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Students' Online Learning Motivation in China: Integrating the Technology Acceptance Model and Community of Inquiry in Vocational Education

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Abstract

This study examines the relationships between technology acceptance and online learning motivation (OLM) in the context of Chinese vocational education by integrating the Technology Acceptance Model (TAM) and the Community of Inquiry (CoI) framework. Survey data from 962 students were analyzed using partial least squares structural equation modelling (PLS-SEM) to assess how perceptions of technology and presence dimensions influence OLM. The findings reveal that self-efficacy (SE) is the primary determinant of OLM, followed by perceived ease of use (EU) and perceived usefulness (PU). Consistent with TAM, EU positively influences PU. In the CoI framework, teaching presence (TP) is found to have significant direct and indirect effects on OLM, acting as a mediator between SE, EU, and OLM. However, social presence (SP) and cognitive presence (CP) show no significant mediating effects on motivation. This study extends both TAM and CoI theory by demonstrating the pivotal role of teaching presence in vocational education contexts. It also highlights the importance of contextual factors in shaping online learning motivation, suggesting that the relative strength of CoI dimensions may differ across educational settings. The findings have important implications for the design of online learning environments, particularly in vocational training, where motivational factors play a key role in student engagement and success.

1. Introduction

Vocational education in China stands at a pivotal moment of transformation, as the nation strives to cultivate a highly skilled and digitally literate workforce aligned with the demands of the modern economy (Guo et al., 2019; Tingran, 2020). At the heart of this shift is the strategic integration of online learning, propelled by national initiatives such as the Education Informatisation 2.0 Action Plan and the Modern Vocational Education System Construction Plan (Ministry of Education of China, 2018). These national policies have accelerated the integration of online platforms, highlighting the need for adaptive, accessible, and skill-oriented learning models (Huang et al., 2021; World Economic Forum, 2023). In vocational education, incorporating real-world applications and practical simulations in online modules has been shown to strengthen students' perceptions of the learning activity's value (Alamri et al., 2020; Yi et al., 2018).

Motivation remains a key determinant of student engagement and success in online learning environments (Kumar et al., 2021). However, vocational learners often face unique challenges, including varied digital literacy, limited infrastructure in rural areas, and a need for hands-on training, which may influence their perceptions and motivation toward online learning (Liu & Yuan, 2015; Elneel et al., 2023; Huang et al., 2021). These disparities raise critical questions about how online learning can be effectively implemented and sustained in vocational contexts.

Research on student motivation in online learning has mainly relied on the Technology Acceptance Model (TAM), which highlights perceived usefulness (PU), ease of use (EU), and self-efficacy (SE) as important factors influencing technology adoption (Al-Adwan et al., 2023; Rosli et al., 2022; Venkatesh & Davis, 2000). At the same time, the Community of Inquiry (CoI) framework, including teaching presence (TP), social presence (SP), and cognitive presence (CP), provides a complementary view centred on the learning environment (Garrison et al., 2000; Richardson et al., 2012). Despite their relevance, few studies have integrated TAM and CoI to explain online learning motivation in vocational education. Prior research often

treats these models in isolation, overlooks mediation effects (Chen & Gao, 2024; Lin & Yeh, 2019), or excludes vocational learners altogether (Al-Adwan, 2020; Dempsey & Zhang, 2019). This creates a significant gap in understanding how technology acceptance and learning presence interact to shape motivation. To address this, the present study develops and tests an integrated TAM-CoI model to explain online learning motivation among vocational students in China. Specifically, it investigates:

1. The relationship between self-efficacy, ease of use, and perceived usefulness in vocational education contexts.
2. How self-efficacy, ease of use, and perceived usefulness influence online learning motivation.
3. How do the CoI dimensions (TP, SP, CP) mediate the relationships between TAM factors and online learning motivation?

This study offers new insights by empirically confirming the mediating roles of CoI dimensions (TP, SP, and CP), with TP emerging as the strongest mediator. Additionally, it identifies SE as the most influential predictor of motivation, surpassing PU and EU, findings that challenge traditional TAM assumptions (Venkatesh & Davis, 2000). Moreover, the study offers context-specific insights for vocational educators, emphasizing the importance of user-friendly tools (EU's impact on SP/TP) and confidence-building interventions (SE's direct effect on OLM) to enhance student engagement in online learning environments.

2. Literature review and hypotheses

2.1 Technology Acceptance Model (TAM) and Community of Inquiry (CoI)

This study integrates the Technology Acceptance Model (TAM) and the Community of Inquiry (CoI) framework to examine online learning motivation among vocational students. TAM, proposed by Davis (1986), explains users' acceptance of technology based on perceived usefulness (PU) and ease of use (EU). In educational settings, self-efficacy (SE) has been identified as an influential addition to these constructs, significantly shaping students' beliefs and behaviours regarding technology use (Almulla, 2021; Park et al., 2012). Research also indicates that online learning engagement behaviour is primarily influenced by perceived usefulness, perceived ease of use, learning self-efficacy, and other factors (Li & Liu, 2023).

