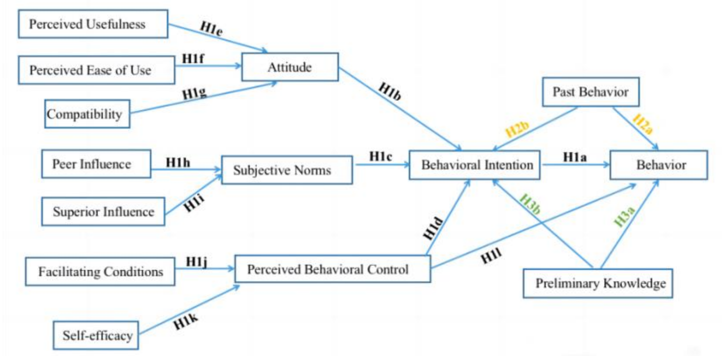

Figure 1: Hypotheses of the Study

2. Methods and Techniques of the Study

This study utilized a self-developed questionnaire, incorporating demographic information, to collect data. The questionnaire's reliability and authenticity were ensured through statistical methods like Cronbach's alpha, exploratory factor analysis, and expert review. Descriptive statistics provided insights into participant profiles. The study employed Partial Least Squares Structural Equation Model (PLS-SEM) analysis using SmartPLS 4.0 software[10] to examine the relationship between predictive factors and self-directed learning behavior among higher vocational students in blended teaching, identifying the most influential factors.

3. Presentation, Analysis and Interpretation of Data

3.1 Profile of the Participants

Table 1: Profile of the Participants

Measure	Item	N	Percentage
Gender	Male	158	45.0%
	Female	193	55.0%
Grade Level	Grade 1	211	60.1%
	Grade 2	52	14.8%
	Grade 3	88	25.1%
Major	Air Service	204	58.1%
	Aviation All Media Operations	38	10.8%
	Aviation Mechanical Maintenance	109	31.1%

Demographic characteristics of the 351 participants who took part in the study demonstrates in Table 1. These demographic details provide an overview of the participants' sex, grade level, and major, establishing a foundation for further analysis and interpretation of the study's findings.

3.2 Reliability of the Influencing Factors Model

This study utilized structural equation modeling (SEM), specifically the partial least squares (PLS) method, to analyze the data. The validity of the measurement model and the validation of research hypotheses were assessed using SmartPLS 4.0 software. Before analyzing the structural equation model, it is crucial to evaluate the reliability and validity of the measurement model. This ensures that the measurement model meets established criteria for reliability and validity, which is essential for meaningful outcomes from the structural equation model analysis. The reliability of the measurement model was assessed using three widely recognized techniques: Cronbach's alpha, composite reliability, and average variance extraction (AVE). These techniques provide insights into the internal consistency and overall reliability of the observed variables that measure the underlying structure within the model.

Cronbach's alpha serves as a statistical metric employed to gauge the extent to which items within a construct exhibit interrelatedness and coherence. This assessment quantifies the degree of internal consistency by evaluating the collective capability of items to measure the fundamental constructs. A Cronbach's alpha value exceeding 0.6 signifies the scale's validity[11]. Notably, a higher value of Cronbach's alpha indicates robust internal consistency, affirming that the items consistently assess the same construct.

Conversely, composite reliability evaluates the comprehensive reliability of the measured model, encompassing the internal consistency of items and the average variance extraction (AVE) of latent constructs. This evaluation offers a more holistic reliability measure by determining the shared variance among items and their ability to encapsulate the latent structure. As proposed by Qin[12], a composite reliability (rho A) value surpassing 0.8 and an AVE value exceeding 0.5 are recommended to ensure sound convergent validity, aligned with Denton, Chi & Gursoy[13].

