International Journal of Instruction *January 2026 ● Vol.19, No.1*
e-ISSN: 1308-1470 ● www.e-iji.net *p-ISSN: 1694-609X*
pp. 749-774

Article submission code: 20250606031339
Received: 06/06/2025
Revision: 14/09/2025
Accepted: 26/09/2025
OnlineFirst: 07/10/2025

Factors Affecting Critical Thinking Disposition of English Major Undergraduates Using Artificial Intelligence (AI) Learning Tools

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Given the expanding role of artificial intelligence within teaching and learning environments, it is crucial to understand the factors that shape students' critical thinking disposition (CTD), as CTD determines how effectively learners engage with AI-driven tools and environments. This research uses the Stimulus-Organism-Response (SOR) model to explore the potential factors affecting CTD of Chinese English-major undergraduates with AI learning tools, integrating constructs of the Technology Acceptance Model (TAM). A sample of 283 students from five universities in Eastern China was collected, and PLS-SEM was conducted. The findings indicate that AIL potentially significantly impacts PEOU and PU. PEOU is directly related to PU positively and MO negatively, whereas PU is positively related to MO. The analysis indicates that PEOU does not directly predict CTD, whereas PU and MO are each positively and significantly related to CTD. According to PLSpredict, the relevance prediction is moderate for the PLS-SEM model. It is noteworthy as a novelty that this research combines TAM with the SOR model in the context of CTD, and thus fills the gap between the AI technology, cognitive, and affective factors that influence CTD. By confirming this model in a Chinese setting, the study also adds clarity to how these constructs are related and contributes a model that can be tested worldwide.

Keywords: Perceived Ease of Use (PEOU), Perceived Usefulness (PU), English major undergraduates, AI literacy, Critical Thinking Disposition (CTD)

INTRODUCTION

With the rapid advancement of digital technologies and the expanding presence of artificial intelligence in everyday contexts, individuals are increasingly confronted with vast amounts of information, not all of which can be deemed reliable (Butler & Halpern,

Citation: Hao, L., Piaw, C. Y., & Yusoff, S. M. (2026). Factors affecting critical thinking disposition of English major undergraduates using artificial intelligence (AI) learning tools. *International Journal of Instruction*, *19*(1), 749-774. https://doi.org/10.29333/iji.2026.19138a

2020). Consequently, the demand for critical thinkers is more pressing than ever (Liu & Pásztor, 2022). Investigating what influences critical thinking is vital. A key yet often underestimated element is critical thinking disposition, which concerns a person's readiness to engage in reflective judgment and constitutes a necessary condition for the cultivation of critical thinking abilities (Liu & Pásztor, 2022). Furthermore, employers worldwide are actively seeking individuals who demonstrate critical thinking dispositions (World Economic Forum, 2016). In addition, Cruz et al. (2021) discovered that within workforce contexts, critical thinking disposition is cited more frequently than critical thinking skills, appearing in 69% of references compared to 39%. This highlights the practical importance of focusing on critical thinking disposition in the present study.

The tendency to think critically is not only valued by employers, but the requirement for this ability is also reflected in China's policies. The policy "Made in China 2025" requires the talents to be proficient in innovative problem solving and critical thinking to ensure successful implementation of industrial upgrade and transformation (State Council, 2015). As the direct training unit of the talent workforce, the development of higher educational institutions has become the focus of this policy (Wang & Seepho, 2017). Among all the majors, English deserves special attention not only because of the language skills required by the policy but also due to some problems it faced. According to surveys of some employers, they are more willing to accept talents with language advantages. But what bothers them is that these language talents lack the tendency to think critically and the ability to solve problems (Moeiniasl et al., 2022). Besides, the lack of training in this area and the traditional passive teaching method makes it difficult for English majors to cultivate critical thinking tendencies (Zainuddin et al., 2019). This problem makes it urgent and necessary to explore the influencing factors of the critical thinking tendencies of English majors in Chinese higher educational institutions in the technological era.

Technology and digitalization have transformed traditional learning methods to a wider range of learning materials, supporting a shift from teacher-centred to multi-source learning environments (Allman et al., 2024). Consequently, most English major undergraduates now turn to AI learning tools to enhance and extend their learning. The benefits of using AI learning tools in learning English are multifaceted, particularly in terms of enhancing motivation (Maphoto et al., 2024), psychology (Alshammari, 2025), engagement (Chasokela, 2025) and other learning outcomes because of its personalized learning experiences, immediate feedback as well as some real-world scenarios (Darwin et al., 2024, Benek, 2025). Research on factors affecting critical thinking dispositions when using AI learning tools is currently limited. Consequently, the researcher has turned to the existing literature to make informed assumptions.

Prior research has shown that students' motivation to learn (MO) positively influences their critical thinking disposition (CTD) (Asigigan & Samur, 2021; Cha & Kim, 2020). In addition, the Technology Acceptance Model suggests that perceived ease of use (PEOU) and perceived usefulness (PU) significantly shape learners' attitudes and motivation, with motivation in turn exerting a positive effect on CTD (Nuryakin et al., 2023). Moreover, considering the predicating extension of the model, AI literacy (AIL) is related to PU and PEOU and has the predicating role (Machdar, 2019). The existing correlations among various variables offer valuable insights; however, a comprehensive theory that unifies these variables to elucidate the predictors of Critical Thinking Dispositions (CTD) is notably absent. Moreover, there is a discernible lack of knowledge and research concerning the factors that potentially predict critical thinking dispositions among English major undergraduates employing AI learning tools. These gaps underscore the importance of this research, which is theoretically innovative and practically valuable for learners, educators, employers, and entrepreneurs.

LITERATURE REVIEW

Stimulus Organism Response Theory

The relationships among the study variables were interpreted through the Stimulus–Organism–Response (SOR) framework. First proposed by Mehrabian and Russell (1974), this model describes how external stimuli shape individuals' internal states, which in turn drive their behavioural responses. In this framework, the stimulus includes external environmental factors; the organism encompasses the cognitive and affective states of individuals; and the response involves user behaviours or intentions (Buxbaum, 2016). Based on the theoretical explanations, several empirical studies have vividly illustrated the structure. For example, Cai (2022) demonstrates that within social e-commerce platforms, the quality of products and services acts as a stimulus that shapes consumer actions, with PU and PEOU serving as intermediary organism factors that channel these influences into purchasing behaviour. Similarly, Pan et al. (2024) centered on interaction in e-learning by relating the stimulus in the e-learning setting; the concept is the learners' perceived usability and usefulness, and the response is the learners' output on learning achievement. Additionally, Duong (2023) reveals that educational stimulants, lecturers' competence, entrepreneurial education, and students' cognitive and emotional reactions have positive effects on students' entrepreneurial action. Further, Buxbaum (2016) underscored the significance of a favorable learning environment and personalized teaching-learning techniques to help students attain better learning outcomes through evoking favorable emotional and cognitive responses in the SOR model.