The CoI framework developed by Garrison et al. (2000) complements TAM by conceptualising online learning through teaching presence (TP), social presence (SP), and cognitive presence (CP). These three presences form a dynamic learning environment that supports knowledge construction, interpersonal interaction, and instructional guidance. Prior studies confirm the positive impact of TP, SP, and CP on student engagement, satisfaction, and cognitive effort in online education (Fiock, 2020; Richardson et al., 2017). This study positions TP, SP, and CP as mediators between TAM factors and online learning motivation (OLM). While engagement is typically associated with behavioural participation (Fredricks et al., 2004), motivation reflects internal drivers such as goal orientation, interest, and value perception (Ryan & Deci, 2020). Motivation influences students' willingness to begin, persist in, and regulate their online learning. Meaningful and contextually relevant learning activities significantly enhance student motivation and participation (Bin Saeed

et al., 2019). Similarly, higher levels of motivation in online settings lead to improved academic outcomes (Pamungkas et al., 2023).

2.1.1 Perceived Usefulness (PU)

In online learning, PU refers to students' belief that digital platforms will enhance their academic outcomes (Rafique et al., 2020; Sukendro et al., 2020). PU is particularly relevant in vocational education, where learners seek practical, career-aligned competencies (Choi et al., 2019; Demir & Tavil, 2021). When students perceive online content as directly applicable to their future roles, it enhances their motivation and engagement (Ashraf et al., 2022). PU also influences the CoI dimensions. Useful platforms can strengthen TP through structured instruction (Richardson et al., 2012), promote SP by supporting collaboration, and foster CP by enabling deeper cognitive engagement (Garrison et al., 2000). The following hypotheses are therefore proposed:

H1: Perceived usefulness has a positive effect on cognitive presence.

H2: Perceived usefulness has a positive effect on social presence.

H3: Perceived usefulness has a positive direct effect on teaching presence.

H4: Perceived usefulness has a positive effect on online learning motivation (OLM).

H5: Perceived usefulness has a positive effect on OLM through social presence, teaching presence, and cognitive presence.

2.1.2 Perceived Ease of Use (EU)

The EU represents the extent to which students find online platforms user-friendly and easy to navigate. Studies have shown that intuitive platforms enhance user satisfaction and reduce technological barriers, thereby supporting sustained engagement (He et al., 2018; Wang et al., 2023). In the CoI context, the EU facilitates: CP, by reducing cognitive load and enabling focus on content; SP, by making communication tools more accessible; and TP, by enabling effective course design and delivery (Wilson et al., 2021; Kemp et al., 2019). Improving the EU in online vocational learning requires simplifying user interfaces and offering technical support (Tubaishat, 2018). Based on these insights, the following hypotheses are formulated:

H6: Ease of use has a positive effect on cognitive presence.

H7: Ease of use has a positive effect on social presence.

H8: Ease of use has a positive effect on teaching presence.

H9: Ease of use has a positive effect on online learning motivation (OLM).

H10: Ease of use has a positive effect on OLM through social presence, teaching presence, and cognitive presence.

2.1.3 Self-Efficacy (SE)

Self-efficacy represents students' confidence in using technological tools effectively, which influences their adoption and sustained use of educational technologies (Schunk & DiBenedetto, 2021). High self-efficacy is associated with greater digital engagement, active learning, and improved academic performance, while low self-efficacy can lead to avoidance behaviours, reduced persistence, and suboptimal learning outcomes (Eller et al., 2018; Farmer et al., 2021).

Self-efficacy enhances students' cognitive presence, as students are more likely to approach tasks with a problem-solving mindset and persist through challenges (Schunk & DiBenedetto, 2021). It also positively affects social presence, enabling students to participate confidently in peer interactions and collaborative activities (Kundu, 2020). Similarly, high self-efficacy contributes to teaching presence, as students actively respond to instructional cues and align their efforts with the course objectives (Zhang et al., 2022). Students with high self-efficacy are more likely to engage in meaningful discourse, persist in understanding complex materials, and actively respond to instructor guidance (Luo et al., 2023).

Vocational students often aim to develop career-specific competencies, and those with high self-efficacy demonstrate a greater ability to leverage learning tools to meet these goals (Wang & Huang, 2019; Zhang et al., 2022). Research highlights that strategies such as fostering early success experiences, providing collaborative opportunities, and offering continuous instructor support can enhance students' confidence in their technological abilities (Alenezi, 2023; Fong et al., 2019). Additionally, iterative improvements in platform design based on student feedback further bolster self-efficacy by reducing technological barriers and promoting user satisfaction (Aulia & Kusuma, 2020; Chen et al., 2018). Self-efficacy can significantly impact students' online learning motivation (OLM) by fostering a sense of competence and readiness to engage in digital learning experiences. This influence could further be mediated by the CoI framework's core constructs, emphasizing the interconnectedness of these elements in driving motivation (Granić & Marangunić, 2019; Ryan & Deci, 2000). These insights inform the following hypotheses:

H11: Self-efficacy has a positive effect on cognitive presence.