Table 2: Reliability test results of the model

	Cronbach's alpha	Composite Reliability (rho_a)	AVE
Attitude(A)	0.853	0.879	0.626
Behavior(B)	0.906	0.920	0.680
Behavioral Intention(BI)	0.798	0.808	0.713
Compatibility(C)	0.832	0.638	0.493
Facilitating Conditions(FC)	0.852	0.875	0.688
Past Behavior(PB)	0.894	0.912	0.701
Peer Influence(PI)	0.880	0.915	0.673
Perceived Behavioral Control(PBC)	0.893	0.894	0.700
Perceived Ease of Use(PEU)	0.871	0.909	0.658
Perceived Usefulness(PU)	0.894	0.913	0.702
Preliminary Knowledge(PK)	0.902	0.937	0.715
Self_efficacy(Se)	0.886	0.915	0.690
Subjective Norms(SN)	0.891	0.905	0.697
Superior Influence(SI)	0.884	0.919	0.670

Table 2 presents the results of the reliability analysis, including Cronbach's alpha and composite reliability values for each latent construction.

As can be seen from Table 2, Cronbach's alpha coefficients of all variables are above 0.6, indicating that these variables have quite good reliability.

From the perspective of CR, all variables, except compatibility, are above 0.8, indicating a high level of internal consistency and reliability for these variables. These CR values demonstrate that the observed variables can consistently and reliably measure potential constructs. However, it is worth noting that a lower CR value for the Compatibility variable indicates a relatively weak level of internal consistency and reliability for this particular structure. This may indicate that items within Compatibility may not be as strongly related to each other.

As for AVE, except Compatibility, AVE values of all other variables are greater than 0.6, which indicates that the model has a good convergent validity. An AVE value lower than 0.5 indicates

Compatibility possesses a relatively weaker level of convergence among the measured items within the construct. This result further indicates that the items within the Compatibility variable own less variance with the construct.

3.3 Validity of the Influencing Factors Model

The focus of this section is the evaluation of the validity of the measurement model from two perspectives: convergent validity and discriminant validity. Validity is a critical aspect of any measurement instrument because it ensures that the intended constructs are accurately measured. Convergent validity examines the alignment and agreement of different measures that target the same construct. In contrast, discriminant validity assesses the distinctiveness of different constructs. It confirms that they do not overlap. By examining both convergent and discriminant validity within the measurement model, researchers can be confident in the accuracy and robustness of the measurement tools used.

Convergent validity stands as a vital component of measurement model validation, assessing the consistency of multiple measurements for the same construct[16]. It gauges the degree of alignment or agreement among diverse indicators or items designed to measure the same construct. This is primarily substantiated through two indicators: factor loadings and AVE (Average Variance Extracted). Generally, factor loadings are deemed acceptable if they exceed 0.5, while AVE should surpass 0.5. When these two criteria are met, it signifies strong convergent validity, ensuring the reliability of measurement items and the overall questionnaire quality. In addition to factor loading measurements, the T-values and the significance of each item are also assessed. The outcome of these tests is displayed in Table 3.

In the evaluation of the measurement model, the convergent validity of the latent variables was appraised by scrutinizing the factor loadings, T-values, and P-values for each indicator (refer to Table 3 for comprehensive details). Factor loadings signify the strength of the relationship between each indicator and its respective latent variable. T-values established the statistical significance of these factor loadings, while P-values determined whether these factor loadings significantly deviated from zero. A significance threshold of $p < 0.05$ was utilized to ascertain statistical significance.

Table 3 presents the outcomes of the measurement model's validity assessment, outlining the factor loadings, T-values, and P-values for each indicator, as well as AVE values for each latent variable. Almost all factor loadings surpass 0.6, excluding Q1 and Q4 of Compatibility, which suggests that these two indicators exhibit relatively weaker associations with their underlying constructs. All factor loadings were statistically significant ($p < 0.05$), with T-values ranging between 2.627 and 130.412.

These results indicate that the majority of the indicators exhibit robust associations with their respective underlying variables, thereby offering substantial backing for the evaluation of the model's convergent validity. The presence of statistically significant factor loadings attests to the effectiveness of these indicators in capturing the intended underlying constructs.