Based on theoretical and empirical research, this study repositions the SOR model to embrace AI literacy as a stimulus infused into AI learning tools. AI literacy acts as the initial stimulus, which triggers all cognitive processes for understanding AI technologies and dealing with their use in practice. The degree of acceptance is predicated upon this foundation. This cognitive domain, PEOU (Perceived Ease of Use) and PU (Perceived Usefulness, which constitute the core constructs of TAM (Technology Acceptance Model)), is where the organism phase occurs. It is where the user appraises technology's ease and its utility. Although primarily cognitive, these constructs also affect emotional responses by altering comfort levels and attitudes towards technology. Situated within the affective domain of the organism phase, furthermore, motivation plays an important role in mediating these responses as observed in studies which have empirical backing behind them. Cognitive and affective assessments of that type are necessary for determining the acceptance and use of AI tools. In turn, this may finally affect the achievement of learning goals. This disposition of critical thought emerges as the behavioral response; through these internal cognitive and affective states, it shows how successfully people employ critical thinking when utilizing AI applications. Figure 1 presents the theoretical framework for the study. This has laid down principles on which subsequent hypotheses will be based.

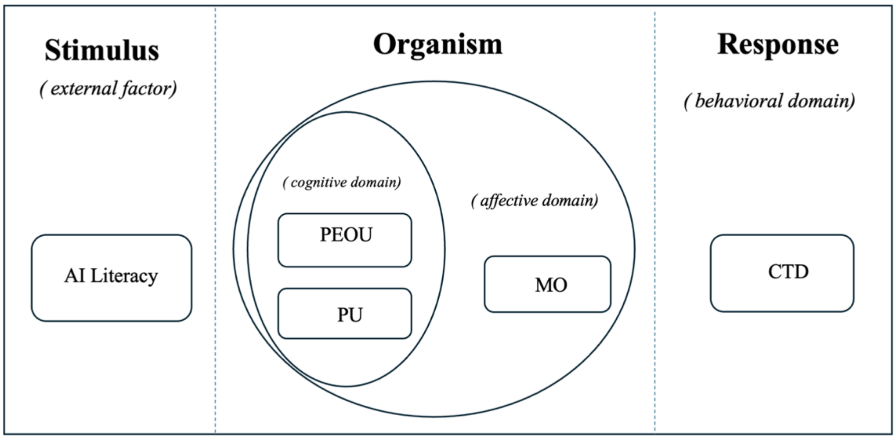

Figure 1
Theoretical framework

Related Studies and Hypotheses Development

According to the theoretical hypothesis, CT disposition is taken as the result of the different influencing factors, thus it is the dependent variable in this study. Critical thinking dispositions are considered a prerequisite to the development of reflective learning, involvement in high-impact practices, and the capacity to critically assess alternative viewpoints, all of which are necessary for academic and personal growth (Álvarez-Huerta et al., 2023). It has been repeatedly demonstrated, in numerous studies, that there is a robust relationship between the disposition of critical thinking and a plethora of positive ends (Álvarez-Huerta et al., 2023; Boonsathirakul & Kerdsomboon, 2021; Ibrahim et al., 2020). Given the advantages of critical thinking dispositions that have been substantiated, researchers have investigated the ways to develop critical thinking in various fields (Yu & Zin, 2023).

Research to date has largely examined critical thinking disposition through stand-alone instructional approaches, yet it has paid limited attention to the broader contextual dimensions introduced by AI and technological developments. Additionally, there have not been theoretical models for a systematic examination of these factors and their interconnections. This paper fills this research gap by systematically incorporating the AI contextual factors into the SOR model to investigate their effect on critical thinking disposition.

AI literacy, as the driver of the SOR model, refers to the capacity for understanding and deployment of artificial intelligence technologies.(Ng et al., 2024) While the advantages of AI literacy are many: people who possess it make better decisions, possess improved problem-solving skills, and ways of leveraging various professional and personal tools, including AI (Long & Magerko, 2020). Because of its numerous benefits, some scholars not only regarded it as a forerunner of TAM in technology contexts but also incorporated its core components: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). Many research investigations showed that AIL and PEOU are correlated, as well as PU. Yao and Wang (2024) found that digital literacy has a positive relationship with learners' perceptions of AI in education, influencing both its perceived usefulness and ease of use. In addition, a qualitative investigation was undertaken to gather insights into students' attitudes, interpret them in a comparative manner, and assess their potential consequences. In the conclusions, Idroes et al. (2023) found that students basically hold knowledge of AI and venerate AI literacy in education, which is poised to enhance both PU and PEOU. Also, Xiong and Zhang (2024) showed that digital literacy has a positive effect on PEOU and one which is statistically significant. Drawing on the established theoretical framework and prior empirical evidence, the study advances the following hypotheses.

H1: AIL has a positive and significant influence on PEOU.

H2: AIL has a positive and significant impact on PU.

In addition to examining the stimulus effects of artificial intelligence literacy (AIL) on perceived usefulness (PU) and perceived ease of use (PEOU), previous research has investigated the relationship between these constructs within the Technology Acceptance Model (TAM). Perceived ease of use (PEOU) refers to the extent to which an individual believes that using a system requires minimal effort, whereas perceived usefulness (PU) denotes the degree to which a system is believed to enhance performance (Davis, 1989). Substantial evidence indicates that PEOU is a significant determinant of PU. Numerous studies have consistently demonstrated the influence of PEOU on PU (Hamid et al., 2016; Siagian et al., 2022). Based on these findings, hypothesis H3 was formulated.

H3: PEOU has a positive and significant influence on PU.

