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Understanding influential factors for college instructors' adoption of LLM-based applications using analytic hierarchy process

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Abstract
With the accessibility of advanced artificial intelligence (AI)-based tools, particularly large language models (LLMs) such as ChatGPT, integrating LLMs into higher education has been considered a transformative shift in educational paradigms. However, instructors have numerous objections against the adoption of LLM-based applications. To promote the proper adoption of LLM-based applications for Chinese college instructors, this study investigates and assesses factors that affect instructors' adoption. Specifically, this study proposes a multi-criteria decision-making model drawing upon technology acceptance theories such as the value-based adoption model to determine four key influential factors and their sub-factors. After collecting expert data from 22 Chinese college instructors with experience in integrating AI applications into classrooms across seven provinces, an analytic hierarchy process is adopted to weigh and prioritize these factors. Results show that "Usefulness" is the most important factor for encouraging instructors' use of LLM-based applications, while "Effort" is of less concern. Among the sub-factors, "Effectiveness" and "Efficiency" are of intermediate importance in LLM-based application adoption, while "Perceived fee" has the least influence. Based on the findings, the study provides insights into Chinese college instructors' adoption experiences of LLM applications as well as suggestions for promoting LLMs' integration into instruction.

Keywords Large language models · LLM-based applications · Analytic hierarchy process (AHP) · Adoption intention · Value-based adoption model (VAM)

Introduction

Owing to advances in technology development, higher education has undergone a deep transformation in instructional resources and approaches especially driven by the fast development and prevalent use of artificial intelligence (AI)

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technologies, especially the cutting-edged large language models (LLMs) (Cambra-Fierro et al., 2024). As a popular LLM-based application, ChatGPT has gained massive attention because of its amazing capabilities in understanding and producing human-like languages and has brought broad discussion on its potential to advance education. Educators and researchers raising arguments from different views have acknowledged both advantages and disadvantages regarding the educational applications of LLMs (Adams et al., 2023). The advantages mainly focus on the personalization of instruction, accessibility, and support for special needs; however, there are also ethical concerns with regard to plagiarism, privacy security, etc.

According to Yan et al. (2024), higher education is also encountering challenges in relation to LLMs' potential for advancing education's future and technology-enhanced instruction and learning approach implementation. This is important because technologies are gradually playing crucial roles in transforming conventional instruction methods into up-to-date pedagogies. In line with this, instructors' willingness and efforts to use novel applications and instructional approaches empowered by LLMs become significant in enriching higher education with cutting-edge technological elements. Thus, it appears essential to comprehensively understand instructors' adoption of LLM-based applications and its influential factors in promoting technologies' integration into their instructional practices.

Based on the review of published research articles regarding the usage of LLM-based applications like ChatGPT in higher education, the majority of the extant academic works have been conducted from a theoretical or exploratory perspective (Cambra-Fierro et al., 2024; Farrokhnia et al., 2024), whereas more empirical evidence is needed. Moreover, studies on adoption intention for LLM-based applications in higher education contexts concentrate mainly on learners' perspectives and perceptions; however, relatively limited attention has been paid to instructors' adoption of this new technology. Since college instructors play a vital role in implementing LLM-based applications in the instruction process, it is necessary to explore what factors could affect the adoption of LLM-based applications from instructors' perspective. By understanding LLM-based applications such as ChatGPT's influence on higher educational teaching, instructors can balance the benefits and disadvantages of integrating them into practice.

To that end, this study aims to recognize factors that affect Chinese college instructors' adoption of LLM-based applications and assesses the degree to which these factors influence technology adoption. Specifically, this study first reviews prior studies on LLMs and their applications in education as well as popular technology acceptance theories. Subsequently, based on the reviewed theories, this study proposes a multi-criteria decision model with the guidance of the value acceptance model to categorize and specify influential factors and their sub-factors for the adoption of LLM-based applications among Chinese college instructors from the perspectives of "Usefulness", "Enjoyment", "Technicality", and "Effort". Thereafter, based on opinion data collected from 22 experts familiar with AI-integrated instruction via a questionnaire survey, an analytic hierarchy process (AHP) was utilized to weight the comparative importance between the factors and sub-factors in the framework to recognize the main factors that influence LLM-based application adoption by Chinese college instructors. Finally, the results of the analysis are interpreted to understand instructors' experiences and the adoption of LLM-based applications. Accordingly, three research questions (RQs) are addressed.

RQ1: Based on the technology acceptance theories, what factors should be considered in the multi-criteria decision-making framework?
RQ2: What are the most important factors that influence Chinese college instructors' integration of LLM-based applications into teaching?
RQ3: What are the insights into Chinese college instructors' experience and attitude towards integrating LLM-based applications into teaching?

The contributions of this study consist of three aspects. First, by revealing technology adoption from the perspective of instructors, this study is expected to promote the proper implementation of LLM-based applications in Chinese higher education contexts, allowing instructors in decision-making about effective instructional solutions according to their personal requirements and instruction styles. Second, the multi-criteria decision-making framework can serve as a general tool for helping instructors and colleges verify LLM-based applications' qualifications, thus promoting the proper integration of LLM-based applications into higher education instruction. Additionally, stakeholders such as instructors, students, and colleges could benefit from the proper adoption of LLM-based applications aligning with authentic instructional needs and content to promote learning outcomes and personalized learning, thus achieving educational equality.

Literature review

LLM-empowered chatbots such as ChatGPT have been considered promising in education. Capable of imitating human-like talks and supporting natural language processing, ChatGPT is believed to transform instructional approaches by assisting instructors in managing teaching tasks in a more efficient manner, offering opportunities for personalized learning, providing learners with timely feedback, promoting learners' self-directed learning, and promoting real-time interaction between learners through collaborative problem-based learning.

There are studies touching upon LLM-based chatbots' application in education. For example, based on the exploration of ChatGPT's potential for promoting personalized instruction, Al-Emran et al. (2023) demonstrated its effectiveness in tailoring support to learners according to individual requirements and learning styles. By investigating how the integration of AI-based chatbots as feedback tools into online instructional videos affected pre-service teacher learners' performance and intrinsic motivations, Fidan and Gencel (2022) discovered an improvement in learner engagement and idea exchanges among learners when ChatGPT bots were incorporated into discussion boards.