H12: Self-efficacy has a positive effect on social presence.

H13: Self-efficacy has a positive effect on teaching presence.

H14: Self-efficacy positively affects Online Learning Motivation.

H15: Self-efficacy has a positive effect on OLM through social presence, teaching presence, and cognitive presence.

Additionally, the study by Zuo et al. (2021) further argued that TP influences both CP and SP. Similarly, they found that SP has a significant effect on CP. This study investigates this relationship further by suggesting the following hypothesis:

H16: Teaching presence has a positive impact on cognitive presence.

H17: Teaching presence has a positive impact on social presence.

H18: Social presence has a positive impact on cognitive presence.

2.1.4 Interrelationships among usefulness (PU), ease of use (EU), and Self-efficacy (SE)

Within TAM, perceived usefulness refers to the belief that online learning improves academic performance, while ease of use reflects how effortless the system is to operate (Davis, 1989). EU has been shown to positively influence PU by reducing cognitive load and enhancing user confidence (Almulla, 2021; Teo et al., 2019; Venkatesh & Davis, 2000). Self-efficacy also shapes PU and EU. Students with higher SE tend to find systems easier to use (Bandura, 1997; Huang et al., 2020) and are more likely to perceive them as useful for achieving learning goals (Almulla, 2021). However, some research shows that SE's effect on PU may vary with context (Park et al., 2012). In vocational online learning, strengthening SE through user-centred design and support can positively influence both EU and PU. Based on the above discussion, the following hypotheses can be formulated in relation to online learning environments:

H19: Self-efficacy has a significant positive effect on Perceived Usefulness.

H20: Self-efficacy has a significant positive effect on Perceived Ease of Use.

H21: Perceived Ease of Use has a significant positive effect on Perceived.

2.2 Proposed model

The study proposes an integrated model combining TAM and the CoI framework to explore online learning motivation among K-12 vocational students in China (see Fig. 1). The model posits that CoI dimensions (TP, SP, CP) mediate the effects of SE, EU, and PU on online learning motivation (OLM). This model emphasises the interplay between technology acceptance, learning presence, and motivational dynamics in vocational online education.

3. Methods

3.1 Strategy and participants

We employed a quantitative approach, analysing data from 962 vocational students in China. Participants were primarily freshmen (62.9%) and sophomores (36.9%), with 86.5% female and 13.5% male representation (Table 1). A convenience sampling method was used to distribute an online questionnaire to students. While convenience sampling limits generalizability, it is efficient for exploratory research (Cohen et al., 2017). After data cleaning, only valid responses were retained. The study examined online learning models: synchronous (live online lectures, MOOCs, and discussions) and asynchronous (in-person learning supplemented by online activities). All courses used China's Star platform (Chaoxing) for structured digital delivery, integrating discussions, assignments, and resources.

Table 1
Respondents' Characteristics

		N = 962	
Variable	Category	Frequency	Percent
Grade	Freshman	605	62.9
	Sophomore	355	36.9
	Junior	1	0.1
	Others	1	0.1
Gender	Female	832	86.5
	Male	130	13.5
Source: Based on survey results			

3.2 Instruments

The survey began with a brief description of the purpose of the research. Students were asked to complete a survey based on their online learning experience to optimise their course design. The questionnaire consisted of two main parts. Part one collected data on respondents' characteristics such as Department, Level, and Gender. Part two consisted of questions on constructs, including self-efficacy, ease of use, perceived usefulness, cognitive presence, teaching presence, social presence, and online learning motivation. The construct items were adapted from the instrument validated by Zuo et al. (2022). The items were obtained by professionally translating the original items into Chinese using the forward-backwards method, which allows one to verify the accuracy and clarity of the translation to ensure "face validity". Finally, each item corresponding to the constructs was measured using a 5-point Likert scale, ranging from 1 (Disagree strongly) to 5(Agree strongly). The higher the score, the higher the degree of agreement. After data collection, we tested the reliability and validity of the questionnaire items and constructs for subsequent structural equation modelling.

3.3 Data analysis

The analysis generated descriptive statistics using SPSS version 29, and partial least squares structural equation modelling (PLS-SEM) using SmartPLS 4.0.8. PLS-SEM was selected for its robustness with small samples and complex mediation models (Hair et al., 2021), while effectively handling both formative and reflective constructs (Sarstedt et al., 2017).