Some researchers have investigated the precursors and core structure of TAM, and others have researched indicator variables of TAM (Önal, 2017). TAM has been subsequently expanded to account for constructs such as engagement, motivation, and attitude that encapsulate the secondary effects of technology adoption (Nikou & Economides, 2017). Motivation has been less frequently investigated among all the outcome variables, as compared to others. Nonetheless, some studies continue to reveal the strong impact of PEOU and PU on motivation, indicating that PEOU and PU play vital roles in shaping users' motivation to use technologies. Park and Kim (2023) highlighted the correlations between PEOU, PU, and MO, but they did not specify the precise direction of these relationships. Moreover, Gutierrez-Aguilar et al. (2022) demonstrated that perceived ease of use exerts a positive causal influence on student motivation. Their findings indicate that when university students view a technology as user-friendly, their willingness to engage with it is strengthened, even under the demanding circumstances of the COVID-19 pandemic. Li (2023) in the study concluded that both PEOU and PU have a significant impact on motivation, particularly in an educational context. When students perceive a system as easy to use and useful, their motivation to engage with the system increases. Moreover, Zuo et al. (2022) revealed that PU and PEOU have a significant positive effect on online learning motivation (MO) among K-12 students. PU has a larger impact by enhancing students' motivation when they perceive the online learning tools as beneficial for their educational goals. Similarly, PEOU positively influences motivation by making the learning process more accessible and user-friendly, reducing the barriers to engagement and encouraging students to stay motivated in their online learning activities. Based on those studies, H4 and H5 were proposed as follows.

H4: PEOU has a positive and significant effect on MO.

H5: PU has a positive and significant effect on MO.

Other consequent variables of the TAM are learning outcomes, among which critical thinking dispositions was one of the most important elements. However, while CTD serves as a consequence variable, it is rarely directly predicted by PEOU and PU. In contrast, motivation, another key outcome of TAM, has been consistently correlated with CTD in numerous empirical studies. Parejo-Jiménez et al. (2022) found clear evidence of a positive association between motivation and critical thinking disposition, with the strongest connection emerging in relation to intrinsic motivation. Furthermore, Valenzuela et al. (2023) quantified the effect of MO on CTD, illustrating that the motivational variables explain the variance in the performance of critical thinking dispositions ranging from 8% to 17%. Therefore, H6 was proposed.

H6: MO has a significant and positive effect on CTD.

Building on the discussion in the preceding section, both perceived ease of use (PEOU) and perceived usefulness (PU) were found to exert significant positive effects on learners' motivation (MO), which in turn plays a crucial role in shaping their disposition toward critical thinking (CTD). Consequently, it can be deduced that PEOU and PU indirectly affect CTD through MO. This hypothesis is confirmed by the few existing empirical studies. Nie et al. (2024) reported that both perceived usefulness and perceived ease of use are significant predictors of preservice teachers' critical thinking in Shanxi, China. Similarly, Aldraiweesh and Alturki (2023) identified a significant effect of perceived usefulness on critical thinking. These empirical findings informed the formulation of hypotheses H7 and H8.

H7: PEOU has a positive and significant effect on CTD.

H8: PU has a positive and significant effect on CTD.

Conceptual Framework

Drawing on the reviewed literature and prior empirical findings, the proposed conceptual framework is presented in Figure 2.

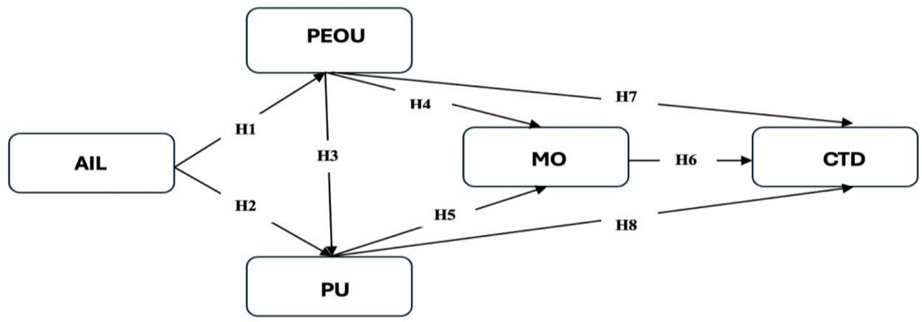

Figure 2
Conceptual framework

Figure 2 illustrates that the response variable, critical thinking disposition (CTD), is affected by several factors within the SOR framework. In this model, AI literacy (AIL) functions as the stimulus and is posited to exert a positive and significant influence on the cognitive constructs—perceived ease of use (PEOU) and perceived usefulness (PU)—which represent the 'organism' component of the framework. The other component of the organism involves affective factors, specifically motivation (MO). According to the conceptual framework, the cognitive elements (PEOU and PU) are expected to influence the affective element, MO. Additionally, MO is predicted to impact CTD directly, while PEOU and PU are also proposed to influence CTD deductively based on prior theoretical deductions and empirical findings. This integrated framework therefore provides the basis for formulating the research objectives and hypotheses examined in the present study.

METHOD

Research Design

This study employed a quantitative cross-sectional survey to examine the relationships among artificial intelligence (AI) literacy (AIL), perceived ease of use (PEOU), perceived usefulness (PU), motivation (MO), and critical thinking disposition (CTD) within the Stimulus–Organism–Response (SOR) framework and the combined Technology Acceptance Model (TAM). The primary objective was to test these hypotheses using partial least squares structural equation modeling (PLS-SEM) and to provide empirical evidence supporting the integrated SOR–TAM approach. Employing a cross-sectional design was deemed appropriate for examining theory-driven links among latent variables—a practice commonly accepted in studies on technology acceptance and educational psychology (Hair et al., 2019). Additionally, applying PLS predict increased the model's predictive capabilities and reinforced the theoretical framework, thereby enhancing both the clarity and credibility of the findings.

Participants

Calculation of the sample size of the present study was based on heuristic and simulation-based methods to ensure sufficient statistical power for a PLS-SEM model that included explicit mediating and moderating effects. According to the 10-times rule (Hair et al., 2019), ten times the maximum number of incoming structural paths is to be considered, which is CTD with 3 paths (PU, MO, and PEOU), indicating that 30 participants, as a conservative floor, should be fulfilled. To supplement the sample size as well as to reduce model complexity, a Monte Carlo simulation power analysis was performed based on 10,000 replications, at moderate effect size ($\beta = 0.30$) and α coefficient of 0.05; the required sample size to attain 0.80 statistical power was estimated to be a minimum of $n = 220$ (Muthén & Muthén, 2002). A 25% buffer for potential non-response/invalid responses was employed according to guidelines of Mitchell and Jolley (2010), which led to the final sample size of 283 valid responses, sufficient for dependable and valid model estimation. Thus, after a total of 283 complete subjects were collected, the data collection was terminated.