Although LLM-based applications' potential for advancing education is widely discussed, instructors still hold reservations against using them. To promote their successful implementation, there is a need to comprehend the factors that can influence their adoption. However, currently, studies on LLM-powered chatbots' acceptance and adoption primarily concentrate on learners' perspectives and perceptions. For example, Liu and Ma (2024) conceptualized English learners' attitudes and intentions for adopting ChatGPTs in informal learning with the guidance of the technology acceptance model (TAM). By investigating learners' acceptance of ChatGPTs for self-regulated learning, Dahri et al. (2024) highlighted the significance of ChatGPTs that are user-friendly with desired functions for supporting independent learning.

Comparatively, instructors' behaviours and intentions for adopting LLM-based applications have received less attention, although their perceptions and attitudes play important roles in the successful integration of technologies, resulting in instructors' hesitance in usage of and misuse of them integrated into their practical instruction (Du & Gao, 2022). In Chinese higher education, understanding instructors' adoption of LLM-based applications seems to be more important as their application in China is just beginning. Therefore, the present study proposes to introduce a practical instrument for measuring instructors' acceptance and adoption of LLM-based applications and promote decision-making about suitable products or services aligning with different instructional styles and pedagogical needs.

Theoretical framework

To explain Chinese college instructors' adoption of LLM-based applications and develop a multi-criteria decision-making framework, this study draws on three technology acceptance theories that are commonly adopted in research on users' technology adoption: TAM, value acceptance model (VAM), and unified theory of acceptance and use of technology (UTAUT). Specifically, the key variables in these three modes, including perceived usefulness, perceived ease of use, hedonic motivation, price value, perceived profit gain, and perceived profit loss, are integrated to form four main factors: "Usefulness", "Enjoyment", "Technicality", and "Effort". We further determine 15 sub-factors (see Appendix 1) comprising these four main factors based on an integrative literature review to identify, organize, and merge variables mentioned in previous studies.

Usefulness and its subfactors

Usefulness, akin to the perceived usefulness in TAM assesses the value and practicality of using LLM-based applications for instructors (Kim et al., 2007). This study defines four sub-factors of usefulness: effectiveness, efficiency, rewards, and professional development.

Specifically, effectiveness is the possibility of enhancing instructors' performance and teaching quality with the help of LLM-based applications. Second, efficiency involves the reduction of repetitive teaching workload brought about by the adoption of new technologies. Third, rewards, as extrinsic motivations including but not limited to equipment and financial support from schools or society, are considered to drive instructors to experiment with new technologies. Additionally, professional development refers to the opportunities given by the use of LLM-based applications to make changes in instructional practices and enhancements of learning outcomes.

Enjoyment and its subfactors

Enjoyment, as a positive emotional response that can make individuals happy and satisfied, has a moderating influence on attitudes and behavioural intentions (Humida et al., 2022). In our study, enjoyment focuses on the positive feelings brought by the LLM-based applications to teachers in the process of using it and can be divided into two sub-factors: pleasure and satisfaction.

Pleasure measures the positive mental state and pleasant experience obtained by instructors through the use of LLM-based applications. Satisfaction refers to effective responses when individuals achieve pre-set goals. In this study, satisfaction indicates instructors' satisfaction with the teaching results brought by integrating LLM-based applications into classrooms, thus making them more willing to continue using them.

Technicality and its subfactors

Technicality, which emphasizes the non-monetary cost required for using new technology, is an important factor that can affect individuals' adoption willingness (Decuypere, 2019). In this study, technicality refers to the technical features of LLM-based applications required for instructors to adopt them and can be defined from the perspectives of complexity and flexibility.

Complexity refers to the complexity of the operation of LLM-based applications; that is to say, complexity measures the degree to which instructors can easily master the use of LLM-based applications. Flexibility measures the flexibility of adopting LLM-based applications without time and space restrictions, and according to instructors' teaching styles.

Effort and its subfactors

Effort is meant to understand the efforts related to emotions, time, energy, and other aspects of investment in adopting new technologies (Lv et al., 2024). This study focuses on instructors' perceived time and perceived fee on using LLM-based applications when exploring the influencing factors for their adoption in Chinese colleges.

Perceived time refers to the additional work hours required to spend on using LLM-based applications. If the perceived time for adopting the LLM-based applications exceeds instructors' expectations, their willingness to adopt them will be reduced. Perceived fee measures the money that instructors are likely to spend in order to use LLM-based applications.

Methodology

Once the multi-criteria decision-making framework was established, the AHP, acting as a systematic hierarchical analysis approach based on both qualitative and quantitative perspectives, was utilized to weigh and rank the comparative importance of factors involved in the framework. The whole process of identifying relevant factors through an integrated literature review and measuring the weights of these factors based on AHP is illustrated in Fig. 1.

Establishment of AHP hierarchy

In AHP, a multi-criteria decision problem is divided into at least three levels: target, criterion, and scheme layers, where the target layer is the ultimate goal to be achieved, the criterion layer includes the main factors for achieving the goal, and the scheme layer is the specific plan or decision option to realize this goal. In the present study, the ultimate goal is "influencing factors for Chinese college instructors' adoption of LLM-based applications". The criterion layer involves four main factors: "Usefulness", "Enjoyment", "Technicality", and "Effort", with their sub-factors presented in the scheme layer that can influence the adoption of LLM-based applications by Chinese college instructors.

Collection of data from the experts

A questionnaire survey proposed based on the theoretical framework was used to measure the main factors and their sub-factors involved in the AHP hierarchy for understanding Chinese college instructors' willingness to adopt LLM-based applications. The first part of the questionnaire introduces the definitions of relevant factors and sub-factors and the use of a seven-level Likert scale for importance comparison. The second part involves the paired comparison matrices of the factors affecting the instructors' adoption. The third part containing closed and open-ended questions was utilized to collect participants' basic information and their usage experiences of LLM-based applications in teaching. Examples of open-ended questions are "What do you think LLM-based applications can be used for in teaching?" and "What challenges do you think might be encountered in adopting LLM-based applications to teaching?" To improve questionnaire accuracy, we invited two experts familiar

