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Factors Influencing Learning Adjustment of Vocational Undergraduates: An AI Chat GPT Perspective using SmartPLS Model

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Abstract

In the era of digital education, using Artificial Intelligence ChatGPT as an example, this study aims to explore the primary influencing factors of learning adjustment among vocational undergraduates and establish a semi-structured model. Statistical analysis, modeling, and path analysis were conducted using SPSS 29.0 and SmartPLS 4. The study sample consisted of students from vocational universities to ensure the relevance of research results and policy recommendations. The research findings indicate: (1) There is minimal change in learning adjustment among freshman vocational college students over a semester, and it tends to be overall low; (2) The most influential factors affecting learning adjustment among vocational college students are teaching methods, followed by learning attitudes; (3) A semi-structured internal model of learning adjustment was constructed. Based on these findings, the study proposes suggestions for optimizing learning adjustment empowered by generative Artificial Intelligence ChatGPT. This research not only enriches theoretical studies in the intersection of vocational education and artificial intelligence but also provides empirical evidence and practical guidance for educational managers, policymakers, and educational practitioners to better support the learning and development of vocational college students.

Keywords: Artificial Intelligence, ChatGPT, vocational undergraduates, student learning adjustment

Introduction

In recent years, the phenomenon of poor learning adaptation among freshmen has been notably significant. Particularly in the era of AI-integrated education, and especially with the application of generative AI technologies like Chat GPT, there has been a fundamental change in learning adjustment. While AI technology has made learning resources richer and more comprehensive, learners are no longer limited to traditional textbooks and classroom resources (Alam, 2021). However, issues such as learning anxiety and poor adaptation still persist. This raises the question of whether Chinese education should continue along the path of digitization (Mahoney, 2023; Mo et al., 2013). What are the main influences on the learning of vocational college students in China (Zeng, 2023)? In the trend towards informatization, what insights do educators receive (Judijanto et al., 2024)?

Influenced by inertia, vocational undergraduate education in China unconsciously continued to mold vocational education into a "four-year specialized associate degree" model. This has led to current issues such as unclear talent cultivation and low educational quality. In the process of attempting reforms, vocational undergraduate education has entered a second phase. Due to the absence of a policy system that matches the development of vocational education types, vocational undergraduate education has had to transition towards the operational models and educational positioning of applied or academic undergraduate education to secure adequate development resources. However, this transition has resulted in phenomena such as academic drift. This study advocates investigating the status and influencing factors of learning adjustment among vocational college students. Using Chat GPT's application in education as an example, it proposes flexible suggestions for teaching and learning in the AI era specifically tailored to vocational undergraduate students, along with corresponding solutions.

Literature Review

The Artificial Intelligence ChatGPT in the Field of Education

Artificial Intelligence ChatGPT has played a significant role in course assistance (Kaur, 2024; Yu, 2023). Interacting with ChatGPT makes learning ubiquitous and personalized. It is noteworthy that while ChatGPT learns human languages, it also acquires knowledge at the level of human ethical reasoning. This collaborative form of course assistance not only enhances learning efficiency but also promotes students' autonomy and critical thinking skills (Kaur, 2024). Furthermore, ChatGPT supports personalized learning by tailoring learning content and plans according to students' individual needs and learning characteristics (Graefen and Fazal, 2024).

In Chinese vocational undergraduate education, the application of Artificial Intelligence Chat GPT has been gradually promoted and utilized (Lai, 2024; Zeng, 2023; Zhu et al., 2024). Through interaction with ChatGPT, students can acquire relevant vocational knowledge, skills training, understand industry dynamics, and career development trends, thereby enhancing their competitiveness and employability (Prananta, 2023). Additionally, ChatGPT provides intelligent teaching tools and support for vocational undergraduate teachers, assisting them in implementing personalized teaching and career guidance, thereby promoting students' overall quality improvement and career development (Parker, 2024).