These participants were selected from five universities in Eastern China. The selection of respondents from Eastern China is motivated by the region's robust job market, where companies demand strong critical thinking dispositions from graduates, heightening the urgency and relevance of this research focus. Additionally, Eastern China is more developed, with advanced teaching concepts, methods, and assessments. Students in this region are more likely to utilize artificial intelligence learning tools in their studies, providing a solid foundation for sample collection. Ethical approval for the study was obtained from the university ethics committees. To facilitate the distribution of the online questionnaires, the researcher enlisted the help of five teacher acquaintances at the five universities. The questionnaire links were shared by these teachers with their English major classes over WJX, a Chinese online survey platform. Prior to distributing the questionnaire, teachers clarified the purpose of the research and informed students that their involvement was voluntary and all responses would remain confidential. Only those students who were already familiar with AI-based learning tools were considered as participants; non-users were not represented in the sample. Written consent was obtained from all participants before they filled out the survey. In all, 283 usable questionnaires were collected and subsequently used to conduct this study.

Instruments

Five instruments were involved in the present study including AI literacy, PEOU, PU, MO and CTD. The AI literacy scale, based on Ng et al. (2024), comprised nine items that evaluated cognitive (four items) and affective (five items) dimensions. PEOU and PU were measured by six items each (Davis, 1989). The MO scale contained factors for intrinsic motivation (six items) and amotivation (seven items) (Lirola et al., 2021). The scale for CTD (based on Liu and Pásztor, 2022) included two sub-scales with 11 items: Instant judgment (four items) and habitual truth-seeking (seven items). With the exception of the AI Literacy scale, which utilized a 5-point Likert scale, all other research instruments employed a 7-point Likert scale.

Several checks were carried out to check the applicability and validity for the respondents. Blind back-translation was done by a panel of two English translators to test the validity and consistency of the instruments. Six domain experts afterwards appraised the instruments for content validity (C-CVI, S-CVI) and CVR with respect to clarity, relevancy, and essentiality. A pilot study involving 50 participants was conducted to further verify reliability and validity. The data from these participants were excluded from the main dataset. Analysis of the pilot results through SPSS revealed robust instrument reliability, as indicated by high Cronbach's alpha scores. The results provided strong support for the consistency of the measurement tools used in this research (AIL = 0.902, PEOU = 0.937, PU = 0.915, MO = 0.867, and CTD = 0.884).

Procedure

Data for this research were examined using responses from 283 undergraduate students majoring in English. Prior to distributing the instruments, their validity and reliability—including both content validity and internal consistency—were confirmed through expert evaluation and preliminary testing. Before distributing the questionnaire to the respondents, ethics committee approval and participant consent were followed, and the questionnaire was disseminated online. The survey lasted one month, and after removing incomplete or inconsistent responses, a total of 283 valid responses were obtained. The researchers then used Smart-PLS to analyze the data. Smart-PLS was chosen because it can handle complex models and small sample sizes.

Data Analysis

The measurement model and the overall structural model were assessed using partial least squares structural equation modeling (PLS-SEM). The analysis utilized the standard PLS-SEM algorithm in combination with bootstrapping techniques. The model included five reflective constructs based on existing theory, and the indicators were reflections of their latent variables (Hair et al., 2019).

A confirmatory factor analysis was conducted to assess convergent validity and measurement reliability for all models. Subsequently, the structural model was evaluated to examine relationships among the proposed constructs and to empirically test the study hypotheses.

In structural equation modeling, measurement models are conceptualized as latent variables. To ensure their reliability, Cronbach's alpha and composite reliability should each reach a minimum value of 0.70. Similarly, construct validity is confirmed when every indicator demonstrates a factor loading of at least 0.70 on its designated construct, and the average variance extracted (AVE) is at least 0.50 for each model (Hair et al., 2022). Discriminant validity is evaluated using three main techniques. First, the heterotrait–monotrait (HTMT) ratio should not exceed 0.90. Second, the Fornell–Larcker criterion requires that the square root of a construct's average variance extracted (AVE) is greater than its correlations with other constructs. Third, cross-loading analysis ensures that each item loads most strongly on its respective latent construct. Collinearity was also assessed to identify multicollinearity among items within the measurement models. A variance inflation factor (VIF) above 5.0 was used as the threshold for potential multicollinearity (Hair et al., 2024).

After establishing the reliability and validity of the measurement models, the structural model was assessed using the PLS-SEM bootstrapping method. This process enabled hypothesis testing via statistical measures such as path coefficients (β), t-statistics, and p-values. Additionally, R^2 and f^2 metrics were analyzed to understand the proportion of variance accounted for in CTD, as well as the effect sizes of various predictors. The predictive relevance of the model was also examined using PLSpredict, offering information about its predictive accuracy and generalizability. Interpretations of these findings are discussed in the next section.

FINDINGS

This section details the findings from data analysis regarding both the measurement and structural models.

Measurement Model

The hypothesized model includes five measurement models with multiple items: AIL, PEOU, PU, MO, and CTD. MO and CTD are reflective-reflective two order models. IM and AM are first order models of MO, while IJ and HTD are first order models of CTD. The results of the confirmatory factor analysis show that the loadings of some of the items (AL4, AL5, CL2, IM1, IM6, AM2, IJ1, HTD5, HTD6, HTD7) were below the benchmark of 0.70. After removing the invalid items, further analysis showed that all the measurement models achieved construct reliability (Cronbach's alpha (CA) and composite reliability (CR) > 0.70) and construct validity (loadings > 0.7 and AVE > 0.5) (see Table 1).