Confirmatory Factor Analysis demonstrated excellent suitability (KMO = 0.98, $p < 0.001$). The measurement model exhibited strong reliability, with all constructs exceeding thresholds for composite reliability (CR > 0.7) and Cronbach's alpha ($\alpha > 0.7$). Convergent validity was established through average variance extracted (AVE > 0.5) and high indicator loadings (> 0.800). Discriminant validity was confirmed via the Fornell-Larcker criterion, with √AVE exceeding inter-construct correlations (Table 3). Multicollinearity assessment led to the removal of one perceived usefulness item (PU3) due to high VIF (> 10) (Diamantopoulos & Siguaw, 2006; Henseler et al., 2015; O'Brien, 2007). Model fit indices yielded excellent results (SRMR = 0.024), supported by

supplementary metrics, including NFI and the chi-square value. Predictive relevance was confirmed through Q^2 predict values and error measures (RMSE, MAE). Bayesian Information Criterion evaluation ensured optimal model complexity. Effect sizes (f^2) were interpreted as: 0.02 (small), 0.15 (medium), and 0.35 (large). The comprehensive validation process followed established guidelines (Fornell & Larcker, 1981; Hair et al., 2017), ensuring robust examination of hypothesised relationships while maintaining statistical rigour throughout the analytical framework.

4. Results of the study

4.1 Reliability and validity of constructs

The SRMR value (0.024), the d_ULS (0.482), d_G (1.015), the chi-square (5981.338), and NFI (0.913), confirmed the model's suitability to the data. Constructs such as Online Learning Motivation (OLM) demonstrated a high Q^2 predict value (0.905), indicating strong predictive power. Similarly, Cognitive Presence (CP), Social Presence (SP), and Teaching Presence (TP) showed high predictive relevance, with Q^2 predict values of 0.754, 0.707, and 0.649, respectively. The predictive accuracy of the constructs was confirmed by low RMSE and MAE values, demonstrating the robustness of the PLS-SEM analysis. Lower BIC values for constructs such as OLM (-2377.793) and CP (-2214.614) highlighted their explanatory power relative to the model's complexity. The model below *(*Fig. 2*)* illustrates the adjusted R-squared, path coefficients and their statistical significance within the final PLS-SEM model, offering an overview of the key relationships and validation of the measurement model.

As shown in Table 2 below, all constructs reported CA values well above the recommended threshold of 0.7 (Nunnally & Bernstein, 1994). Composite Reliability values for all constructs exceeded the threshold of 0.7 (Hair et al., 2017), confirming the constructs' reliability. The standardised loadings of all items were greater than 0.800, exceeding the minimum acceptable threshold of 0.7 (Hair et al., 2017). All constructs achieved AVE values above the 0.5 threshold (Fornell & Larcker, 1981), confirming that the construct items explain a significant portion of the variance. Online Learning Motivation (OLM) had the highest Adjusted R^2 value of 0.919, suggesting that the independent variables explain 91.9% of the variance in OLM. Constructs like Cognitive Presence (CP) and Ease of Use (EU) also demonstrated high Adjusted R^2 values of 0.904 and 0.807, respectively, highlighting their strong predictive relevance. The constructs demonstrate excellent reliability and validity, meeting all recommended thresholds.

Table 2
Construct reliability and validity

Constructs	Items	Loading	CA	CR (rho_a)	CR (rho_c)	AVE)	Adjusted R^2
CP	7	> 0.900	0.981	0.981	0.984	0.896	0.904
EU	3	> 0.900	0.967	0.967	0.978	0.937	0.807
OLM	8	> 0.800	0.973	0.974	0.977	0.843	0.919
PU	2	> 0.900	0.954	0.954	0.977	0.956	0.871
SE	6	> 0.900	0.975	0.975	0.980	0.889	-
SP	7	> 0.900	0.980	0.980	0.983	0.891	0.838
TP	7	> 0.900	0.974	0.974	0.978	0.865	0.652
Source: Based on survey results							

4.1.1 Discriminant validity (Fornell–Larcker Criterion)

The discriminant validity of the constructs in the model was evaluated using the Fornell–Larcker Criterion. In this case, the square root of the AVE for each construct exceeds the off-diagonal values, confirming discriminant validity across all constructs. These results suggest that each construct is more closely related to its indicators than to those of other constructs, thus supporting discriminant validity in line with existing research (Fornell & Larcker, 1981). The Fornell–Larcker Criterion results in Table 3 support the discriminant validity of the constructs, indicating they are conceptually distinct but closely related, which is typical in educational and social science research (Hair et al., 2017). The findings from the discriminant validity test suggest that the constructs used in this study are well-differentiated (Henseler et al., 2015).

Table 3
Correlations between components and the AVE of the components

Constructs	CP	EU	OLM	PU	SE	SP	TP
Cognitive presence (CP)	**0.947**						
Ease of use (EU)	0.834	**0.968**					
Online learning motivation (OLM)	0.877	0.897	**0.918**				
Perceived usefulness (PU)	0.833	0.886	0.921	**0.978**			
Self-efficacy (SE)	0.855	0.898	0.939	0.925	**0.943**		
Social presence (SP)	0.935	0.811	0.852	0.812	0.822	**0.944**	
Teaching presence (TP)	0.884	0.780	0.825	0.773	0.789	0.892	**0.930**

Source

Based on survey results.