Learning Adjustment in Chinese College Students

In the era of artificial intelligence, especially with the advent of generative AI technologies like Chat GPT, there has been a fundamental shift in learning adjustment, making learning more personalized and enhancing autonomy. Learners can interact with Chat GPT to access personalized and real-time learning content and guidance, thereby enriching learning resources beyond traditional textbooks and classroom materials (Graefen and Fazal, 2024; Kaur, 2024).

Many researchers have classified the complex process of learning and measured adjustment based on students' cognitive levels to assess its changes. However, most studies treat adjustment as a sub-project rather than evaluating it comprehensively. For example, Zitow's CARS (1984) developed the College Students' Adjustment Level Questionnaire (CARS) to study students' adjustment to college life pressures, which forms a small part of the research on adjustment to learning pressures. Similarly, Rianto et al. (2020) developed the College Student Adaptation Questionnaire (SACQ) to study adaptation in terms of learning, social, and emotional aspects among university students, which would require extensive localization if used in China. Recent studies in China, such as Ma's (2024) research on the impact of MOOC learning adjustment and engagement on university students' satisfaction, Sun and Zhao's (2023) exploration of the relationship between professional identity and learning adjustment among university students, and Sun's (2023) study on the correlation between learning adjustment, psychological help-seeking delay, and mental health levels among university students, focus on the psychological analysis of reasons and strategies for maladaptive learning behaviors, particularly among freshmen. These studies indicate that lack of motivation, disinterest in the major, psychological and emotional maladjustment are primary reasons for learning maladaptation.

Moreover, Feng et al.'s (2006) College Students' Learning Adjustment Scale (CSLAS) is tailored to test learning adjustment among contemporary Chinese university students based on the Chinese education model and societal expectations. Notably, as of 2024, Feng et al.'s (2006) paper has been cited 646 times by the CNKI database, indicating widespread adoption and acknowledgment of their theories and scale in assessing learning adjustment.

Methodology

Sample and Data Collection

The study sample consisted of 374 students who completed pre-test and post-test questionnaires on vocational college learning adjustment. However, due to missing data in either the pre-test or post-test questionnaires among some students, the questionnaires did not match. After screening and excluding invalid questionnaires, the study ultimately obtained 318 valid responses. To ensure sample homogeneity, all 318 students were from vocational colleges and were freshmen in their first year. They shared the same academic majors and undertook similar types of courses. The age range of the participants was between 18 and 22 years old. Among the participants, 102 were male, accounting for 31.7% of the total sample, while the remaining 219 students (68.3%) were female.

Given the pre-test and post-test nature of the questionnaires, each questionnaire was reserved with the student's name. Both parties signed confidentiality agreements to ensure the privacy of student information. The study did not disclose specific student identities or interfere with their subsequent university careers.

Findings

Correlation Analysis

Before comparing the proposed theoretical model using structural equation modeling, this study conducted a comprehensive examination of the measurement model through descriptive statistical analysis and analysis of variance (ANOVA) to test the intra-group significance levels of learning adjustment dimensions among the variables included in the study (as shown in Table 1). The results indicate that among the 318 vocational college students involved in the study over 18 weeks of learning, there were significant differences in learning motivation, learning attitude, educational mode, learning ability, environmental factors, and pre-post adjustment tests, with statistical significance ($p < .001$). Furthermore, these significant differences demonstrate that each dimension manifests differently among students and affects vocational college students' learning adjustment to varying degrees. Therefore, this study suggests the need for further investigation into the extent of each dimension's impact on learning adjustment.