Table 1
Construct reliability and construct validity of the instruments

Factors	Items	Loadings	CA	CR	AVE
AL	AL1	0.922	0.898	0.936	0.830
	AL2	0.893			
	AL3	0.918			
CL	CL1	0.818	0.810	0.889	0.727
	CL3	0.806			
	CL4	0.929			
PEOU	PEOU1	0.847	0.928	0.945	0.741
	PEOU2	0.910			
	PEOU3	0.868			
	PEOU4	0.918			
	PEOU5	0.706			
	PEOU6	0.898			
PU	PU1	0.824	0.939	0.952	0.768
	PU2	0.910			
	PU3	0.812			
	PU4	0.891			
	PU5	0.921			
	PU6	0.895			
IM	IM2	0.754	0.897	0.923	0.709
	IM3	0.917			
	IM4	0.766			
	IM5	0.807			
AM	AM1	0.806	0.932	0.945	0.713
	AM3	0.880			
	AM4	0.886			
	AM5	0.788			
	AM6	0.807			
	AM7	0.824			
IJ	IJ2	0.895	0.818	0.892	0.733
	IJ3	0.810			
	IJ4	0.861			
HTD	HTD1	0.866	0.885	0.919	0.741
	HTD2	0.804			
	HTD3	0.877			
	HTD4	0.893			

Notes. AL: affective level; CL: cognitive level; AM: amotivation; IM: intrinsic motivation; HTD: habitual truth-digging; IJ: instant judgement; PEOU: perceived ease of use; PU: perceived usefulness

As for the discriminant validity, Table 2 indicates that all the values of HTMT were below 0.9, indicating that no overlapping in concepts between the measurement models were found, and thus discriminant validity achieved by referring to HTMT.

Table 2
The HTMT values for assessing discriminant validity

	AL	AM	CL	HTD	IJ	IM	PEOU	PU
AL								
AM	0.68							
CL	0.867	0.849						
HTD	0.711	0.46	0.611					
IJ	0.204	0.571	0.373	0.199				
IM	0.661	0.453	0.347	0.553	0.297			
PEOU	0.811	0.698	0.806	0.424	0.282	0.684		
PU	0.738	0.602	0.715	0.505	0.155	0.775	0.819	

Notes. AL: affective level; CL: cognitive level; AM: amotivation; IM: intrinsic motivation; HTD: habitual truth-digging; IJ: instant judgement; PEOU: perceived ease of use; PU: perceived usefulness

As shown in Table 3, the square root values of the AVEs for each construct exceeded their respective inter-construct correlations, thereby demonstrating that the discriminant validity of the measurement models was adequately established. Furthermore, for cross-ladings, the loadings of the items for the eight measurement models are larger than the loadings of the items associated with other correlated measurement models in the model. Taken together, the results from the three discriminant validity assessments confirm that all measurement models demonstrate satisfactory discriminant validity.

Table 3
The results of fornell-lacker criterion for assessing discriminant validity

	AL	AM	CL	HTD	IJ	IM	PEOU	PU
AL	0.911							
AM	0.6	0.833						
CL	0.742	0.725	0.853					
HTD	0.605	0.33	0.473	0.861				
IJ	0.091	0.497	0.285	0.021	0.856			
IM	0.519	0.294	0.188	0.456	0.203	0.813		
PEOU	0.749	0.641	0.705	0.369	0.06	0.532	0.861	
PU	0.681	0.536	0.625	0.443	0.063	0.635	0.765	0.876

Notes. AL: affective level; CL: cognitive level; AM: amotivation; IM: intrinsic motivation; HTD: habitual truth-digging; IJ: instant judgement; PEOU: perceived ease of use; PU: perceived usefulness

Multicollinearity occurs when high intercorrelations between two or more items in a measurement model are observed. Multicollinearity would lead to skewed or misleading results due to the overlapping of concepts between the items. According to Hair et al. (2022), the occurrence of multicollinearity among the items of each measurement model should be assessed before analysing the structural model. Multicollinearity exists when the VIF value of a measurement item is greater than 5.0. In this study, all VIF values of the items in each measurement model were found to be less than 5.0, confirming that multicollinearity is not a concern.

Structural Model

Table 4 presents the results of the structural model analysis, indicating several statistically significant associations among the constructs in line with the proposed hypotheses. Regarding H1, which posits a positive effect of AIL on PEOU, is strongly supported with a large path coefficient (β = 0.813, t = 26.212, CI = 0.749 to 0.870, $p < 0.001$).

Table 4
The results of hypotheses testing

	Path coefficient	T statistics	P values	97.5% CI	Results
H1: AIL -> PEOU	0.813	26.212	0.000	(0.749, 0.870)	supported
H2: AIL -> PU	0.681	14.273	0.000	(0.580, 0.770)	supported
H3: PEOU -> PU	0.644	8.473	0.000	(0.481, 0.776)	supported
H4: PEOU -> MO	-0.381	2.551	0.011	(-0.658, -0.064)	supported
H5: PU -> MO	0.465	3.606	0.000	(0.190, 0.698)	supported
H6: MO -> CTD	0.502	6.693	0.000	(0.360, 0.649)	supported
H7: PEOU -> CTD	-0.058	0.619	0.536	(-0.257, 0.116)	reject
H8: PU -> CTD	0.311	3.35	0.001	(0.130, 0.496)	supported

Notes. AIL: AI literacy; PEOU: perceived ease of use; PU: perceived usefulness; MO: motivation; CTD: critical thinking disposition.

Similarly, H2 to H6 are supported. The results in Table 4 show a positive and significant effect of AIL on PU (β = 0.681, t = 14.273, CI = 0.580 to 0.770, $p < 0.001$) [H2], a positive and significant effect of PEOU on PU (β = 0.644, t = 8.473, CI = 0.481 to 0.776, $p < 0.001$) [H3], a negative and significant effect of PEOU on MO (β = -0.381, t = 2.551, CI = -0.658 to -0.064, $p < 0.05$) [H4], a positive and significant effect of PU on MO (β = 0.465, t = 3/606, CI = 0.190 to 0.698, $p < 0.001$) [H5], and a positive and significant effect of MO on CTD (β = 0.502, t = 6.693, CI = 0.360 to 0.649, $p < 0.001$) [H6].

However, H7, which proposed a relationship between PEOU and CTD, was not supported as the effect was non-significant (β = -0.058, t = 0.619, CI = -0.257 to 0.116, $p = 0.536 > 0.05$). Finally, H8, which hypothesized a positive impact of PU on CTD, was supported (β = 0.311, t = 3.35, CI = 0.130 to 0.496, $p = 0.001 < 0.05$). These findings collectively suggest robust support for most of the hypothesized relationships, with the exception of the non-significant causal relationship between PEOU and CTD. Figure 3 shows the final structural model after removing the non-significant path of PEOU → CTD.