Note

The diagonal values in the table are the square root values of the AVE of each component. The non-diagonal absolute value is the correlation coefficient of each factor. All the correlations were significant ($p < 0.001$).

4.2 Hypothesis testing for direct relationships

Table 4 presents the findings for direct relationships among variables using bootstrapping (5000 subsamples). For perceived usefulness (PU), the results show significant positive relationships with SP (β = 0.141*), supporting H2; TP (β = 0.172*), supporting H3; and OLM (β = 0.242***), supporting H4. However, PU does not significantly predict CP (β = 0.014), leading to the rejection of H1. These findings suggest that while PU enhances teaching and social presence and motivates students, it does not directly increase cognitive engagement.

For perceived ease of use (EU), significant positive relationships were found with SP (β = 0.116*), TP (β = 0.320*), and OLM (β = 0.121*), supporting H7, H8, and H9, respectively. However, the EU does not significantly predict CP (β = 0.056), rejecting *H6.* Additionally, the EU significantly predicts PU (β = 0.284*), supporting *H21*. These findings show that ease of use promotes teaching and social presence, enhances motivation, and strengthens students' perception of usefulness but does not directly impact cognitive engagement.

Self-efficacy (SE) significantly influences CP (β = 0.187*), TP (β = 0.343*), OLM (β = 0.416*), PU (β = 0.670*), and EU (β = 0.898***), supporting *H11, H13, H14, H19*, and *H20*. However, SE does not significantly affect SP (β = 0.106), rejecting *H12.* These results suggest that SE enhances cognitive engagement, teaching presence, motivation, and perceived usefulness/ease of use, but not social interactions.

Finally, TP has a significant positive effect on CP (β = 0.173*), supporting *H16*, and on SP (β = 0.609*), supporting *H17*. SP also directly affects CP (β = 0.570***), supporting *H18*. These findings highlight the pivotal role of teaching presence in fostering both cognitive and social engagement, and the importance of peer interaction in supporting deeper learning.

Table 4
Hypothesis testing for direct relationships

Hypotheses	Path	f^2	Mean	SD	T statistics	P values	Lower 2.50%	Upper 97.50%	Decision
H1: PU -> CP	0.014	0.000	0.020	0.056	0.242	0.809	-0.089	0.132	Rejected
H2: PU -> SP	0.141	0.016	0.138	0.067	2.097	0.036	0.002	0.264	Supported
H3: PU -> TP	0.172	0.011	0.176	0.081	2.121	0.034	0.023	0.339	Supported
H4: PU -> OLM	0.242	0.091	0.239	0.063	3.835	0.000	0.115	0.359	Supported
H6: EU -> CP	0.056	0.005	0.055	0.041	1.360	0.174	-0.027	0.139	Rejected
H7: EU -> SP	0.116	0.014	0.118	0.054	2.136	0.033	0.011	0.225	Supported
H8: EU -> TP	0.320	0.051	0.318	0.064	4.976	0.000	0.196	0.447	Supported
H9: EU -> OLM	0.121	0.029	0.122	0.047	2.575	0.010	0.034	0.216	Supported
H11: SE -> CP	0.187	0.040	0.187	0.047	3.960	0.000	0.097	0.281	Supported
H12: SE -> SP	0.106	0.008	0.110	0.067	1.587	0.113	-0.021	0.243	Rejected
H13: SE -> TP	0.343	0.039	0.341	0.083	4.115	0.000	0.175	0.502	Supported
H14: SE -> OLM	0.416	0.227	0.416	0.059	7.044	0.000	0.300	0.531	Supported
H16: TP -> CP	0.173	0.060	0.171	0.037	4.719	0.000	0.102	0.245	Supported
H17: TP -> SP	0.609	0.798	0.606	0.055	11.091	0.000	0.494	0.709	Supported
H18: SP -> CP	0.570	0.544	0.567	0.052	10.893	0.000	0.460	0.665	Supported
H19: SE -> PU	0.670	0.676	0.668	0.055	12.112	0.000	0.557	0.773	Supported
H20: SE -> EU	0.898	4.179	0.898	0.012	74.513	0.000	0.873	0.920	Supported
H21: EU -> PU	0.284	0.121	0.286	0.059	4.793	0.000	0.171	0.403	Supported

Source: Based on survey results

4.3 Hypothesis testing of mediating relationships

The study examined mediating relationships using the Preacher and Hayes model for PLS-SEM. Results in Table 5 revealed that neither social presence (SP) nor cognitive presence (CP) significantly mediated the effects of perceived usefulness (PU) on online learning motivation (OLM) (β = 0.006 and β = 0.001, respectively), leading to the rejection of *H5a* and *H*5b. Similarly, teaching presence (TP) did not show a significant mediating role between PU and OLM (β = 0.015), resulting in the rejection of H5c. For perceived ease of use (EU), while SP (β = 0.005) and CP (β = 0.006) were not significant mediators, TP demonstrated a significant indirect effect on the EU→OLM relationship (β = 0.028*), supporting *H1*0b. Likewise, self-efficacy (SE) indirectly influenced OLM through TP (β = 0.030*), supporting *H1*5b, but not through SP (β = 0.005) or CP (β = 0.019). These findings highlight TP as the primary mediator in enhancing OLM, particularly for EU and SE, whereas other pathways remained non-significant.