Table 1: ANOVA P-Test of Inter-Group Variances in Learning Adjustment Dimensions

Dependent variable: N（N=318）					
Pre-test & Post-test	III Sum of squares	Degrees of freedom	Mean square	F	Significance
Pre-test of learning motivation	649263.646	20	32463.182	42.456	<.001
Post-test of learning motivation	651954.532	23	28345.849	37.137	<.001
Pre-test of educational mode	648417.125	23	28192.049	36.364	<.001
Post-test of educational mode	661591.978	23	28764.869	39.371	<.001
Pre-test of learning ability	649965.322	25	25998.613	33.534	<.001
Post-test of learning ability	652610.758	26	25100.414	32.646	<.001
Pre-test of learning attitude	645907.205	26	24842.585	31.373	<.001
Post-test of learning attitude	651131.644	25	26045.266	33.768	<.001
Pre-test of environmental factors	650827.402	21	30991.781	40.675	<.001
Post-test of environmental factors	651031.163	20	32551.558	42.905	<.001
Pre-test of adjustment	646047.674	16	40377.980	52.771	<.001
Post-test of adjustment	653785.897	15	43585.726	59.132	<.001
Total	877123.000	318			

a. $R^2 = .740$（Adjusted $R^2 = .723$）

This study applied paired sample t-tests to analyze the significant differences in various dimensions before and after (between groups). The results are shown in Tables 2 and 3 below. Over the 18-week study period, freshmen adapted to the educational mode to some extent, but other dimensions showed varying degrees of decline. Significant differences were observed between the pre-test and post-test scores for learning motivation (Avg=0.1477, SD=0.5692, $p< 0.001$) and learning attitudes (Avg=0.1219, SD=0.5439, p< 0.001). The findings indicate that the 318 vocational undergraduate freshmen participating in the study experienced varying degrees of adaptation issues during their first semester. Most students expressed dissatisfaction with the current curriculum, teaching methods, and school management as reflected in the survey. After one semester in university, students exhibited inadequate adaptation in motivation, attitudes, and abilities. This highlights the continued reliance of vocational colleges on traditional teaching methods, which fail to fully engage students and meet their learning needs. Many teachers lack familiarity with and training in educational technology tools and platforms, resulting in suboptimal effectiveness of digital teaching methods. The potential of artificial intelligence technology remains underutilized, exacerbating issues related to personalized learning support, classroom interactivity, and feedback mechanisms, thereby intensifying students' adaptation challenges. Addressing these issues requires vocational colleges to further advance educational informatization, enhance teachers' digital teaching capabilities, increase the application and promotion of AI technology, and provide more personalized, interactive learning support and feedback mechanisms to help students better adapt to university life.

Table 2: Analysis of Variance Pre- and Post- Learning Adjustment Between Groups

Pre-test & Post-test		Mean	N	Standard deviation	SEM
Pair 1	Pre-test of learning motivation	3.7084	318	.5954	.0333
	Post-test of learning motivation	3.5606	318	.634	.0355
Pair 2	Post-test of educational mode	3.5332	318	.5808	.0325
	Pre-test of educational mode	3.5876	318	.6121	.0343
Pair 3	Post-test of learning ability	3.7820	318	.5004	.0281
	Pre-test of learning ability	3.7390	318	.5471	.0307
Pair 4	Post-test of learning attitude	4.0076	318	.5759	.0322
	Pre-test of learning attitude	3.8857	318	.6197	.0347
Pair 5	Post-test of environmental factors	3.4403	318	.6625	.0372
	Pre-test of environmental factors	3.4266	318	.7301	.0409
Pair 6	Post-test of learning adjustment	3.8100	318	.5323	.0298
	Pre-test of learning adjustment	3.7860	318	.6029	.0338

Table 3: Paired t-Test for Learning Adjustment Pre and Post Phrase

	Paired Sample t-test								
	The 95% confidence interval for the difference							Significance	
	Mean	SD	SEM	Min	Max	T	DF	One-sided P	Two-sided P
Pre-test of learning motivation - Post-test of learning motivation	.1477	.5692	.0319	.0849	.2105	4.630	317	<.001	<.001
Pre-test of educational mode - Post-test of educational mode	-.0543	.6084	.034	-.0127	.1214	1.593	317	.056	.112
Pre-test of learning ability - Post-test of learning ability	.0428	.5195	.0291	-.0145	.1001	1.468	317	.072	.143
Pre-test of learning attitude - Post-test of learning attitude	.1219	.5439	.0305	.0619	.1819	3.998	317	<.001	<.001
Pre-test of environmental factors Post-test of environmental factors	.0136	.6735	.0378	-.0607	.0879	.3608	317	.3592	.7185
Pre-test of adjustment - Post-test of adjustment	.0239	.6011	.0337	-.0424	.0902	.709	317	.239	.479