Regarding discriminant validity, this study employed the Fornell-Larcker criterion and HTMT test to assess the discriminant validity of the research model. According to Fornell and Larcker[14], a model has strong discriminant validity when the square root of the AVE value for each latent variable is greater than the absolute value of the correlation coefficient between the latent variables. This also indicates a clear distinction between the latent variables. Additionally, the HTMT analysis, a novel method for assessing discriminant validity introduced by Henseler [15], was utilized. An HTMT value lower than 0.9 conforms to the criteria for meeting the requirement of discriminant validity[12].

Table 3: Convergent validity test results of the model

Latent Variable	Indicators	Factor loadings	Sample mean (M)	Standard Deviation	T Values	P values	AVE
Attitude(A)	Attitude_Q1	0.853	0.85	0.014	61.074	0.000	0.626
	Attitude_Q2	0.719	0.718	0.035	20.275	0.000	
	Attitude_Q3	0.800	0.802	0.025	32.081	0.000	
	Attitude_Q4	0.737	0.735	0.028	26.094	0.000	
	Attitude_Q5	0.838	0.838	0.02	40.971	0.000	
Behavioral Intention(BI)	Behavioral Intention_Q1	0.861	0.861	0.018	48.47	0.000	0.713
	Behavioral Intention_Q2	0.887	0.886	0.013	70.145	0.000	
	Behavioral Intention_Q3	0.783	0.782	0.029	27.001	0.000	
Behavior(B)	Behavior_Q1	0.716	0.715	0.028	25.379	0.000	0.68
	Behavior_Q2	0.817	0.816	0.019	43.658	0.000	
	Behavior_Q3	0.877	0.877	0.013	68.565	0.000	
	Behavior_Q4	0.821	0.821	0.018	45.934	0.000	
	Behavior_Q5	0.875	0.874	0.012	71.573	0.000	
	Behavior_Q6	0.831	0.831	0.017	48.881	0.000	
Compatibility(C)	Compatibility_Q1	0.585	0.521	0.217	2.699	0.007	0.493
	Compatibility_Q2	0.759	0.695	0.169	4.493	0.000	
	Compatibility_Q3	0.878	0.814	0.203	4.325	0.000	
	Compatibility_Q4	0.567	0.501	0.216	2.627	0.009	
	Compatibility_Q5	0.674	0.611	0.182	3.711	0.000	
Facilitating_Conditions (FC)	Facilitating_Conditions_Q1	0.834	0.834	0.02	41.203	0.000	0.688
	Facilitating_Conditions_Q2	0.833	0.83	0.025	33.428	0.000	
	Facilitating_Conditions_Q3	0.826	0.826	0.025	33.7	0.000	
	Facilitating_Conditions_Q4	0.826	0.822	0.031	26.35	0.000	
Perceived Behavioral Control(PBC)	Perceived Behavioral Control_Q1	0.774	0.774	0.02	37.78	0.000	0.700
	Perceived Behavioral Control_Q2	0.850	0.849	0.017	48.822	0.000	
	Perceived Behavioral Control_Q3	0.865	0.865	0.011	78.527	0.000	
	Perceived Behavioral Control_Q4	0.851	0.85	0.013	64.87	0.000	
	Perceived Behavioral Control_Q5	0.840	0.84	0.017	48.979	0.000	
Past Behavior(PB)	Past Behavior_Q1	0.837	0.837	0.015	56.856	0.000	0.701
	Past Behavior_Q2	0.773	0.772	0.022	35.3	0.000	
	Past Behavior_Q3	0.855	0.854	0.016	53.626	0.000	
	Past Behavior_Q4	0.857	0.858	0.011	78.794	0.000	
	Past Behavior_Q5	0.861	0.861	0.013	63.924	0.000	
Perceived Ease of Use(PEU)	Perceived Ease of Use_Q1	0.825	0.825	0.014	59.418	0.000	0.658
	Perceived Ease of Use_Q2	0.913	0.912	0.011	80.205	0.000	
	Perceived Ease of Use_Q3	0.659	0.657	0.039	17.046	0.000	
	Perceived Ease of Use_Q4	0.797	0.795	0.024	32.813	0.000	
	Perceived Ease of Use_Q5	0.840	0.84	0.018	46.485	0.000	
Peer Influence(PI)	Peer Influence_Q1	0.815	0.814	0.024	33.804	0.000	0.673
	Peer Influence_Q2	0.729	0.729	0.029	25.567	0.000	
	Peer Influence_Q3	0.852	0.85	0.018	47.949	0.000	
	Peer Influence_Q4	0.870	0.871	0.013	65.913	0.000	
	Peer Influence_Q5	0.829	0.828	0.021	39.485	0.000	
Preliminary Knowledge (PK)	Preliminary Knowledge_Q1	0.854	0.854	0.015	55.907	0.000	0.715
	Preliminary Knowledge_Q2	0.898	0.898	0.007	130.412	0.000	
	Preliminary Knowledge_Q3	0.793	0.793	0.019	41.256	0.000	
	Preliminary Knowledge_Q4	0.805	0.804	0.025	32.375	0.000	
	Preliminary Knowledge_Q5	0.874	0.873	0.015	58.634	0.000	
Perceived Usefulness (PU)	Perceived Usefulness_Q1	0.873	0.873	0.011	76.747	0.000	0.702
	Perceived Usefulness_Q2	0.820	0.821	0.018	46.618	0.000	
	Perceived Usefulness_Q3	0.798	0.796	0.023	34.597	0.000	
	Perceived Usefulness_Q4	0.789	0.788	0.028	28.191	0.000	
	Perceived Usefulness_Q5	0.902	0.902	0.009	96.817	0.000	
Subjective Norms(SN)	Subjective Norms_Q1	0.842	0.841	0.019	45.031	0.000	0.697
	Subjective Norms_Q2	0.884	0.884	0.013	70.043	0.000	
	Subjective Norms_Q3	0.767	0.766	0.028	27.378	0.000	
	Subjective Norms_Q4	0.882	0.882	0.012	73.98	0.000	
	Subjective Norms_Q5	0.793	0.793	0.024	32.618	0.000	
Superior Influence(SI)	Superior Influence_Q1	0.847	0.845	0.02	42.425	0.000	0.67
	Superior Influence_Q2	0.866	0.867	0.012	73.19	0.000	
	Superior Influence_Q3	0.703	0.699	0.042	16.682	0.000	
	Superior Influence_Q4	0.777	0.775	0.029	26.572	0.000	
	Superior Influence_Q5	0.886	0.886	0.013	70.389	0.000	
Self_efficacy (Se)	Self_efficacy_Q1	0.853	0.852	0.016	53.268	0.000	0.69
	Self_efficacy_Q2	0.709	0.707	0.036	19.568	0.000	
	Self_efficacy_Q3	0.845	0.844	0.019	45.042	0.000	
	Self_efficacy_Q4	0.911	0.911	0.012	73.47	0.000	
	Self_efficacy_Q5	0.823	0.821	0.021	39.627	0.000	