Table 5
Assessment of Specific Indirect Effects

Hypotheses	Path	mean (M)	SD	T statistics	P values	Lower 2.50%	Upper 97.50%	Decision
H5a: PU -> SP -> OLM	0.006	0.007	0.008	0.784	0.433	-0.005	0.025	Rejected
H5b: PU -> CP -> OLM	0.001	0.002	0.007	0.207	0.836	-0.010	0.018	Rejected
$H5_c$: PU -> TP -> OLM	0.015	0.015	0.010	1.556	0.120	0.001	0.037	Rejected
H10a: EU -> SP -> OLM	0.005	0.005	0.006	0.854	0.393	-0.006	0.018	Rejected
$H10_b$: EU -> TP -> OLM	0.028	0.027	0.011	2.422	0.015	0.006	0.052	Supported
$H10_c$: EU -> CP -> OLM	0.006	0.005	0.006	0.989	0.323	-0.003	0.019	Rejected
$H15_a$: SE -> SP -> OLM	0.005	0.005	0.007	0.709	0.478	-0.005	0.021	Rejected
$H15_b$: SE -> TP -> OLM	0.030	0.030	0.014	2.053	0.040	0.006	0.062	Supported
$H15_c$: SE -> CP -> OLM	0.019	0.019	0.012	1.521	0.128	-0.003	0.047	Rejected
Source: Based on survey results								

Table 6
Assessment of Total Effects and Total Indirect Effects

Effect	Path	Path Coef	T statistics	P values	Hypotheses
Total effects	EU -> OLM	0.191	3.812	0.000	H5
	PU -> OLM	0.286	4.577	0.000	H10
	SE -> OLM	0.502	8.750	0.000	H15
Total indirect effects	EU -> OLM	0.071	3.481	0.001	H5
	PU -> OLM	0.044	2.376	0.018	H10
	SE -> OLM	0.087	3.184	0.001	H15
Source: Based on survey results					

5. Discussion and implications of findings

This study examined how self-efficacy (SE), perceived ease of use (EU), and perceived usefulness (PU) influence online learning motivation (OLM) among vocational high school students in an online learning environment, and how these relationships are mediated by Community of Inquiry (CoI) dimensions. The sample (N = 962) consisted of first- and second-year students from Chinese vocational high schools, with 86.5% female participation. While the institution follows a K-12 vocational education system, our specific findings reflect the experiences of students in grades 10–11 (equivalent to U.S. freshman and sophomore levels), as juniors and other grades represented only 0.2% of participants. The subsequent discussion helps to understand how TAM and CoI variables interact to shape these vocational students' online learning motivation, particularly for early high school level learners.

5.1 The Role of PU, EU, and SE in fostering motivation for online learning

Self-efficacy emerged as the strongest direct predictor of online learning motivation (β = 0.416, f^2 = 0.227), also influencing teaching presence (TP) and cognitive presence (CP). This confirms Bandura's (1997) theory that confidence in one's ability is central to motivation and performance and aligns with prior research linking SE to increased engagement and persistence in digital learning environments (Eller et al., 2018; Farmer et al., 2021; Li & Liu, 2023; Schunk & DiBenedetto, 2021; Zhang et al., 2022). However, the expected relationship between SE and social presence (SP) was not supported, diverging from studies that emphasize SE's role in facilitating peer collaboration (Kundu, 2020).

Perceived usefulness (PU) significantly influenced OLM, supporting previous studies that highlight the importance of perceived relevance in shaping learners' motivation (Hamidi & Chavoshi, 2018; Li & Liu, 2023; Venkatesh et al., 2012; Nguyen, 2020). Although PU significantly influenced TP and SP, its effect was modest, and it had no significant impact on CP. This suggests that vocational students may value the practical benefits of online tools but do not necessarily view them as central to deep cognitive engagement.

Ease of use (EU) also had a statistically significant effect on OLM ($f^2 = 0.029$), as well as on PU, TP, and SP, but not CP. This underscores the importance of intuitive, user-friendly online platforms in encouraging sustained participation and reducing barriers to entry, especially in vocational contexts where digital literacy levels vary. These findings support research emphasizing the role of usability in enhancing learning outcomes and student satisfaction (Caffaro et al., 2020; He et al., 2018; Li & Liu, 2023; Wang et al., 2023).

5.2 Relationships among PU, EU, and SE

The findings affirm strong interconnections between SE, EU, and PU in online learning contexts. Consistent with TAM extensions, SE significantly enhances EU and PU by reducing anxiety and enabling students to better perceive the value of technology (Almulla, 2021; Fong et al., 2019; Huang et al., 2020; Park et al., 2012). This reinforces SE's role as a catalyst for digital engagement and technology adoption.