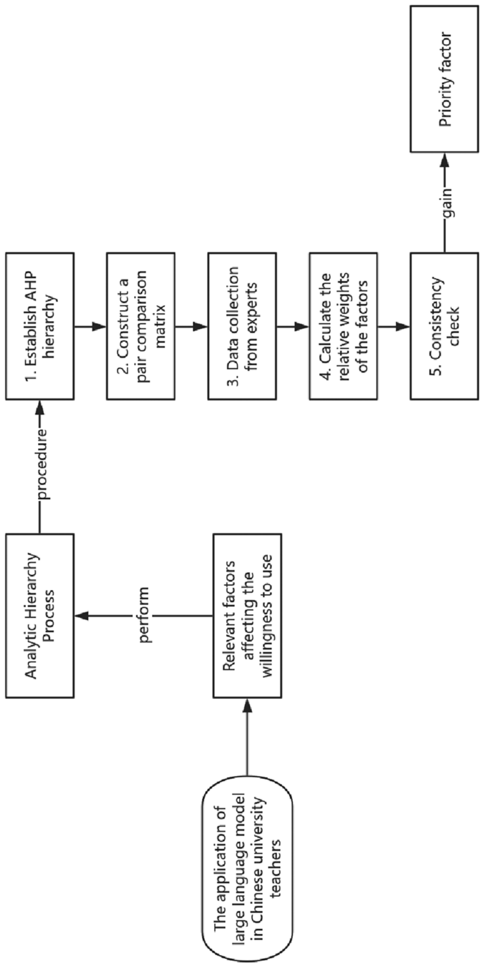

Fig. 1 The research design and analysis process

with integrating LLM-based applications into instruction to give advice and modify expressions. The final questionnaire is presented in Appendices 2 and 3.

The questionnaire was distributed to 22 instructors with experiences of adopting LLM-based applications in their teaching from 9 universities across 7 provinces in China. Appendix 4 shows the profiles of the 22 instructors, among which 90% were over 30 years old, and 86% believed that using LLM-based applications produced positive effects on teaching. All instructors have used LLM-based applications such as ChatGPT, ERNIE Bot, and IFlytek Spark. According to the scaling method of relative importance (Appendix 2), the 22 instructors anonymously scored the importance between factors in the pair comparison matrices to obtain their relative weights.

Construction of pair-wise comparison matrices

Based on the collected expert data and the AHP hierarchical model with four main factors and their 10 sub-factors, a hierarchical structure system suitable for analysis was constructed (see Table 1) for analysing influential factors for the adoption of LLM-based applications among Chinese college instructors.

The 22 experts compared the factors at the same level pairwise, and gave values of relative importance, thereby forming a pair-wise comparison matrix. The pair-wise comparison matrices of sub-factors presented in the scheme layer for the main factors were also obtained.

Consistency check

Considering the subjectivity of experts in making judgments, after calculating the relative weights, a consistency test of the comparison matrices was performed to ensure usability based on $CR = CI/RI$ and $CI = (\lambda\_\max - n)/(n - 1)$, in which $\lambda\_\max$ is the largest eigenvalue, n is the order of comparison matrix, and random index (RI) values.

Results

Comparison matrices and consistency test results

Table 2 presents the comparison matrix of the main factors, alongside the consistency test results, and Tables 3, 4, 5 and 6 describe the sub-factor comparison matrices, together with the consistency test results of each sub-factor comparison matrix. Results show that for all the matrices, the CR values of below 0.10 indicate a high level of consistency, and thus the weights are acceptable.

Specifically, according to Table 2, "Usefulness" is the most influential factor, with a weight of 52.216%, which, consistent with TAM, indicates that instructors consider the usefulness of LLM-based applications as the primary driver in their adoption decisions. "Enjoyment", with a weight of 20.327%, ranks second in importance,

Table 1 Hierarchical structure system

Target layer (G)	Criterion layer (C_i) (main factors)	Scheme layer ($C_{i,j}$) (sub-factors)
Influential factors for the adoption of LLM-based applications among Chinese college instructors (G)	Usefulness (C_1)	Effectiveness ($C_{1,1}$)
		Efficiency ($C_{1,2}$)
		Rewards ($C_{1,3}$)
		Professional development ($C_{1,4}$)
	Enjoyment (C_2)	Pleasure ($C_{2,1}$)
		Satisfaction ($C_{2,2}$)
	Technicality (C_3)	Complexity ($C_{3,1}$)
		Flexibility ($C_{3,2}$)
	Effort (C_4)	Perceived time ($C_{4,1}$)
		Perceived fee ($C_{4,2}$)

Table 2 Comparison matrix of main factors

	Usefulness	Enjoyment	Technicality	Effort	Weights (%)	Consistency	Consistency test result
Usefulness	1.000	4.015	3.136	3.606	52.216	CI = 0.064 RI = 0.890 CR = 0.072	Pass
Enjoyment	0.249	1.000	2.015	1.830	20.327		
Technicality	0.319	0.496	1.000	2.452	17.077		
Effort	0.277	0.547	0.408	1.000	10.380		

suggesting that instructors' enjoyment and satisfaction with the application is also significant in the adoption process, although to a lesser extent than "Usefulness". Technicality (with a weight of 17.077%) ranks third, revealing that while technical factors such as the application's complexity and flexibility are important, they are considered less critical than "Usefulness" and "Enjoyment"; thus, instructors are more focused on the practical benefits and user experience rather than the underlying technical aspects. "Effort", with the lowest weight of 10.380%, is the least influential factor, suggesting that while factors such as perceived time and fees associated with using LLM-based applications are relevant, they have a relatively smaller impact. Overall, the findings suggest that instructors prioritize practical benefits and user experience when evaluating LLM-based applications.

According to Table 3 that shows the comparison matrix of the sub-factors under the "Usefulness" category, "Effectiveness" is the most influential, with the highest weight (46.861%), indicating that college instructors prioritize how well an LLM-based application improves teaching and learning outcomes. "Efficiency" ranks second, with a weight of 27.642%, signifying that instructors also value the ability of applications to streamline tasks such as grading, content generation, and administrative work. "Rewards" (weighted at 12.984%) is the third most influential, suggesting that while incentives such as institutional support can encourage adoption, they are not as critical as the practical benefits of effectiveness and efficiency. "Professional Development" holds the lowest weight (12.513%), indicating that they are not the primary driving force behind adoption; thus, instructors prioritize immediate teaching benefits over long-term professional advancements when deciding whether to adopt LLM-based applications.

According to Table 4 that presents the comparison matrix for the "Enjoyment" category, "Pleasure" is the more influential, with a weight of 65.935%, indicating that the level of enjoyment and engagement experienced while using an LLM-based application plays a critical role in adoption. "Satisfaction" holds a lower weight of 34.065%, suggesting that while overall contentment with the technology (e.g., meeting expectations and aligning with teaching needs) is relevant, it is secondary to the immediate pleasure derived from using the application. These findings suggest that instructors prioritize their personal enjoyment and engagement with the tool over long-term satisfaction when making adoption decisions; thus, it is important to design LLM-integrated instructional tools that are functional and enjoyable to use.