Table 4 Measurement Results Show Significant Differences in Learning adjustment Pre- and Post- Testing Among 318 Participants. Pre-test (Avg=3.731, SD=0.49, t=90.469, p < 0.001) and Post-test (Avg=3.663, SD=0.546, t=79.592, p < 0.001) indicate significant differences in students' learning adjustment.

Table 4: The t-Test for Pre- and Post- Learning Adjustment

Learning adjustment	*t* value	Sample	Avg	SD	t	p
Pre-test -t	0.001	318	3.731	0.49	90.469	0.000***
Post-test-t	0.001	318	3.663	0.546	79.592	0.000***

* $p < .05$, **$p < .01$, ***$p < .001$

SEM Model

This study used SPSS 29.0 to conduct confirmatory factor analysis to verify if the data met the conditions for modeling. The results, as shown in Tables 5 and 6, indicate that the data (KMO > 0.7, Sig < 0.001) met the prerequisites for confirmatory factor analysis. Furthermore, based on the rotated factor component results, specific items with strong correlations between dimensions were identified. For instance, the item most strongly associated with learning motivation was Item 4: "I have my own learning methods and plans, and I can put them into practice"; Item 41: "My learning is effective." Item 21 showed the highest correlation with Teaching mode: "University management differs from that in high school."

Table 5: KMO and Bartlett's Test

KMO sampling adequacy measure		.907
Bartlett's sphericity test	Approximate chi-square	2545.082
	Degrees of freedom	231
	Significance	<.001

Table 6: Rotated Component Matrix[a] for Learning Adjustment

	Learning ability	Learning motivation	Learning attitudes	Environment factor	Teaching mode
Learning motivation Q5		.752			
Learning motivation Q35		.672			
Learning motivation Q37		.657			
Learning motivation Q42		.747			
Learning motivation Q43		.561			
Teaching mode Q21					.684
Teaching mode Q22					.722
Teaching mode Q26					.703
Learning ability Q8	.669				
Learning ability Q11	.745				
Learning ability Q14	.716				
Learning ability Q18	.674				
Learning ability Q28	.740				
Learning attitude Q16			.733		
Learning attitude Q19			.671		
Learning attitude Q23			.603		
Learning attitude Q25			.685		
Learning attitude Q29			.591		

Environmental factors Q13	.717
Environmental factors Q30	.751
Environmental factors Q31	.608
Environmental factors Q41	.624

Note: Extraction Method: Principal Component Analysis; Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

Based on the two-step structural equation modeling analysis method, this study used SmartPLS 4.0 statistical software to test the measurement properties of the measurement model. Except for the AVE value of environmental factors being below the critical level, the AVE values of all latent factors were greater than 0.5 (minimum value 0.520, maximum value 0.616), indicating that the model has acceptable convergent validity (see Table 7). According to the Fornell-Larcker Criterion for assessing discriminant validity of the measurement model, as shown in Table 8, since the square roots of the AVE values of all latent factors are greater than the correlation coefficients of any factor, the model's discriminant validity is satisfactory.