Table 4 and Table 5 respectively show the discriminant validity test results (Fornell-Larcker criterion) and HTMT values of the model.

Table 4: Fornell-Larcker criterion values of the model

	A	B	BI	C	FC	PB	PI	PBC	PEU	PU	PK	Se	SN	SI
A	**0.791**													
B	0.353	**0.824**												
BI	0.202	0.300	**0.845**											
C	0.244	0.335	0.272	**0.702**										
FC	0.510	0.476	0.352	0.295	**0.830**									
PB	0.537	0.453	0.481	0.299	0.599	**0.837**								
PI	0.222	0.519	0.288	0.172	0.324	0.279	**0.821**							
PBC	0.239	0.478	0.245	0.298	0.304	0.319	0.599	**0.837**						
PEU	0.500	0.407	0.267	0.205	0.382	0.348	0.511	0.451	**0.811**					
PU	0.397	0.497	0.405	0.435	0.566	0.528	0.425	0.324	0.503	**0.838**				
PK	0.246	0.582	0.319	0.264	0.390	0.551	0.497	0.507	0.385	0.484	**0.846**			
Se	0.279	0.521	0.204	0.169	0.339	0.320	0.440	0.347	0.154	0.402	0.542	**0.831**		
SN	0.353	0.269	0.220	0.300	0.312	0.211	0.395	0.476	0.343	0.360	0.318	0.253	**0.835**	
SI	0.553	0.373	0.147	0.342	0.586	0.570	0.355	0.375	0.466	0.550	0.569	0.426	0.406	**0.819**