Table 3 Comparison matrix of "usefulness"

	Effectiveness	Efficiency	Rewards	Professional development	Weights (%)	Consistency	Consistency test result
Effectiveness	1.000	2.383	3.500	2.873	46.861	CI = 0.026	Pass
Efficiency	0.420	1.000	2.803	2.363	27.642	RI = 0.890	
Rewards	0.286	0.357	1.000	1.285	12.984	CR = 0.030	
Professional development	0.348	0.423	0.778	1.000	12.513		

Table 4 Comparison matrix of "Enjoyment"

	Pleasure	Satisfaction	Weights (%)	Consistency	Consistency test result
Pleasure	1.000	1.936	65.935	CI = 0.000 RI = 0.000 CR = 0.000	Pass
Satisfaction	0.517	1.000	34.065		

Table 5 Comparison matrix of "technicality"

	Complexity	Flexibility	Weights (%)	Consistency	Consistency test result
Complexity	1.000	1.656	62.346	CI = 0.000 RI = 0.000 CR = 0.000	Pass
Flexibility	0.604	1.000	37.654		

Table 6 Comparison matrix of "effort"

	Perceived time	Perceived fee	Weights (%)	Consistency	Consistency test result
Perceived time	1.000	3.106	75.646	CI = 0.000 RI = 0.000 CR = 0.000	Pass
Perceived fee	0.322	1.000	24.354		

According to Table 5 which presents the comparison matrix for the "Technicality" category, "Complexity" is the dominant, with a weight of 62.346%, indicating that the perceived difficulty of understanding, integrating, and using LLM-based applications is a major concern for instructors. "Flexibility" holds a lower weight of 37.654%, suggesting that while flexibility can enhance an instructor's ability to tailor LLM tools to their specific teaching needs, its impact on adoption is not as critical as the perceived ease of use and technical simplicity. These findings highlight the importance of intuitive user interfaces, clear guidance, and technical support to facilitate adoption.

According to Table 6 which presents the comparison matrix for the "Effort" category, "Perceived Time" is the most influential, with a weight of 75.646%, indicating that the amount of time required to learn, integrate, and use LLM-based applications is a critical concern for instructors. "Perceived Fee" holds a lower weight of 24.354%, suggesting that while affordability and cost-related concerns may influence decision-making, they appear to be secondary to the time burden associated with adopting LLM-based applications. These findings demonstrate the significance of minimizing the time burden related to learning and using LLM-based applications through user-friendly interfaces, streamlined implementation processes, and adequate training support.

Specifically, according to Table 2, among the four main factors, "Usefulness" (weight value = 52.216%) has the highest impact on Chinese college instructors' adoption of LLM-based applications. The remaining three factors are "Enjoyment" (weight = 20.327%), "Technicality" (weight = 17.077%), and "Effort" (weight = 10.380%) in order of importance. Overall, the importance of "Usefulness" occupies more than half of the weight, whereas the other three factors have lower and relatively close weights.

For sub-factors of "Usefulness" (see Table 3), "Effectiveness" (weight = 46.861%) is the most important, followed by "Efficiency" (weight = 27.642%), "Rewards" (weight = 12.984%), and "Professional Development" (weight = 12.513%), with the latter two showing significantly lower weights than the former two that account together for nearly 75% of the importance of "Usefulness". Regarding "Enjoyment" (see Table 4), "Pleasure" (weight = 65.935%) is nearly twice as important as "Satisfaction" (weight = 34.065%). For "Technicality" (see Table 5), "Complexity" (weight = 62.346%) was more important than "Flexibility" (weight = 37.654%), with a difference in importance values approaching 25%. Regarding "Effort" (see Table 6), experts believe that "Perceived time" (weight = 75.646%) is nearly three times more important than "Perceived fee" (weight = 24.354%).

Local and global weights of all factors

Based on the local weights of the 4 main factors and 10 sub-factors, this study further calculated the global weights of each sub-factor (see Table 7). Results show that "Effectiveness" (global weight = 24.469%) and "Efficiency" (14.434%) are the top two in the ranking of importance, together accounting for nearly 40% of the total weight. "Pleasure" ranked third (13.403%) and "Complexity" ranked fourth (10.647%) are also important factors influencing Chinese college instructors' adoption of LLM-based applications. On the contrary, "Perceived fee" (2.528%) ranked the last with the least importance. In addition, "Perceived time" (7.852%), "Satisfaction" (6.924%), "Rewards" (6.780%), "Professional development" (6.534%), and "Flexibility" (6.430%) have almost the same medium degree of influence on instructors' adoption.

Table 7 Local and global weights of all factors

Main factors	Weights (%)	Sub-factors	Local weights (%)	Global weights (%)	Rank
Usefulness	52.216	Effectiveness	46.861	24.469	1
		Efficiency	27.642	14.434	2
		Rewards	12.984	6.780	7
		Professional development	12.513	6.534	8
Enjoyment	20.327	Pleasure	65.935	13.403	3
		Satisfaction	34.065	6.924	6
Technicality	17.077	Complexity	62.346	10.647	4
		Flexibility	37.654	6.430	9
Effort	10.380	Perceived time	75.646	7.852	5
		Perceived fee	24.354	2.528	10

Discussion

In order to recognize the influential factors for college instructors' adoption of LLM-based applications, this study first proposed a multicriteria decision-making framework with four main factors and their sub-factors based on technology acceptance theories and an integrated literature review. Subsequently, survey data from 22 experts was collected and analysed using AHP to determine the weights and importance of these factors. Based on the calculated weights of factors and expert insights, the use of LLM-based applications among college instructors was interpreted.

Main factors analysis (RQ1)

Results in Table 2 indicated that the "Usefulness" of LLM-based applications was the top priority with 52.216% importance for instructors' behavioural intention to adopt them in real-world instruction. In other words, when instructors perceive tangible benefits (e.g., providing personalized feedback, automating routine tasks, and offering adaptive learning experiences) demonstrated by LLM-based applications, it is more likely for them to increase their willingness to employ them in instructional practices. The importance of the usefulness of technologies' adoption in education contexts has also been highlighted by Papakostas et al. (2023) who revealed a positive influence of perceived usefulness on engineering learners' intention to use augmented reality tools, and similarly. This result can be explained by TAM which considers instructors' perceived usefulness for enhancing instructional performance a primary determinant for their intention to use LLM-based applications. From the perspective of performance expectancy in UTAUT, the higher the extent to which instructors trust that adopting LLM-based applications helps with their work performance, the higher levels of their usage intention.

