Hivereads Press

Large Language Models: Empowering Educational Reform and Innovation

Feng Han, Tianjing Xin*

Zhejiang Business Technology Institute, Ningbo, 315012, China

Abstract: The rapid advancement of artificial intelligence technology has opened new possibilities for educational reform through Large Language Models (LLMs). This research uses the 'Marketing Skills Sandbox Training' course as a case study to introduce the 'Large Language Model Structured Teaching Method' (LLM-STM). The method implements a four-step cycle of 'Lecture, Imitation, Practice, Evaluation' to explore pathways for deep integration of technology with teaching. The project combines cognitive learning theory, constructivism, and social learning theory to optimize course content and practical components. A mixed evaluation approach validates the reform outcomes. Research findings indicate that performance expectancy and facilitating conditions of LLMs significantly impact learning effectiveness. This study provides both theoretical and practical references for the digital transformation of vocational education.

Keywords: Large Language Models (LLMs); Teaching Reform; Structured Teaching Method; Marketing Sandbox Training; Personalized Learning

1. Introduction

Generative artificial intelligence has developed rapidly in recent years, shifting educational models from 'knowledge transmission' to 'ability cultivation.' Vocational education, as a core platform for cultivating skilled talent, urgently needs technological innovation to address issues in traditional teaching such as insufficient interaction and weak practical components. Large Language Models (LLMs), with their powerful natural language processing and generation capabilities, provide real-time interaction, personalized feedback, and resource support for teaching, making them important tools for educational reform. This research uses the 'Marketing Skills Sandbox Training' course as a case study to introduce the 'Large Language Model Structured Teaching Method' (LLM-STM). The method implements a four-step cycle of 'Lecture, Imitation, Practice, Evaluation' to explore pathways for deep integration of technology with teaching. This study employs the UTAUT model as its theoretical foundation to examine how Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC) affect learning effectiveness. The project is based on cognitive learning theory, constructivist learning theory, and social learning theory to develop the Large Language Model Structured Teaching Method. These theories provide both a solid theoretical foundation for the project and clear guidance for teaching strategies and assessment during implementation. This combination of theory and practice ensures more systematic and effective project implementation.

2. Teaching Innovation Model: LLM-STM Four-Step Method

Based on cognitive learning theory [1], constructivist learning theory [2] and social learning theory [3], the "Lecture-Imitation-Practice-Evaluation" cycle model (Figure 1) is proposed: This model provides a comprehensive and effective teaching framework. In the Lecture stage, teachers use large language models to refine and convey key knowledge points. In the Imitation stage, students imitate teacher operations, with the model providing personalized guidance for incorrect steps. During the Practice stage, students engage in task-based practice, with the large language model providing high-efficiency assistance in task completion and building confidence. Finally, in the Evaluation stage, the model assists in evaluation and feedback, automatically generating learning reports that, combined with teacher feedback, initiate a new learning cycle.

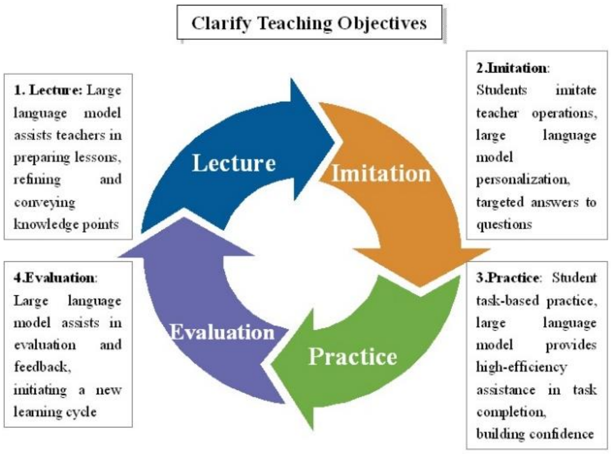

Figure 1. Large Language Model Structured Teaching Method (LLM-STM)

3. Theory and Research Hypotheses

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a technology acceptance model proposed by Venkatesh et al. [4] that integrates eight different theories and identifies four key factors affecting technology acceptance and use. These four factors are: Performance Expectancy, which refers to the degree to which an individual believes that using the system will help improve job performance; Effort Expectancy, which refers to the degree of ease associated with system use; Social Influence, which refers to the degree to which important others believe the individual should use the system; and Facilitating Conditions, which refers to the degree to which organizational and technical infrastructure exists to support system use. Therefore, this research proposes the following hypotheses:

H1: Performance Expectancy has a significant positive impact on learning effectiveness when using the LLM-STM.

H2: Effort Expectancy has a significant positive impact on learning effectiveness when using the LLM-STM.

H3: Social Influence has a significant positive impact on learning effectiveness when using the LLM-STM.

H4: Facilitating Conditions have a significant positive impact on learning effectiveness when using the LLM-STM.

4. Methodology

This research distributed questionnaires to students who had taken the "Marketing Skills Sandbox Training" course through the Wenjuanxing (https://www.wjx.cn/) platform. These students were first-year vocational marketing majors. A total of 157 questionnaires were distributed, with males accounting for 46.5% of respondents. 98.09% of the students learned about generative artificial intelligence technology through teacher classroom instruction.

For the scale design, this research developed scales based on the UTAUT model, with 5 items each for Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC), plus 5 items for the learning effectiveness scale.

This study uses PLS-SEM for data analysis. The conceptual model is shown in Figure 2.