Table 5: HTMT values of the model

	A	B	BI	C	FC	PB	PI	PBC	PEU	PU	PK	Se	SN	SI
A														
B	0.370													
BI	0.249	0.348												
C	0.218	0.491	0.361											
FC	0.598	0.522	0.413	0.326										
PB	0.600	0.480	0.543	0.313	0.651									
PI	0.268	0.544	0.345	0.410	0.327	0.305								
PBC	0.268	0.519	0.291	0.471	0.331	0.369	0.656							
PEU	0.520	0.474	0.349	0.289	0.431	0.417	0.628	0.561						
PU	0.417	0.525	0.481	0.373	0.620	0.595	0.514	0.370	0.569					
PK	0.292	0.607	0.371	0.323	0.437	0.600	0.561	0.569	0.497	0.548				
Se	0.310	0.574	0.236	0.231	0.389	0.350	0.479	0.378	0.270	0.449	0.592			
SN	0.382	0.309	0.264	0.292	0.374	0.235	0.411	0.535	0.387	0.391	0.354	0.286		
SI	0.603	0.409	0.248	0.363	0.656	0.670	0.399	0.399	0.515	0.595	0.656	0.496	0.390	

As can be seen from Table 4, the AVE square root (bold number) of all latent variables is larger than other numbers in that column, indicating that the discriminant validity of the model meets the requirements. As can be seen from the data in Table 5, the values of all HTMT are less than 0.9, indicating that the model has good discriminant validity.

3.4 Path Analysis and Hypotheses Testing

This part presents the results of path analysis and hypothesis testing. This analysis examines the relationships between potential variables in the research model and tests the proposed hypotheses. These results provide insights into the strength and importance of these relationships, revealing the impact of predictors on outcome variables.

The results of the path analysis, shown in Table 6 and Figure 2, include the path coefficients (Beta, β), sample mean, standard deviation, T-values, p-values, and 95% confidence intervals for each path. The interpretation of these results will help to reveal the strength and significance of the relationship between the variables, and help to fully understand the influencing factors of higher vocational students' self-directed learning behavior under the blended teaching mode.

Perceived Behavioral Control ($\beta = 0.232$, $t = 4.973$, $p<0.001$), Past Behavior ($\beta = 0.153$, $t = 3.360$, $p<0.01$), and Preliminary Knowledge ($\beta = 0.363$, $t = 7.344$, $p<0.001$) were found to have a significant and positive impact on the self-directed learning behavior of the higher vocational students, supporting H1l, H2a, and H3a. These results consist of the findings of previous studies [16] However, the relationship between Behavior and Behavioral Intention tested $p=0.315 > 0.05$ in this study, indicating that there is no significant relationship between these two variables. This result aligns with the limitation of the DTPB mentioned in the previous section and previous studies [17].

Therefore, H1a is not supported based on the findings of the study.

For the influencing factors of Behavioral Intention, this study found that Attitude (β= -0.128, t= 2.146, p<0.05), Subjective Norms (β= 0.134, t= 2.388, p<0.05) and Past Behavior (β= 0.503, t= 9.577, p<0.001) have significant impact on students' behavioral intention. The above results support H1e, H1c, and H2b. This result can also be found in the existing literature [18]. As for the other 2 proposed variables, Perceived Behavioral Control (p= 0.43) and Preliminary Knowledge (p= 0.915) both tested p>0.05, failed to reject the null hypothesis of H1d and H3b.

The path analysis revealed that Perceived Usefulness (β= 0.152, t= 2.829, p<0.001) and Perceived Ease of Use (β= 0.404, t= 8.713, p<0.001) has a significant and positive impact on students' attitude toward self-directed learning behavior. However, according to the result shown in the SmartPLS, there is no significant impact Compatibility has on attitude (p= 0,341 >0.05). Thus, H1e and H1f were established, while H1g was rejected.