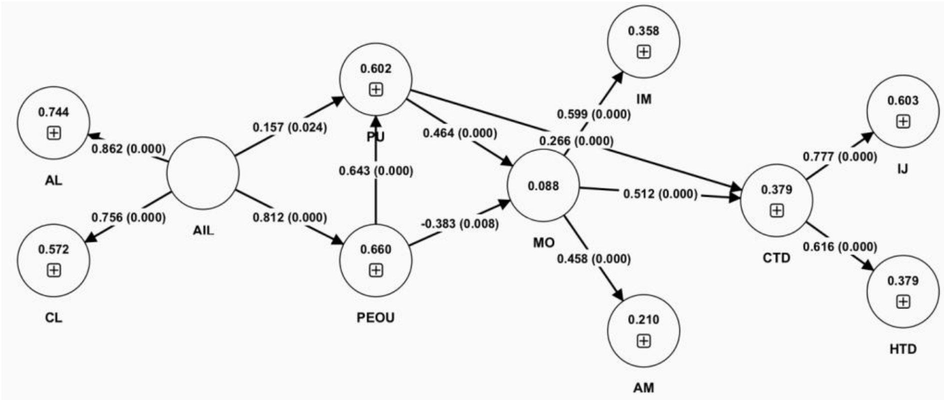

Figure 3
The final model

In the subsequent stage, the model was examined through the R^2 and f^2 statistics, which provide a comprehensive assessment of its explanatory strength and the relative contribution of each predictor, thereby reinforcing both its theoretical soundness and practical relevance.

R^2 indicates how much of the variation in endogenous latent variables is accounted for by their related exogenous predictors. When interpreting R^2, a value of 0.67 or above represents high predictive accuracy, scores between 0.33 and 0.67 show moderate predictive strength, values ranging from 0.19 to 0.33 signal weak explanatory power, and results below 0.19 imply minimal predictive relevance (Hair et al., 2022).

The R^2 value for MO is 0.086, indicating that 8.6% of the variance in MO is explained by its predictors (PU and PEOU). According to the specified thresholds, this R^2 value indicates a very weak predictive relevance, suggesting that the predictors of MO have a limited impact in explaining its variance within this model.

The R^2 value for CTD is 0.380, indicating that PEOU, PU, and MO together account for 38% of its variance. Based on established benchmarks, this reflects a moderate level of predictive relevance. In other words, these three predictors collectively play an important role in explaining the variance in CTD within the proposed structural model.
To gain deeper understanding of which predictors exert the greatest influence on MO and CTD, the f^2 values provide useful guidance. The f^2 statistic reflects the unique contribution of each predictor to the R^2 of the dependent variable by comparing the model with and without that predictor. According to Cohen (1988), an f^2 value at or below 0.02 represents a small effect, values ranging from 0.02 to 0.15 indicate a medium effect, and those of 0.35 or more reflect a large effect. Table 5 shows the f^2 effect sizes for each predictor concerning MO and CTD.

Table 5
Predicative relevance of f^2

	CTD	MO
MO	0.369	
PEOU	0.002	0.066
PU	0.059	0.098

Notes. PEOU: perceived ease of use; PU: perceived usefulness; MO: motivation; CTD: critical thinking disposition.

According to Table 5, the effect size of PEOU on MO is 0.006, which is a small effect size, while the value of PU on MO is 0.098, indicating a medium effect size. In the meantime, the f^2 of MO on CTD is 0.369, indicating a large effect size and making MO the most significant predictor of CTD. The effect size of PEOU on CTD is 0.002, which indicates a very small effect size, and PU has an effect size of 0.059, indicating a medium effect size. Thus, while MO has the largest impact on CTD, PEOU and PU have moderate impacts, with PEOU having the least effect.

Predictive relevance of the final model

After confirming the strength and dependability of the parameter estimates using PLS-SEM bootstrapping, the PLSpredict method can then be used to assess how well the model predicts new data. Another 106 English AI learning tool users were invited to perform the predictive relevance of the final model. According to the histogram of prediction errors, most of them are symmetrically distributed, therefore, this study applied the indices of Q^2 and PLS-SEM_RMSE and LM_RMSE to interpret its predictive relevance. The Q^2 is used to interpret the cross-validated redundancy, which should be above 0. The values of PLS-SEM_RMSE should be lower than LM_RMSE. If all the indicators meet these criteria, indicating high predictive power, for a majority refers to medium power, minority for low power (Shmueli et al., 2019). Table 6 presents the findings regarding the model's predictive relevance.

Table 6 displays how the items perform in comparison, including their root mean square error (RMSE) values, as evaluated using both Partial Least Squares Structural Equation Modeling (PLS-SEM) and Linear Modeling (LM). Notably, the values of $Q^2 > 0$ [0.001-0.678] indicate that the exogenous construct has predictive relevance for the endogenous construct, suggests varying levels of predictive accuracy across different constructs. Most items exhibit lower PLS-SEM_RMSE values compared to LM_RMSE, suggesting that the PLS-SEM model has better predictive accuracy, as per the benchmark of Shmueli et al. (2019), which implies medium predictive power. Moreover, in cases such as AL1, IM3, and PU1, where the PLS-SEM_RMSE and LM_RMSE values are equal, it implies that the PLS model and the simple linear regression model deliver similar predictive results for these items, as both demonstrate nearly equivalent accuracy and error rates.