From an affective perceptive, "Enjoyment" with a medium importance (20.327%) can also affect instructors' willingness to employ LLM-based applications. As an intrinsic construct, enjoyment indicates the degree to which individuals perceive technology adoption as enjoyable. In line with intrinsic motivation theory (Deci & Ryan, 2013), when enjoyment is derived from using and interacting with LLM-based applications through, for example, engaging with user-friendly interfaces, opportunities for creation, or achieving a sense of accomplishment, that contribute to fostering positive emotional connections, instructors tend to increase motivation to adopt and continue using these technologies. This finding comes in line with the outcomes reported by Su and Chiu (2021) who identified perceived enjoyment as an important factor in promoting elementary school students' use of interactive videos.

Technically speaking, the results also showed the influence of "Technicality" with medium importance (17.077%) on instructors' adoption of LLM-based applications. This result is consistent with Du and Gao (2022) who highlighted technicality's moderate effect on English instructors' use of AI-empowered tools. As a non-monetary cost in technology use, technicality, which encompasses factors such as system reliability, connectivity, and efficiency, can demonstrate a direct impact on how easy or difficult a technology is to use. According to TAM which identifies perceived ease of use as an essential factor for technology adoption, it is more likely for instructors to be willing to integrate LLM-based applications into instruction when they are perceived to be technically straightforward, with reliable performance, strong connectivity, and efficient operation. That is to say, the less technically demanding technology is perceived to be, the lower the cognitive and time investment required to learn and integrate it into practical instruction.

On the contrary, the willingness of Chinese college instructors to use LLM-based applications is the least affected by "Effort" (10.380%). This result can be explained by expectancy theory suggesting that an individual is motivated to spare effort when desirable results can be achieved. Instructors are motivated by their expectations of improved teaching outcomes and quality to integrate LLM-based applications into real-world instruction; thus, whether and to what extent these applications can enhance teaching effectiveness and efficiency are priority factors for their adoption decisions Similarly, from a cost–benefit perspective (Mishan & Quah, 2020), when instructors recognize that a LLM-based application provides substantial value to their teaching process and improve teaching outcomes and efficiency, the perceived effort required for adoption becomes less of a barrier.

Sub-factor analysis (RQ2)

Results in Table 7 showed that among the 10 sub-factors, "Effectiveness", "Efficiency" and "Pleasure" with global weights of 24.469%, 14.434%, and 13.403%, respectively, play the most important roles in determining instructors' adoption of LLM-based applications. The significance of these factors in motivating technology acceptance of instructors or learners has also been highlighted by Bansah and Agyei (2022). In this study, most instructor participants used LLM-based applications to shorten the time spent on repetitive tasks such as information retrieval and improve teaching quality and efficiency (e.g., generating test questions and lesson plans, translating teaching materials, and writing codes). Meanwhile, most participants have highlighted the positive emotional value derived from using LLM-based applications. For example, one participant noted that "it is a pleasant experience to seek help from ERNIE Bot for resolving his confusion in preparing for instructional materials, thus increasing my willingness to continue using it".

"Complexity" and "Perceived time" with global weights of 10.647% and 7.852%, respectively, are the second most important sub-factors. Complexity, which relates to how effortless a system or application is to be used, is consistent with the perceived ease of use in TAM, according to which, when instructors perceive LLM-based applications to be simple and intuitive, their willingness to adopt them increases. This is because an application with a user-friendly interface and clear operational processes can largely reduce the cognitive load required for instructors to learn and integrate it into their teaching practices (Ali et al., 2022). On the contrary, when technology is perceived to be complex for usage, requiring significant mental and physical efforts to master, instructors may show subjective resistance to use. While ease of use of an application can encourage adoption, the amount of time needed to learn and adapt it to suit an instructor's teaching styles and instructional needs can still be a barrier. This is because instructors usually have demanding and busy schedules, and tend to be reluctant to invest additional time in mastering new tools, particularly when they need to sacrifice their personal or leisure time. For LLM-based applications such as ChatGPT, although they are designed to be user-friendly, the need for instructors to decompose problems and interact iteratively and continuously with them to obtain desired answers may extend the time required to complete tasks, thus leading to unwillingness to adoption.

Compared to the above sub-factors, "Satisfaction", Rewards", "Professional development", and "Flexibility" with global weights between 6 and 7%, have slight influences on instructors' adoption of LLM-based applications. Firstly, according to TAM, satisfaction, linking often to perceived usefulness and perceived ease of use, is crucial for technology adoption. In this study, most instructor participants have especially expressed satisfaction with the LLM-based applications' ability to retrieve productive information, correct errors in codes, and provide desirable answers, suggesting that these applications can satisfy their instructional needs and requirements effectively. For instance, one participant noted, "I now prefer to use LLM-based applications such as ERNIE Bot, IFlytek Spark instead of traditional browsers for information retrieval because I can get more satisfactory answers". However, despite this, the slight impact of satisfaction on overall adoption may indicate that while satisfaction reinforces instructors' positive attitudes toward the adoption of LLM-based applications, factors such as complexity or time investment, might overshadow satisfaction when they make continuous usage decisions.

Secondly, consistent with Tseng et al. (2022) showing the significance of financial rewards as an extrinsic motivator in promoting the initial adoption of modern information technologies in teaching, instructor participants in this study have indicated that when they perceive the LLM-based applications to be useful and effective, financial support or incentives received from their institutions can encourage them for adoption. However, the slight impact of rewards identified in our results suggests that although incentives can motivate instructors to try LLM-based applications, they are not the primary drivers for their continuance adoption. This finding echoes self-determination theory (Deci & Ryan, 2012) positing that compared to extrinsic rewards, intrinsic motivations such as personal interest and perceived value are more effective in encouraging sustained usage. Therefore, instructors tend to pay more attention to intrinsic factors such as enjoyment and satisfaction than external incentives of rewards regarding their decisions about integrating LLM applications into practical instruction.