The path from Peer Influence to Subjective Norms was found to be positive and statistically significant, with the factor loadings equal to 0.287, t-value equal to 5.151, and p<0.001. Similarly, the path from Superior Influence to Subjective Norms was also positive and statistically significant, with the factor loadings equal to 0.404, t-value equal to 8.713, and p<0.001. H1h and H1i were both established based on the above findings. These findings highlight the influential role of Peer Influence and Superior Influence when shaping higher vocational students' subjective norms.

The results of the path analysis of Facilitating Conditions, Self-efficacy and Perceived Behavioral Control, revealed a significant relationship between the independent variables and dependent variable. Specifically, the path from Facilitating Conditions to Perceived Behavioral Control was found to be statistically significant and positive (β= 0.211, t= 4.391, p<0.001), suggesting that Facilitating Conditions has a direct positive effect on Perceived Behavioral Control. A similar effect was found in the path from Self-efficacy to Perceived Behavioral, with β= 0.276, t= 6.047, p<0.001. These results support H1j and H1k.

The specific results of path analysis are shown in Table 6, and the path diagram after factor loads and corresponding P-values are brought in is shown in Figure 2. After removing all the non-significant paths, the revised path diagram is shown in Figure 3. The revised chart below reflects the significant paths that remain in the model after the non-significant paths are eliminated, giving a clearer representation of the relationships between the variables of interest.

The research model's explanatory ability is measured using R^2 (coefficient of determination)[19]. A higher R^2 indicates better predictive power. In Table 7, the R^2 for behavior is 0.408, suggesting that approximately 40.8% of the variance in behavior is influenced by Perceived Behavioral Control, Past Behavior, and Preliminary Knowledge. This indicates a moderate level of predictive power, explaining nearly half of the behavioral variance. The R^2 of other dependent variables are shown in Table 7 below.