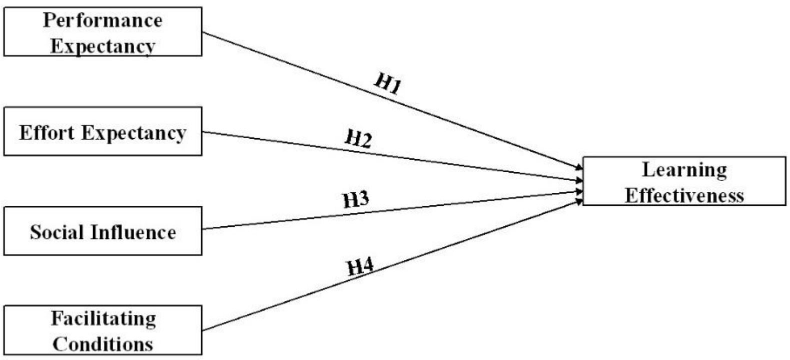

Figure 2. Conceptual Model

5. Results

As shown in Table 1, the reliability of the five latent variables is good, with Cronbach's alpha and composite reliability (CR) values for each latent variable greater than 0.708 [5]. The convergent validity is also good, with outer loadings for each latent variable greater than 0.70 [6], and Average Variance Extracted (AVE) higher than 0.50 [5]. The discriminant validity of the five latent variables in this study is good, with HTMT ratios lower than 0.85. The R^2 for learning effectiveness is 0.761, indicating substantial explanatory power. The Q^2 values greater than 0 suggest that the model has predictive power. Through Bootstrap analysis of 5000 samples, as shown in Table 2, the results indicate that PE and FC have significant effects on learning effectiveness, while the effects of EE and SI on learning effectiveness are not significant.

Table 1. Reliability and Validity

Construct	Code	Factor Loading	Cronbach's α	CR	AVE
Performance Expectancy	PE1	0.933	0.968	0.975	0.888
	PE2	0.946			
	PE3	0.944			
	PE4	0.929			
	PE5	0.96			
Effort Expectancy	EE1	0.872	0.943	0.956	0.815
	EE2	0.86			
	EE3	0.91			
	EE4	0.942			
	EE5	0.926			
Social Influence	SI1	0.907	0.952	0.963	0.839
	SI2	0.927			
	SI3	0.911			
	SI4	0.924			
	SI5	0.911			
Facilitating Conditions	FC1	0.939	0.963	0.971	0.871
	FC2	0.934			
	FC3	0.946			
	FC4	0.918			
	FC5	0.93			
Learning Effectiveness	LE1	0.915	0.957	0.967	0.854
	LE2	0.94			
	LE3	0.92			
	LE4	0.919			
	LE5	0.927			

Table 2. Path Analysis and Hypotheses Results

Hypothesis	β	Std. Dev	t-V	p-V	CI	VIF	Supported
H1: PE -> LE	0.299	0.098	3.041	0.002	[0.116,0.497]	3.757	yes
H2: EE -> LE	0.061	0.067	0.907	0.364	[-0.067,0.195]	1.963	no
H3: SI -> LE	0.142	0.106	1.344	0.179	[-0.054,0.367]	4.756	no
H4: FC -> LE	0.433	0.133	3.269	0.001	[0.157,0.674]	6.206	yes

Note: β=Coefficient, t-V = T-value, p-V = p Value, CI=95% CI

6. Discussion and Conclusions

The "Marketing Skills Sandbox Training" course emphasizes simulating real business scenarios, but traditional teaching approaches face issues such as low student engagement and delayed teacher feedback. This research uses this course as a vehicle to design a structured teaching method based on large language models (LLM-STM), aiming to enhance teaching efficiency and students' comprehensive abilities through technology empowerment, providing an empirical case for vocational education innovation.

This study uses the "Marketing Skills Sandbox Training" course as an example to propose the "Large Language Model Structured Teaching Method (LLM-STM)" through a four-step cycle of "Lecture, Imitation, Practice, Evaluation" to explore pathways for deep integration of technology with teaching. The LLM-STM model provides a replicable framework for educational digital transformation. The study recommends deepening its application in three aspects: developing subject-specific large language model plugins to enhance scenario adaptability; establishing teacher technology training systems to improve human-machine collaborative teaching abilities; and perfecting ethical norms to avoid capability weakening caused by over-reliance on technology. Additionally, empirical research results show that performance expectancy and facilitating conditions have significant effects on learning effectiveness, while the effects of effort expectancy and social influence on learning effectiveness are not significant.

Acknowledgement

This research was supported by the Key Teaching Reform Project of Zhejiang Business Technology Institute in 2024 titled "Large Language Model Empowering Teaching Reform Innovation — Taking the Course 'Marketing Skills Sandbox Training' as an Example" (Project No. jg202409) and the 2024 Annual Science Research Project titled "The Impact of Generative Artificial Intelligence on Vocational College Students' Learning Interest" (Project No. KYND202408). This paper represents a research outcome of the Zhejiang Business Technology Institute Science Research Project.

References

1. Prestine NA, LeGrand BF. Cognitive Learning Theory and the Preparation of Educational Administrators: Implications for Practice and Policy. *Educ. Adm. Q.* **1991**, *27*, 61–89.
2. Hein GE. Constructivist learning theory. *Inst. Inq.* **1991**, *14*.
3. Akers RL, Jennings WG. Social Learning Theory. In Piquero AR, Ed.; *Handb. Criminol. Theory*, 1st ed.; Wiley: **2015**, pp 230–240.
4. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. *MIS Q.* **2003**, *27*, 425.
5. Hair JF, Risher JJ, Sarstedt M, Ringle CM. When to use and how to report the results of PLS-SEM. *Eur. Bus. Rev.* **2019**, *31*, 2–24.
6. Hair JF, Hult GTM, Ringle CM, Sarstedt M. *Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed.; SAGE Publications: **2021**.