Furthermore, opportunities for professional growth, which relates often to the ongoing enhancement of teaching practices and career progression, play a crucial role in motivating instructors to adopt new technologies. In this study, although instructor participants have acknowledged that using LLM-based applications can to some extent help them expand their professional knowledge through teaching material provision, they generally prefer to achieve professional growth through accumulating practical teaching experiences or learning from peers instead of relying on teaching tools. This suggests that although professional development opportunities provided by using LLM-based applications are valued by instructors, they are not decisive factors in their adoption of practical instruction, particularly when instructors' professional growth can be achieved through formal and traditional channels.

In addition, instructor participants have acknowledged the flexibility of LLM-based applications to be implemented on various devices, including personal computers and mobile devices. However, the slight impact of flexibility on technology adoption identified via AHP reflects practical challenges in integrating LLM-based applications into teaching practices, for example, how to create effective prompts and how to align LLM-enriched instruction with pedagogical needs and instructional styles (ElSayary, 2024). According to the task-technology fit model which emphasizes that technology must align well with the tasks it is intended to support so as to improve adoption, LLM-based applications may still require instructors to make significant adjustments to current instructional approaches or do not fit effortlessly into instructional processes.

On the contrary, "Perceived fee" with a global weight of 2.528% is the factor that has the least influence on instructors' adoption of LLM-based applications. Currently, basic versions of most LLM-based applications that can commonly meet the fundamental needs of instructors are accessible without financial commitment, or at a low cost; thus, instructors are allowed to explore and integrate these tools into their instructional practices without or with limited financial barriers, diminishing the perceived importance of cost for their adoption decision-making. Many LLM-based applications have also offered opportunities for one-time purchases, which, consistent with the diffusion of innovations theory (Rogers et al., 2014), is preferable for individual users compared to a subscription-based model to minimize long-term financial commitments. Therefore, instructors tend to be less concerned about the financial costs of adopting LLM-based applications and focus more on the values obtained.

Technological constraints that influence instructors' adoption

In the context of LLM-based educational applications, technological constraints related to infrastructure limitations, lack of technical support and training, integration with existing systems, and data privacy and security concerns can affect the way instructors evaluate the factors of "Usefulness", "Enjoyment", "Technicality", and "Effort" and their sub-factors, ultimately shaping their decisions about whether to adopt the applications.

Specifically, poor infrastructure (e.g., slow internet speeds or outdated hardware) can undermine the perceived "Effectiveness" and "Efficiency" of LLM-based applications. For example, if an LLM application is slow to load or prone to technical failures, instructors may perceive it as ineffective in achieving desired educational outcomes, reducing their interest in adopting it. Also, without adequate infrastructure and technical support, instructors may also feel that adopting LLM applications does not contribute significantly to their "Professional Development", as they may lack the resources or training to effectively use them.

Second, technological constraints such as frequent system crashes, glitches, or interface issues can directly diminish the level of "Pleasure" experienced by instructors when using LLM-based applications. If instructors face technical problems during class or encounter difficulties navigating the application, they may find the experience stressful rather than enjoyable. Moreover, the "Satisfaction" derived from using the application can be significantly impacted if it fails to meet expectations due to usability issues.

Third, the "Complexity" of using an LLM-based application can be exacerbated by requirements of specific technical configurations or incompatibility with existing learning systems, as instructors may feel overwhelmed and perceive it as too complex to implement in their teaching practices. Additionally, concerning "Flexibility" as an important factor in adapting LLM-based applications to instructors' specific teaching needs, limited customization or adaptation options may make them feel restricted in their usage reducing its perceived value and making it less likely to be adopted.

Another technological constraint that could impact adoption is the concern over data privacy and security, especially when adopting LLM-based applications that may involve the collection and processing of sensitive student data. Also, instructors may feel hesitant if they have to devote additional time to ensure compliance with privacy regulations or to understand the security features of the application.

Insights into integrating LLM-based applications into instruction (RQ3)

This study expands the research scope of technology adoption, with findings underscoring the multifaceted factors that influence Chinese college instructors' adoption of LLM-based applications and offering important insights into how LLM-based applications can be effectively integrated into college instruction.

From a theoretical perspective, the multi-criteria decision-making framework developed in this work acts as a valuable tool for instructors and institutions to assess the suitability of an LLM-based application to be used as an integrated component in practical instruction. The integration of technology acceptance theories with the AHP methodologies contributes to understanding technology adoption in educational settings from an interdisciplinary perspective, serving as a practical tool used by policymakers and practitioners for the evaluation and promotion of emerging AI technology adoption.

From a practical perspective, several suggestions are proposed for promoting instructors' adoption of LLM-based applications in college instruction.

First, institutions that have encouraged instructors' adoption of LLM-based applications or are planning to do so ought to clearly communicate the practical benefits to instructors through the use of case studies, pilot programs, and testimonials from early adopters to demonstrate how these applications can improve teaching outcomes and quality in real-world settings.

Second, educational institutions are encouraged to actively provide substantial resources for supporting instructors' integration of LLM-based applications into their practical instruction by, for example, establishing support teams to guide instructors throughout the adoption process and providing training programs tailored to instructors' specific and diverse needs to improve teaching effectiveness and efficiency.

Furthermore, developers of LLM-based applications specific to college instruction ought to focus on how to reduce the cognitive load required for using these tools through iterative testing and continuous refinement of user interfaces and integrating functions that align with instructors' workflows, thus ensuring that they are intuitive, user-friendly, and accessible to instructors with different levels of technological proficiencies.

In addition, to promote personalization in instruction, it is suggested that tools specifically tailored to diverse educational needs (e.g., customizable lesson plans, automated grading, and personalized feedback) can be integrated into LLM-based applications to allow instructors to select and configure these tools that best fit their instructional styles and content. Plus, gamification elements or features such as offering encouragement or motivational prompts and providing instructors with immediate access to expert advice when they encounter technical challenges can also be incorporated into these applications to reduce complexity in usage and meanwhile improve the emotional and psychological aspects of user experience.