Moreover, EU significantly predicts PU, confirming that students who find systems easy to use are more likely to view them as beneficial (Teo et al., 2019; Venkatesh & Davis, 2000). These dynamics are especially relevant for vocational learners, who prioritise straightforward and goal-oriented platforms for acquiring job-relevant skills.

5.3 Mediating roles of CoI dimensions

The CoI framework provided partial explanatory power in mediating the relationships between TAM constructs and OLM. Teaching presence (TP) emerged as a strong predictor of both SP ($f^2 = 0.798$) and CP ($f^2 = 0.060$), aligning with CoI theory (Garrison et al., 2000). However, the expected mediating roles of TP, SP, and CP were weaker than anticipated. Notably, PU did not significantly affect CP, challenging TAM's assumption that perceived value drives cognitive engagement. This may reflect vocational students' emphasis on practical skill acquisition over abstract knowledge construction. Similarly, the non-significant relationship between SE and SP suggests that peer interaction in vocational online learning may be more structured and instructor-led, rather than emerging from student confidence. These findings point to the need for contextual adaptation of Western-developed models like TAM and CoI in vocational education settings. The weaker mediating effects of CoI dimensions, particularly SP, highlight that vocational students' motivation may rely less on collaborative engagement and more on perceived efficiency, clarity of instruction, and alignment with career goals.

This study reinforces prior research noting that the effectiveness of online learning varies by context (Martin et al., 2018; Shea & Bidjerano, 2012) and emphasises that skill-focused environments may require less emphasis on peer-driven collaboration and more on clear instructional design and usability.

5.4 Implications for online learning design

The findings of this study offer implications for designing online learning environments in vocational education, particularly in contexts like China, where teacher-centred pedagogies remain dominant. While the results reaffirm the foundational role of teaching presence (Garrison et al., 2000), they also suggest that collaborative frameworks such as the Community of Inquiry (CoI) require adaptation in online vocational contexts, where instructor-led demonstrations often outweigh peer interaction (Zuo et al., 2021). The weak mediation effects and the unsupported link between perceived usefulness (PU) and cognitive presence (CP)

imply that vocational learners may engage with online learning through mechanisms distinct from those in traditional academic settings (Alamri et al., 2020). This underscores the need to shift from open-ended collaboration toward more structured, career-aligned facilitation, such as guided tutorials or competency-based tasks that directly support skill acquisition (Fiock, 2020).

In terms of technology adoption, the study highlights that usability alone is insufficient; the perceived relevance of digital tools to learners' career goals is critical. Simplified interfaces should be accompanied by just-in-time demonstrations and scaffolded experiences that strengthen learners' self-efficacy and clarify the practical value of online platforms (Fong et al., 2019; Teo et al., 2019). These insights are particularly relevant in the Chinese vocational context, where digital learning must coexist with long-standing, instructor-led models. To support effective online learning, institutions should invest in targeted professional development that enhances teaching presence while aligning content delivery with vocational competencies (Martin et al., 2018). Additionally, onboarding processes should be customised to accommodate varying levels of digital literacy, rather than assuming uniform readiness among students.

Rather than replacing established pedagogical models, this study advocates their context-sensitive adaptation. For example, cognitive presence could be reinterpreted to include instructor-facilitated problem-solving or scenario-based learning (Vaughan et al., 2013), while perceived usefulness might be best understood in terms of direct career relevance (Yi et al., 2018). Future research should test these adaptations across vocational disciplines and examine cultural norms, such as collectivist values, influence student engagement and technology acceptance in online environments. Ultimately, effective online learning in vocational education must integrate digital tools with practical skill development while remaining responsive to cultural and institutional realities.

6. Limitations and directions for future research

While this study offers valuable insights into the motivational dynamics of online learning in vocational education, several limitations should be acknowledged. First, its cross-sectional design restricts the ability to assess how online learning motivation evolves. Longitudinal studies are needed to track changes in motivational factors as students gain more exposure to online platforms and digital instruction.

Second, the research is limited to vocational students in China, which may affect the generalizability of the findings to other countries or educational systems. Although the integration of the Technology Acceptance Model (TAM) and Community of Inquiry (CoI) frameworks add theoretical depth, other influential factors, such as institutional support, teacher quality, and digital infrastructure, were not directly examined.

Further limitations lie in the use of self-reported survey data, which can be subject to response bias. The absence of objective indicators, such as LMS engagement data, course completion rates, or instructor assessments, limits the validation of students' reported motivation levels. Future studies should incorporate multiple data sources to enhance reliability and triangulation.

Additionally, the growing role of emerging technologies such as AI-powered adaptive learning platforms presents new avenues for enhancing personalisation and engagement in online learning. Future research should explore how such technologies interact with motivational constructs and pedagogical frameworks in

vocational contexts. Addressing these limitations will be critical for developing more comprehensive and generalizable models of online learning in vocational education.