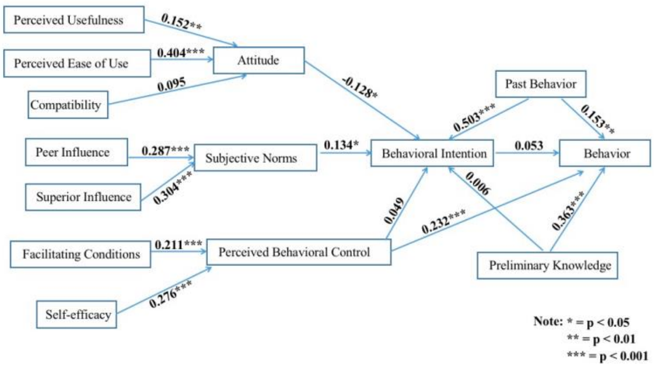

Figure 2: Path Analysis of the Research Model

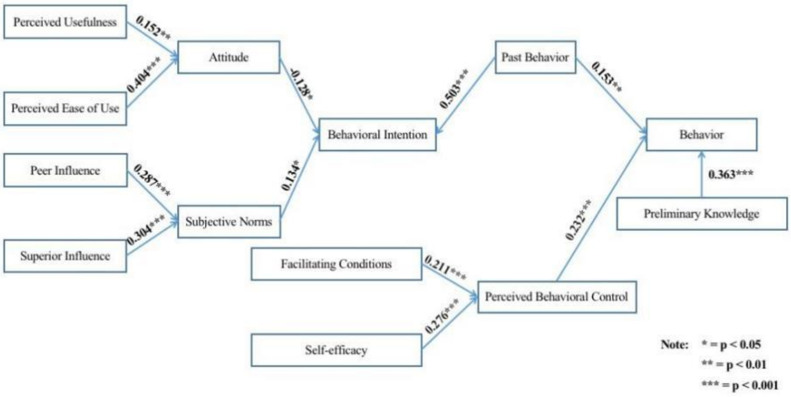

Figure 3: Revised Path Model

Table 6: Path Analysis and Hypothesis Testing of the model

Hypotheses	Path	Beta (β)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	95% Confidence Intervals	Test Result
H1a	Behavioral Intention -> Behavior	0.053	0.052	0.053	1.004	0.316	[-0.054, 0,151]	Not Established
H1b	Attitude -> Behavioral Intention	-0.128	-0.130	0.060	2.146	0.032	[-0.244, -0,014]	Established
H1c	Subjective Norms -> Behavioral Intention	0.134	0.134	0.056	2.388	0.017	[0.021, 0.241]	Established
H1d	Perceived Behavioral Control -> Behavioral Intention	0.049	0.049	0.062	0.790	0.430	[-0.073, 0.170]	Not Established
H1e	Perceived Usefulness -> Attitude	0.152	0.139	0.054	2.829	0.005	[0.019. 0.230]	Established
H1f	Perceived Ease of Use -> Attitude	0.404	0.412	0.046	8.713	0.000	[0.321, 0.500]	Established
H1g	Compatibility -> Attitude	0.095	0.113	0.100	0.952	0.341	[-0.272, 0. 300]	Not Established
H1h	Peer Influence -> Subjective Norms	0.287	0.290	0.056	5.151	0.000	[0.180, 0.400]	Established
H1i	Superior Influence -> Subjective Norms	0.304	0.307	0.038	8.035	0.000	[0.231, 0.381]	Established
H1j	Facilitating_Conditions -> Perceived Behavioral Control	0.211	0.215	0.048	4.391	0.000	[0.124,0.312]	Established
H1k	Self_efficacy -> Perceived Behavioral Control	0.276	0.278	0.046	6.047	0.000	[0.188,0.368]	Established
H1l	Perceived Behavioral Control -> Behavior	0.232	0.232	0.047	4.973	0.000	[0.140, 0.322]	Established
H2a	Past Behavior -> Behavior	0.153	0.155	0.046	3.360	0.001	[0.066, 0.246]	Established
H2b	Past Behavior -> Behavioral Intention	0.503	0.505	0.052	9.577	0.000	[0.399, 0.606]	Established
H3a	Preliminary Knowledge -> Behavior	0.363	0.364	0.049	7.344	0.000	[0.265, 0.459]	Established
H3b	Preliminary Knowledge -> Behavioral Intention	0.006	0.005	0.060	0.106	0.915	[-0.115, 0.124]	Not Established

Table 7: The coefficient determination (R2) of the model

	R-square	R-square adjusted
Attitude	0.286	0.279
Behavior	0.408	0.401
Behavioral Intention	0.259	0.249
Perceived Behavioral Control	0.16	0.155
Subjective Norms	0.237	0.232

4. Conclusions and Recommendations

The study reveals that perceived behavioral control, past behavior, and preliminary knowledge significantly impact self-directed learning behavior in higher vocational students during blended teaching. Promoting conditions and self-efficacy positively influence perceived behavioral control, emphasizing the importance of nurturing autonomy, leveraging past experiences, and enhancing foundational knowledge. However, the study also finds no significant relationship between behavioral intention and self-directed learning behavior in this specific group and teaching approach. This highlights the complexity of factors involved and suggests the need for further exploration and alternative strategies to foster self-directed learning among higher vocational students

Educational institutions and policymakers play a crucial role in fostering a culture of self-directed learning that values autonomy and continuous learning. This involves integrating self-directed learning into curricula, training educators, and providing resources. Technology-driven platforms can enhance engagement and autonomy. Tailored interventions considering individual backgrounds and goals empower students to shape their learning journeys. Future research should explore motivation, learning environment, and strategies, as well as investigate self-directed learning in adult or industrial settings. Longitudinal studies and mixed-methods analysis can provide insights into long-term influences and engagement challenges.

References

[1] Hu A. L. Research on the Path of Internationalization of Higher Vocational Education Based on Computer Aided Technology under the Background of One Belt One Road[C]. Journal of Physics: Conference Series. IOP Publishing, 2020, 1648(2): 022002.