Table 6
The results of predictive relevance of the established model

	Q^2predict	PLS-SEM_RMSE	LM_RMSE	Value Gap
AL1	0.623	0.392	0.392	0
AL2	0.533	0.55	0.561	-0.011
AL3	0.678	0.512	0.514	-0.002
AM1	0.002	1.534	1.536	-0.002
AM3	0.003	0.905	0.895	0.01
AM4	0.004	0.903	0.928	-0.025
AM5	0.002	1.446	1.476	-0.03
AM6	0.003	1.208	1.291	-0.083
AM7	0.003	0.945	0.946	-0.001
CL1	0.399	0.716	0.717	-0.001
CL3	0.38	0.748	0.798	-0.05
CL4	0.45	0.665	0.668	-0.003
HTD1	0.077	0.915	0.949	-0.034
HTD2	0.099	1.23	1.403	-0.173
HTD3	0.063	0.949	0.961	-0.012
HTD4	0.109	0.998	0.996	0.002
IJ2	0.002	1.717	1.731	-0.014
IJ3	0.021	2.064	2.07	-0.006
IJ4	0.04	1.686	1.695	-0.009
IM2	0.002	1.426	1.431	-0.005
IM3	0.001	0.895	0.895	0
IM4	0.002	1.107	1.245	-0.138
IM5	0.002	0.74	0.742	-0.002
PEOU1	0.454	0.816	0.817	-0.001
PEOU2	0.49	0.585	0.586	-0.001
PEOU3	0.515	0.948	0.951	-0.003
PEOU4	0.502	0.641	0.643	-0.002
PEOU5	0.275	0.736	0.738	-0.002
PEOU6	0.637	0.578	0.575	0.003
PU1	0.359	0.657	0.657	0
PU2	0.369	0.668	0.682	-0.014
PU3	0.264	0.718	0.721	-0.003
PU4	0.333	0.676	0.678	-0.002
PU5	0.401	0.551	0.552	-0.001
PU6	0.359	0.578	0.581	-0.003

To sum up, the findings on predictive relevance suggest that the PLS-SEM model typically provides greater predictive accuracy than the LM model. This is demonstrated by lower RMSE values for the majority of items and is classified as having moderate predictive strength based on the criteria of Shmueli et al. (2019).

DISCUSSION

Stimulus AIL and Its Effects

This study finds that AI literacy significantly enhances both perceived ease of use (H1) and perceived usefulness (H2). Although these outcomes are consistent with earlier research, they also reveal some important differences. For instance, Yao and Wang (2024) identified a positive link between digital literacy and the TAM elements of perceived ease of use (PEOU) as well as perceived usefulness (PU). Their research indicates that people with higher digital literacy are more inclined to perceive AI technologies as advantageous. Idroes et al. (2023) highlighted AI literacy's key role in education by showing it improves learners' views on how easy and useful AI-based tools are. Similarly, Xiong and Zhang (2024) also observed that digital literacy positively affects perceived ease of use (PEOU), supporting the general agreement that proficiency in digital and AI technology leads to more positive user perceptions.

Nonetheless, although these works support the current study's recognition of AI literacy's advantages, they typically address the link between AI literacy and TAM elements within the wider context of digital literacy or through qualitative analysis. By comparison, this research concentrates solely on AI literacy and offers concrete quantitative findings on its immediate and meaningful effect on PEOU and PU in the TAM model. This focus on AI literacy as a distinct construct, rather than as part of general digital literacy, allows the present study to contribute more precise and actionable insights into how AI literacy influences users' perceptions of AI technologies. Moreover, this study uniquely applies the SOR model as a theoretical framework, positioning AI literacy as the stimulus that influences PEOU and PU. In contrast, previous studies have not used a specific theoretical model to support the predictive effect of AI literacy on these TAM components.

Considering the previous findings and the research context, the positive relationship observed in the present study is likely attributable to the following factors. Developing AI literacy enables learners to make effective use of AI-assisted English learning tools, thereby strengthening their language proficiency through more tailored and adaptive learning opportunities. Familiarity with technology reduces the learning curve, making AI learning tools more accessible and effective in achieving academic objectives. In Eastern China, higher institutions actively promote teaching innovation, providing students with greater opportunities to engage with AI learning tools. This environment motivates students to utilize these innovative tools, thereby enhancing their perceptions of ease of use and usefulness. Furthermore, the positive cultural attitude towards AI and the alignment of these tools with students' individual learning styles contribute to the high perceived value and usability of AI technologies in their educational experiences.

Relationship among the Organism Elements

The organism element in the SOR model encompasses PEOU, PU, and MO. The study found that PEOU significantly predicts PU (H3), consistent with various empirical studies by other scholars (Hamid et al., 2016; Siagian et al., 2022).

However, PEOU negatively influences MO (H4), which is an unexpected finding contradictory from the findings of (Gutierrez-Aguilar et al., 2022; Li, 2023; Zuo et al., 2022). Previous studies indicate the significant effect of PEOU on MO. They believed that the ease of use reduced barriers to engagement or made the learning process more accessible to encourage sustained engagement, which can push their learning motivation. However, in this study, the negative impact may be due to the possibility that ease of use can lead to superficial engagement, where students feel insufficiently challenged, reducing their intrinsic motivation (Ryan & Deci, 2000; Venkatesh et al., 2012). Additionally, students may view easy-to-use tools as shortcuts, fostering a passive learning approach rather than deep interaction with the material. In the Chinese educational context, where examination-oriented learning prevails, students often see AI tools primarily as aids for test preparation rather than platforms for creative exploration.

To counter these challenges, it is suggested that AI learning tools are provided as part of challenging, curriculum-aligned content with structured pathways that balance ease of use and intellectual stimulation, as well as the need for educators to receive professional development in order to effectively use these tools. It can, therefore, be suggested that teachers should combine such AI tools with some form of well-organized, challenging content that will match students' academic standards. Institutions need to equip teachers to use AI tools that are curriculum-aligned, offering both high-stakes exam preparation and deeper learning—permeated by quality and scalable platforms, as well as decentralized, self-service professional development. AI developers should be creating tools that have adjustable difficulty levels and structured learning paths, which help to reconcile ease of use with mental challenge. Policymakers need to push for educational technology that offers usability and also features to encourage creativity, deep learning, and serious engagement.

In comparison, PU has a significant positive effect on MO (H5), which is consistent with previous results (Li, 2023; Zuo et al., 2022). Previous studies did not target these groups, but covered more general educational environments, for example, K-12 students and typical university students. This unique setting heightens the importance of AI tools going beyond functional utility and being intellectually engaging, to enhance the effect of PU on motivation in a fashion consistent with the specific academic and cultural goals of these students. The PU's strong effect on MO can be justified by the fact that when learners perceive a tool as useful, that will in turn directly improve their intrinsic motivation to use that tool (Li, 2023). Furthermore, the cultural value of studying and the importance of getting a good education in China are so high that Chinese students are highly motivated to use tools that are obviously beneficial for learning (Zhang & Watkins, 2007). Thus, in the English learning process in China, teachers should also emphasize the AI teaching tools with respect to academic goals as well as better learning results. Schools and universities must place emphasis on adopting AI tools that deliver real academic value, which includes training students on how to most effectively use the technology. Future work needs to investigate how various AI-based tools can be tailored to offer better support across different student needs and education settings.