Limitations, reflections, and future work

This work has some limitations. First, as the present study collected 22 expert data from 9 universities across 7 provinces in China, the results are not claimed to be conclusive as we did not fully cover all Chinese institutions. While the sample size of 22 participants may seem small, it is within the accepted range for expert opinion studies, especially when using AHP, which differs from traditional questionnaire surveys where large sample sizes are typically needed to ensure statistical significance, is capable of gathering qualitative judgments from a smaller number of experts and then quantifying those opinions to derive meaningful insights. The AHP methodology inherently accommodates a smaller sample of knowledgeable participants to produce valuable results that are highly applicable to the field of education. For example, in Du and Gao's (2022) study on AI-based applications in English learning, 17 experts were consulted to reveal the key factors that affected instructors' adoption of AI technologies using AHP. In Kukreja et al. (2023) which analysed technology adoption in early childhood education, 30 participants were surveyed, with AHP being employed to prioritize factors that influenced the use of touchscreen devices. These studies demonstrate that AHP studies in educational technology adoption commonly work with smaller, expert-focused samples, and the results remain significant and insightful despite the limited number of participants. Nevertheless, future work may consider including a larger number of participants, possibly from different regions or countries, to promote the validity and generalizability of the findings to achieve more diverse and generalized results and facilitate cross-region or cross-country comparisons. Second, it is acknowledged that AI and LLM technologies evolve quickly; however, the factors and concerns such as "Usefulness", "Enjoyment", "Flexibility", and "Effectiveness" that are central to the decision-making process for instructors considering the integration of LLM tools in their teaching tend to be more stable over time. Nevertheless, future research may consider continuing tracking and monitoring of how the adoption factors evolve over time as the technology advances.

Moreover, in this study, expert participants familiar with AI-integrated instruction were asked to provide their conscious perceptions regarding the factors influencing LLM-based application adoption, whereas subconscious factors were not considered. Conscious perceptions, which allow expert participants to articulate and reflect upon the factors they believe are important in making decisions about technology adoption, are particularly important when evaluating systematic factors such as "Usefulness", "Effectiveness", "Flexibility", and "Professional development", whereas subconscious factors that could influence decision-making may manifest in implicit biases or heuristics that are difficult to capture in a structured, systematic approach like AHP. Furthermore, given the focus of this study on quantitative prioritization using AHP, the conscious perceptions of experts were the most appropriate source of data that allows for directly determining the relative importance of various adoption factors. In studies focusing on educational technology adoption (e.g., Du & Gao, 2022; Kukreja et al., 2023), the conscious perceptions of experts or instructors have also been widely considered. For example, in Du and Gao (2022), 17 EFL teachers were consulted to determine the key factors affecting their adoption of AI technologies to be further prioritized using AHP. In Kukreja et al. (2023), experts were surveyed for their technology adoption in early childhood education, and AHP was employed to prioritize factors that influenced the use of touchscreen devices. Nevertheless, future work can consider including subconscious factors using mixed-methods approaches by combining quantitative data with qualitative insights to allow for a more holistic understanding of adoption factors.

Additionally, methodologically speaking, this study adopts a quantitative AHP approach rather than qualitative methods or includes observational data. As the main purpose of the present work was to quantitatively prioritize the factors influencing LLM adoption by college instructors, AHP was well-suited to achieve this goal because it can not only gather opinions but also quantitatively prioritize factors based on expert insights to understand how each factor contributes. However, this is not easily achievable through qualitative methods or observational data analysis, which, while focusing on gathering qualitative and descriptive information or direct observation of participants, do not offer the same ability to numerically rank or assign weights to the factors. Nevertheless, future work can consider including qualitative approaches or observational data as complementary tools by conducting interviews or focus groups with a larger sample of instructors or observing instructors' real-time experiences with LLM-based applications to provide contextual insights into how instructors interact with these technologies and the factors that ultimately drive adoption.

Conclusion

Alongside technological advances and the calls for education modernization, increasing AI technologies have been integrated into Chinese college teaching. As a recently developed AI technology, LLM-based applications have attracted instructors' attention for their potential to promote instruction quality. Based on TAMs such as VAM, TAM, and UTAUT, a multi-criteria decision-making model framework specifically tailored to understanding influential factors for college teachers' adoption of LLM-based applications was proposed with four main factors: "Usefulness", "Enjoyment", "Technicality", and "Effort". An integrated literature review was further conducted to identify ten sub-factors of these main factors. Based on survey data from 22 experts, the weights of these factors were measured and prioritized using AHP. The results showed that the most important factors that affected instructors' adoption were "Usefulness" and "Enjoyment", with "Effectiveness", "Efficiency", and "Pleasure" as the sub-factors valued the most by instructors, followed by "Complexity" and "Perceived time", while the "Perceived fee" was the least important. The multi-criteria decision-making framework introduced in this study offers educators a standardized tool for assessing LLM-based applications, enabling them to identify and incorporate suitable products based on their requirements and preferences into their teaching methods. From a theoretical standpoint, the present study's key innovation lies in integrating technology acceptance theories with the AHP to evaluate instructors' adoption of LLM-based applications. Furthermore, as the acceptance of LLM technologies has been relatively underexplored, the proposed framework addresses this gap, thus broadening the depth and reach of research on educational technology adoption.

Appendix 1: Influential factors for Chinese college instructors' adoption of LLM-based applications

Main factors	Sub-factors	Description	References
Usefulness	Effectiveness	I think using LLM-based applications to assist teaching is helpful for improving teaching quality	Chatterjee and Bhattacharjee (2020), Gupta and Bhaskar (2020), Kafyulilo et al. (2016) and Whitehill and Movellan (2017)
	Efficiency	I think using LLM-based applications is helpful for reducing the repetitive workload in teaching and improving teaching efficiency	
	Rewards	I think using LLM-based applications is helpful for getting incentives and financial support from schools or society	
	Professional development	I think that integrating LLM-based applications into teaching is helpful for obtaining opportunities to improve my professional development	
Enjoyment	Pleasure	I think the experience of using LLM-based applications is enjoyable	Venkatesh et al. (2012) and Hsu and Lin (2018)
	Satisfaction	I think the results of integrating LLM-based applications into teaching are satisfactory	
Technicality	Complexity	I think it is not so difficult for me to use LLM-based applications	Chatterjee and Bhattacharjee (2020) and Sánchez-Prieto et al. (2019)
	Flexibility	I think it is flexible to use LLM-based applications in time, space, and working styles	
Effort	Perceived time	I think the amount of time needed to spend using LLM-based applications is reasonable	Kafyulilo et al. (2016) and Hsu and Lin (2018)
	Perceived fee	I think the amount of money needed to spend on using LLM-based applications is reasonable	

Appendix 2: Introduction of research variables and relative importance comparison

Usefulness	The value and usefulness of using LLM-based applications for you
Effectiveness	I think using LLM-based applications to assist teaching is helpful for improving teaching quality
Efficiency	I think using LLM-based applications is helpful for reducing the repetitive workload in teaching and improving teaching efficiency
Rewards	I think using LLM-based applications is helpful for getting incentives and financial support from schools or society
Professional development	I think that integrating LLM-based applications into teaching is helpful for obtaining opportunities to improve my professional development