[2] Cheng W. K. & Li N. N. Exploration and practice of online and offline mixed teaching mode based on cloud class in microbiology teaching in higher vocational schools. [J]. Microbiology China: 2018, 45(4): 927-933.

[3] Qin W., Zhu H. D., Chen J. Y., Zhou Y. Y., & Yu Q. G. Optimization Design of Offline and Offline hybrid teaching platform with "Internet + Education" background. [J] Science & Technology for China's Mass Media. 2022, 07, 129-132.

[4] Ministry of Education of the People's Republic of China. Opinions of the Ministry of Education on Deepening the Reform of undergraduate Education and Teaching and comprehensively improving the quality of personnel training[R]. 2019. Retrieved from: http://www.moe.gov.cn/srcsite/A08/s7056/201910/t20191011_402759.html.

[5] Ministry of Education of the People's Republic of China. Notice of the General Office of the Ministry of Education on the implementation of the "Double 10,000 Initiative" for the Construction of first-class undergraduate majors[R]. 2019. Retrieved from: http://www.moe.gov.cn/srcsite/A08/s7056/201904/t20190409_377216.html.

[6] Tan Y. P. The "3544" strategy for online resource construction of blended teaching in higher vocational colleges [J]. Chinese Journal of Vocational and Technical Education, 2019, 11, 65-69.

[7] Liu Y. L. Make good use of modern teaching technology to improve the teaching quality of higher vocational colleges [N]. China Education News, 2019-11-5 p. 10. http://paper.jyb.cn/zgjyb../html/2019-11/05/node_12.htm.

[8] Yu Z. N. The digital pace of vocational education accelerated, the launch of the national vocational education smart education platform [N]. Worker's Daily, 2022-3-29. https://baijiahao.baidu.com/s? id =1728618223954155801 &wfr= spider&for=pc

[9] Qing Q. Q. Research on Influencing Factors of students' autonomous Learning behavior under the mixed teaching mode of Optics [D]. Shanghai: Shanghai Normal University, 2021.

[10] Ringle, Christian M., Wende, Sven, & Becker, Jan-Michael. Smart PLS 4. [M]. Oststeinbek: SmartPLS, 2022. Retrieved from https://www.smartpls.com

[11] Xu L., Zhang J., Ding Y., Zheng J., Sun G., Zhang W. & Philbin S. P. Understanding the role of peer pressure on engineering students' learning behavior: A TPB perspective[J]. Front Public Health, 2023, 10:1069384.

[12] Qin L. Reduction of Academic Burnout in Preservice Teachers: PLS-SEM Approach [J]. Sustainability. 2022, 14:13416.

[13] Denton G., Chi O. H. & Gursoy D. An examination of the gap between carbon offsetting attitudes and behaviors: Role of knowledge, credibility and trust [J]. International Journal of Hospitality Management. 2020, 90.

[14] Fornell C. & Larcker D. F. Evaluating Structural Equation Models with Unobservable Variables and Measurement Error [J]. Journal of Marketing Research. 1981, 18, 39–50

[15] Henseler J., Ringle C. M. & Sarstedt M. A new criterion for assessing discriminant validity in variance-based structural equation modeling [J]. Journal of the Academy of Marketing Science. 2015, 43, 115–135.

[16] Zheng H. H. & Liu T. Research on the development of online autonomous learning ability of engineering students in the Digital Age: Based on the social presence Theory [J]. Higher Engineering Education Research. 2021, 01, 92-97.

[17] Rhodes R. E. & Bruijn G. J. D. How big is the physical activity intention-behaviour gap? A meta-analysis using the action control framework [J]. British Journal of Health Psychology, 2013, 18(2), 296-309.

[18] Chen M. Y., Feng Z., Wen Y. J. & Qiao W. An empirical study on learning motivation and behavior of higher vocational college students and their influencing factors [J]. Chinese Vocational and Technical Education, 2022, (17), 76-82.

[19] Xu A., Wei C., Zheng M., Sun L., Tang D. Influence of Perceived Value on Repurchase Intention of Green Agricultural Products: From the Perspective of Multi-Group Analysis[J]. Sustainability. 2022, 14, 15451.