Table 7: Reliability of the Measurement Model

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Learning motivation	0.814	0.821	0.870	0.574
Learning attitude	0.769	0.791	0.843	0.520
Learning ability	0.844	0.846	0.889	0.616
Teaching mode	0.666	0.689	0.816	0.598
Environmental factors	0.714	0.729	0.813	0.468

Table 8: Fornell-Larcker Criterion Model Discriminant Validity

	Learning motivation	Learning attitude	Learning ability	Learning adjustment	Teaching mode	Environmental factors
Learning motivation	0.758					
Learning attitude	0.527	0.721				
Learning ability	0.572	0.505	0.785			
Teaching mode	0.607	0.497	0.569	0.690		
Environmental factors	0.461	0.469	0.373	0.505	0.774	
Learning motivation	0.461	0.430	0.393	0.417	0.444	0.684

According to the steps for evaluating the result model, the first task is to analyze whether there is a multicollinearity problem among the latent factors in the structural model. In PLS-SEM, multicollinearity among latent factors is typically assessed using the Variance Inflation Factor (VIF). In the structural model of this study (as shown in Figure 1), the VIF values for the predictor variables within each dependent variable are all below the critical value of 5. Therefore, it can be determined that there is no multicollinearity problem among the predictor variables in the structural equation model.

As shown in Tables 9, there is no direct relationship between learning attitude and learning adjustment, educational model and learning ability, or environmental factors and learning ability and learning adjustment, thus these paths are not established. However, in the mediation factor paths, students' learning attitude influences learning adjustment by affecting learning ability and learning motivation. The educational model and environmental factors impact learning adjustment through their mutual influence on learning motivation. Additionally, the results indicate that among the five dimensions-learning motivation, learning attitude, learning ability, environmental factors, and educational model-the educational model has the greatest impact on learning adjustment.