Enjoyment	Experience of using LLM-based applications
Pleasure	I think the experience of using LLM-based applications is enjoyable
Satisfaction	I think the results of integrating LLM-based applications into teaching are satisfactory

Technicality	Technical features related to LLM-based applications
Complexity	I think it is not so difficult for me to use LLM-based applications
Flexibility	I think it is flexible to use LLM-based applications in time, space, and working styles

Effort	The time, effort, and money required for using LLM-based applications
Perceived time	I think the amount of time needed to spend using LLM-based applications is reasonable
Perceived fee	I think the amount of money needed to spend on using LLM-based applications is reasonable

Intensity of importance	Definition	Explanation
1	Equal importance	Two factors considered equally important
3	Moderate importance	One factor is marginally important over another
5	Strong importance	One factor is strongly important over another
7	Extreme importance	The importance of one factor over another is of the highest
2.4.6	Intermediate values	Intermediate Values between two adjacent judgments

LLM-based applications: ChatGPT, ERNIE Bot, IFlytek Spark, etc.Based on the scale of relative importance, please check the following tables. For example:

> "Usefulness/enjoyment = 1" indicates that Usefulness is as important as Enjoyment
> "Usefulness/technicality = 2" indicates that Usefulness is more important than technicality and is twice as important
> "Usefulness/enjoyment = 1/3" indicates that Enjoyment is more important than Usefulness and is three times more important

Comparison of main factors

	7	6	5	4	3	2	1	1/2	1/3	1/4	1/5	1/6	1/7
Usefulness/enjoyment													
Usefulness/technicality													
Usefulness/effort													
Enjoyment/technicality													
Enjoyment/effort													
Technicality/effort													

Comparison of "usefulness"

	7	6	5	4	3	2	1	1/2	1/3	1/4	1/5	1/6	1/7
Effectiveness/efficiency													
Effectiveness/rewards													
Effectiveness/professional development													
Efficiency/rewards													
Efficiency/professional development													
Rewards/professional development													

Comparison of "enjoyment"

	7	6	5	4	3	2	1	1/2	1/3	1/4	1/5	1/6	1/7
Pleasure/satisfaction													

Comparison of "technicality"

	7	6	5	4	3	2	1	1/2	1/3	1/4	1/5	1/6	1/7
Complexity/flexibility													

Comparison of "effort"

	7	6	5	4	3	2	1	1/2	1/3	1/4	1/5	1/6	1/7
Perceived time/perceived fee													

Appendix 3: Closed- and open-ended questions

1. May I ask your gender

A. Male B. Female

2. May I ask your age

A. Less than 30 B. 30–40 C. 40–50 D. Greater than 50

3. What is the subject you are teaching

____

4. How many years of teaching experience do you have

A. Less than 5 years B. 5–10 years C. 10–20 years D. More than 20 years

5. What LLM-based applications (e.g., ChatGPT, ERNIE Bot, IFlytek Spark, etc.) have you used in your teaching?

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6. What do you think can be done with these tools in teaching?

A. Generate teaching materials and presentations

B. Generate test questions

C. Generative instructional design

D. Evaluate and score students' works

E. Generate translation documents of teaching materials

F. Generate basic lesson plans

G. Other ____________________________________(Please specify)

7. What effect do you think can be achieved by integrating LLM-based applications into teaching? (Multiple options available)

A. Positive effects

B. Negative effects

C. No change

8. What challenges do you think might be encountered in integrating LLM-based applications into teaching?

____

Appendix 4: Expert profiles

No.	Sex	Age	Subject	Years of experience with technology-enhanced instruction	Use of LLM-based applications	Perceived effectiveness of LLM-based applications
1	Female	30–40	Educational technology	5–10 years	ERNIE Bot	Positive
2	Female	Over 50	Educational technology	Over 20 years	ChatGPT, ERNIE Bot	Positive and negative
3	Female	Over 50	Educational technology	Over 20 years	ChatGPT, ERNIE Bot	Positive and negative
4	Female	30–40	Learning analytics	Below 5 years	ChatGPT	Positive
5	Female	30–40	Preschool education	Below 5 years	ChatGPT	Positive
6	Female	Below 30	Primary education	Below 5 years	ChatGPT, IFlytek Spark	Positive
7	Male	40–50	Educational technology	10–20 years	ChatGPT	Positive
8	Male	Over 50	Educational technology	Over 20 years	ERNIE Bot, IFlytek Spark	Positive
9	Male	30–40	Educational technology	5–10 years	ERNIE Bot	Positive
10	Male	Over 50	Educational technology	Over 20 years	ERNIE Bot, IFlytek Spark	Positive and negative
11	Male	40–50	Educational technology	5–10 years	ChatGPT, ERNIE Bot, Tongyi Qianwen	Positive
12	Male	30–40	Computer sciences	Below 5 years	ChatGPT	Positive
13	Male	30–40	Computer science and technology	Below 5 years	ChatGPT	Positive
14	Male	30–40	Computer science and technology	Below 5 years	ChatGPT	Positive
15	Male	30–40	Computer sciences	Below 5 years	ChatGPT	Positive
16	Male	30–40	Computer sciences	Below 5 years	ChatGPT	Positive
17	Male	30–40	Economics	Below 5 years	ChatGPT	Positive
18	Male	30–40	Mechanics	Below 5 years	ChatGPT	Positive
19	Male	30–40	Mechanics	Below 5 years	ChatGPT	Positive
20	Male	30–40	Aerospace	Below 5 years	ChatGPT, Gemini	Positive
21	Male	Below 30	Civil engineering	Below 5 years	ChatGPT	Positive

No.	Sex	Age	Subject	Years of experience with technology-enhanced instruction	Use of LLM-based applications	Perceived effectiveness of LLM-based applications
22	Male	30–40	Civil engineering	Below 5 years	ChatGPT, ERNIE Bot	Positive

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Data availability The datasets generated during and/or analyzed during this study are not publicly available, but could become available upon reasonable request from the corresponding author.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethical approval The study was approved by the university's Ethics Committee with ID: GZHUSE2024014. Participants specifically consented to participating in the research by filling out the questionnaire and signing their approval for their qualitative answers to be included in the research. Their privacy rights were strictly observed.

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