Response CTD and Its Predicators

The response element of the SOR model is represented by the CTD. The study results show that PEOU does not significantly influence CTD (H7), while both PU (H8) and MO (H6) positively affect CTD.

The non-influence of PEOU on CTD (H7) disagrees with prior research where PEOU has been reported as contributing to critical thinking (Nie et al., 2024). But here, the lack of complexity may not be provocative enough for students to exercise critical thinking. Several factors may explain why PEOU has the insignificant effect on CTD in this study's setting. First, if AI tools are overly simple, students might see them as lacking intellectual challenge, which could result in passive usage rather than active critical involvement. In a test-driven environment, learners may mostly consider straightforward AI tools as aids for exam preparation, not as means for fostering critical thinking. Additionally, a significant number of AI applications emphasize language skills instead of promoting deep reasoning or analytical abilities. The preference for structured, teacher-centered instruction common in the culture further limits how much PEOU influences CTD, as it discourages independent critical thought. To improve the effect of PEOU on CTD, teachers should pair AI tools with tasks that require critical thinking, like solving problems and engaging in reflective dialogue. AI tool creators are encouraged to develop features that intellectually stimulate students while keeping the interface accessible. Schools should also combine AI tools with critical thinking coursework and offer relevant training to help these resources achieve maximum effectiveness.

The observed positive link between PU and CTD (H8) aligns with previous research (such as Nie et al., 2024), demonstrating that students who recognize the usefulness of tools are more likely to engage deeply with the material and enhance their critical thinking skills. In addition, the strong positive impact of MO on CTD indicates that more positive students may have a higher degree of critical thinking, which has already been noted in Lijie et al.'s results (2024). Likewise, the positive influence of MO on CTD would be indirectly justified and supported by the previous works of Parejo-Jiménez et al. (2022) and Valenzuela et al. (2023). Although both the current study and earlier research show the positive relationship between MO and CTD, the current study is exclusive because it considers this relationship in terms of English major undergraduates and AI learning tools. Interestingly, in contrast to past studies that centered on traditional educational contexts, we examined in the present study how AI tools may be integrated to support motivational pathways towards better CTD. This specific environment implies that AI learning tools could enhance the effect of MO on CTD by providing a more engaging and personalized learning context.

The significant effect of MO on CTD in this research context can be attributed to the fact that motivated learners are more likely to engage in deeper cognitive processing and take initiative in critically analysing information, which is in line with various empirical studies (Lijie et al., 2024). In addition, this relationship is facilitated by the engaging and responsive capabilities of the AI learning tools, that correspond to students' internal motivations, and develop deeper cognitive engagement. Because of these strong effects of PU and MO, it is important to develop features that not only are useful but also sustain learners' behavior with participants' own stakes, such as personalized, involving, and challenging experiences and results where idea-based thinking is needed. Furthermore, institutions should not only create an environment that facilitates both intrinsic and extrinsic motivations of critical thinking and integration among curriculum development and teaching strategies.

CONCLUSION

This study is pioneering in its integration of the TAM within the framework of the SOR theory to explore and correlate various influencing factors on CTD. This innovative methodology not only leads to theoretical progress through the combination of these two models, but also offers an alternative perspective to better comprehend the dynamics of CTD. The framework developed in this study was thoroughly applied and evaluated among undergraduates studying English within Chinese cultural and educational settings. This approach provides important insights into how these variables function in this specific academic and cultural environment.

This research is important because it deepens our knowledge of what influences critical thinking disposition in this setting, and it serves as a solid foundation for additional studies among different groups and learning contexts. By applying this framework to broader populations, the research offers a practical model to inform educational initiatives aimed at enhancing critical thinking skills globally. Furthermore, this study is distinctive for addressing the intersection between AI technology and critical thinking—a topic still relatively unexplored—thereby contributing new insights to literature on AI's educational impact and its potential to support cognitive development.

Beyond its theoretical value, this research may offer practical benefits to various important stakeholders within educational environments. For teachers, it offers practical guidelines on how to incorporate AI learning tools in learning and teaching that guide critical thinking among students. It is hoped that the findings in the present study can be used by institutions or curriculum developers to create well-designed motivation-based programs which address the needs of English-learning undergraduates. Educational technology developers may utilize the findings in the designing process of user-centered technologies oriented to students, which are more considerate of ease of use and perceived usefulness. In general, this research fulfills a bridging function between science and the field by providing specific strategies for enhancing learning also in a variety of educational settings.

While the study makes meaningful contributions, it is not without limitations. One notable constraint is the reliance on cross-sectional data, which restricts the capacity to draw firm causal inferences between the examined constructs. Nevertheless, considering the exploratory aim of the study and the robust theoretical grounding provided by the integrated SOR-TAM framework, the use of cross-sectional survey data serves as an appropriate and informative foundation for the development of the structural model. Future investigations could benefit from employing longitudinal or experimental approaches, which would allow for a more robust exploration of the temporal progression and causal nature of the proposed relationships. Second, the sample size, although sufficient for the statistical analysis, was limited to a specific group of Chinese English major undergraduates from universities in Eastern China. Such constraints limit the extent to which the results can be applied to wider populations, whether in China or in international contexts. The convenience sampling method further limits the ability to generalize the results to other regions or student groups with different educational backgrounds or technological exposure. Third, the study adopts a purely quantitative approach, which, while effective in testing hypotheses and identifying relationships, does not capture the deeper insights that qualitative data could provide, such as students' nuanced perceptions, experiences, and motivations related to AI tools. The use of qualitative approaches, including interviews or focus groups, may provide deeper and more context-sensitive insights into the factors shaping critical thinking disposition. Fourth, the study primarily focuses on internal factors like PEOU, PU, and MO while other external factors were not enough included, such as institutional support, teacher influence, or socio-economic conditions, which may also greatly influence the development of students' critical thinking tendencies. Later studies ought to take these extra elements into account and examine their interactions with the variables assessed here, aiming to develop a more complete framework.

DECLARATIONS

Funding Information

This research received no financial support.

Data Availability Statement

The data produced and examined in this study cannot be shared publicly because of participant confidentiality agreements and privacy considerations. However, the datasets can be obtained from the corresponding author upon reasonable request.

Acknowledgements

Not applicable.

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