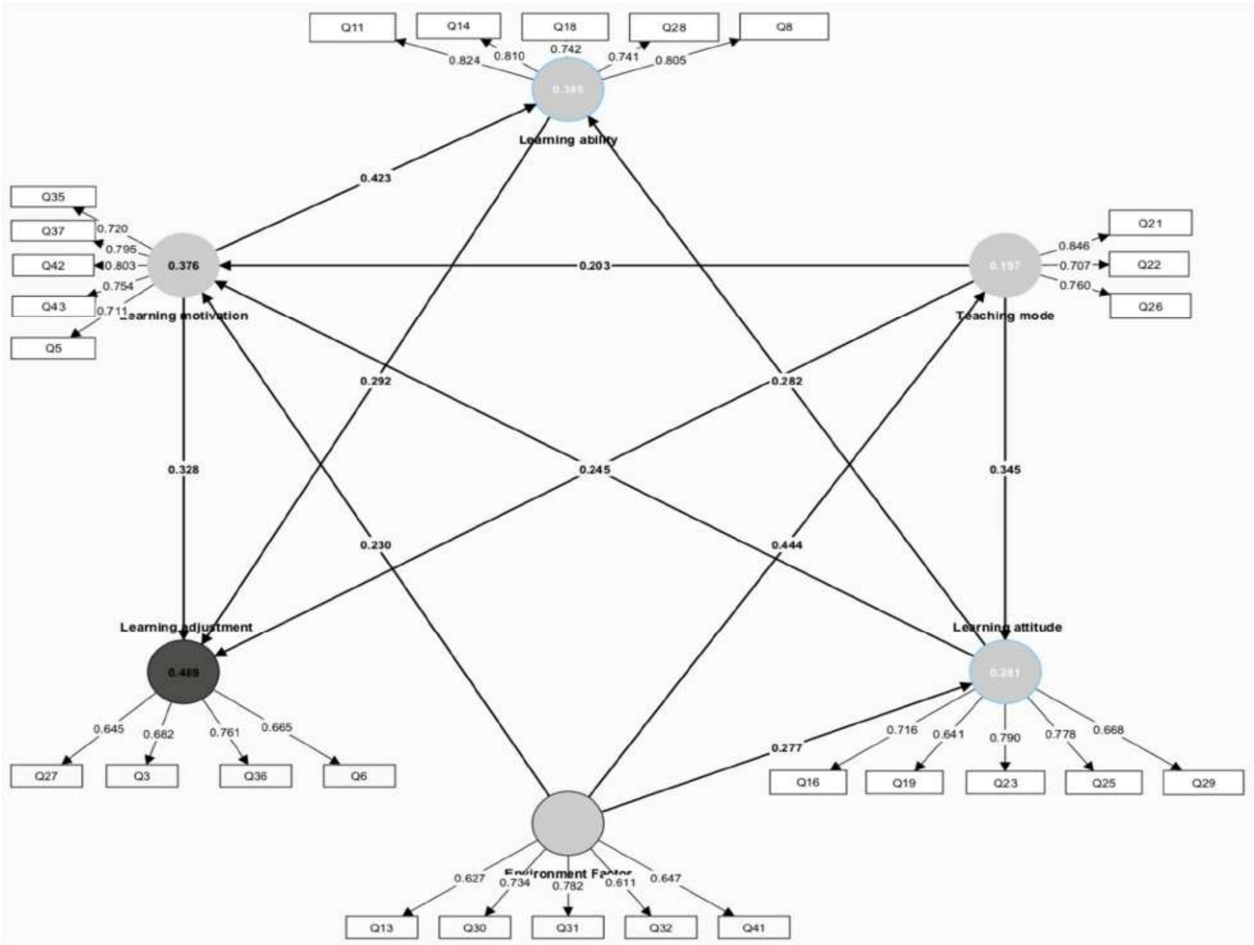

Figure 1: Structural Equation Model (SEM Model in SmartPLS 4)

Table 9: PLS-SEM Mediation Factor Path Analysis (Bootstrapping, N = 5000).

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Learning motivation → Learning ability → Learning adjustment	0.098	0.102	0.034	2.873	0.004
Learning attitude → Learning ability → Learning adjustment	0.063	0.065	0.022	2.822	0.005
Learning attitude → Learning motivation → Learning adjustment	0.097	0.097	0.027	3.577	0.000
Environmental factors → Teaching mode → Learning adjustment	0.093	0.093	0.028	3.286	0.001
Teaching mode → Learning motivation → Learning adjustment	0.059	0.058	0.024	2.507	0.012

Environmental factors → Learning motivation → Learning adjustment	0.066	0.066	0.021	3.080	0.002

Conclusion

Enhancing Learning adjustment with Generative AI ChatGPT

Given the current trends in internet development, the integration of artificial intelligence (AI) into education is inevitable. Currently, vocational education faces challenges such as misalignment between teaching content and student needs, discrepancies between program offerings and social demands, inadequate management mechanisms, and the need for improved teacher quality. The involvement of ChatGPT undoubtedly opens a new avenue for vocational education.

ChatGPT can generate tailored teaching methods and learning recommendations based on individual differences through conversation, thus enhancing learning efficiency and student motivation. Moreover, ChatGPT can assist in optimizing course design. It also enables continuous improvement of course design based on student feedback and evaluations, thereby enhancing course quality and practicality. Teachers can gain valuable teaching experience and refine their understanding of vocational education, thereby improving their teaching skills (Zeng, 2023). Furthermore, ChatGPT can help vocational institutions improve campus management and student assessment mechanisms (Fu, 2023). It can generate appropriate management strategies based on the management mechanisms of vocational and undergraduate institutions under the "vocational undergraduate" framework. ChatGPT can provide career advice and planning suggestions based on students' backgrounds, abilities, and interests, helping them understand their career development directions and goals better.

Future exploration could focus on integrating ChatGPT technology with learning adjustment in several key areas. First, it is essential to investigate how digital literacy skills of vocational undergraduate students can be effectively integrated with practical applications of ChatGPT, including strategies for formulating appropriate questions. Second, exploring the challenges and opportunities presented by AI applications in vocational undergraduate education is crucial. Finally, examining the current state and strategies for utilizing AI in the integration of industry and education within vocational undergraduate settings will provide valuable insights.

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