Declarations

Ethical statement

Informed consent was obtained from all participants before data collection. The study ensured the confidentiality and anonymity of participants' responses. Participants were informed about the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time. Additionally, the ethics committee overseeing the study waived the requirement for consent, as the research was deemed to pose minimal risk to participants.

Author contributions

All authors contributed to the study's conception and design. Material preparation and data collection were performed by Han Mengying. Formal analysis and first draft were performed by Edusei-Mensah William. Li Yushun supervised, commented and validated previous versions of the manuscript. Agbale Belinda proofread and reversed the manuscript. All authors read and approved of the final manuscript.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT 4.0 to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and took full responsibility for the content of the published article.

Declaration of interest statement

The authors declare that they have no competing interests.

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Data availability

The datasets generated during and/or analysed during the current study are available from the corresponding author upon reasonable request.

Clinical trial number

Not applicable

Consent to publish declaration

Not applicable

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Figures

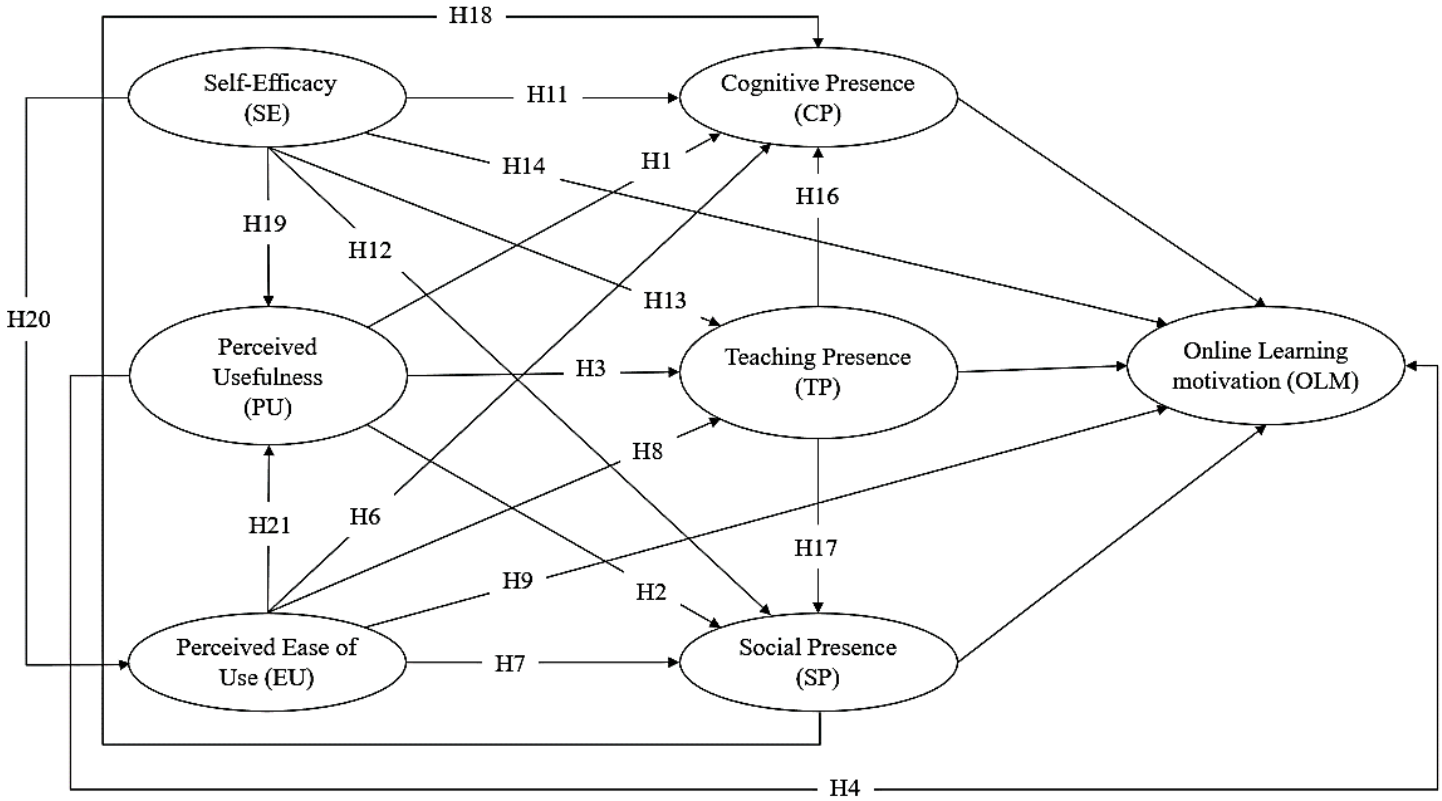

Figure 1

The hypothesised relationship among the seven (7) research constructs

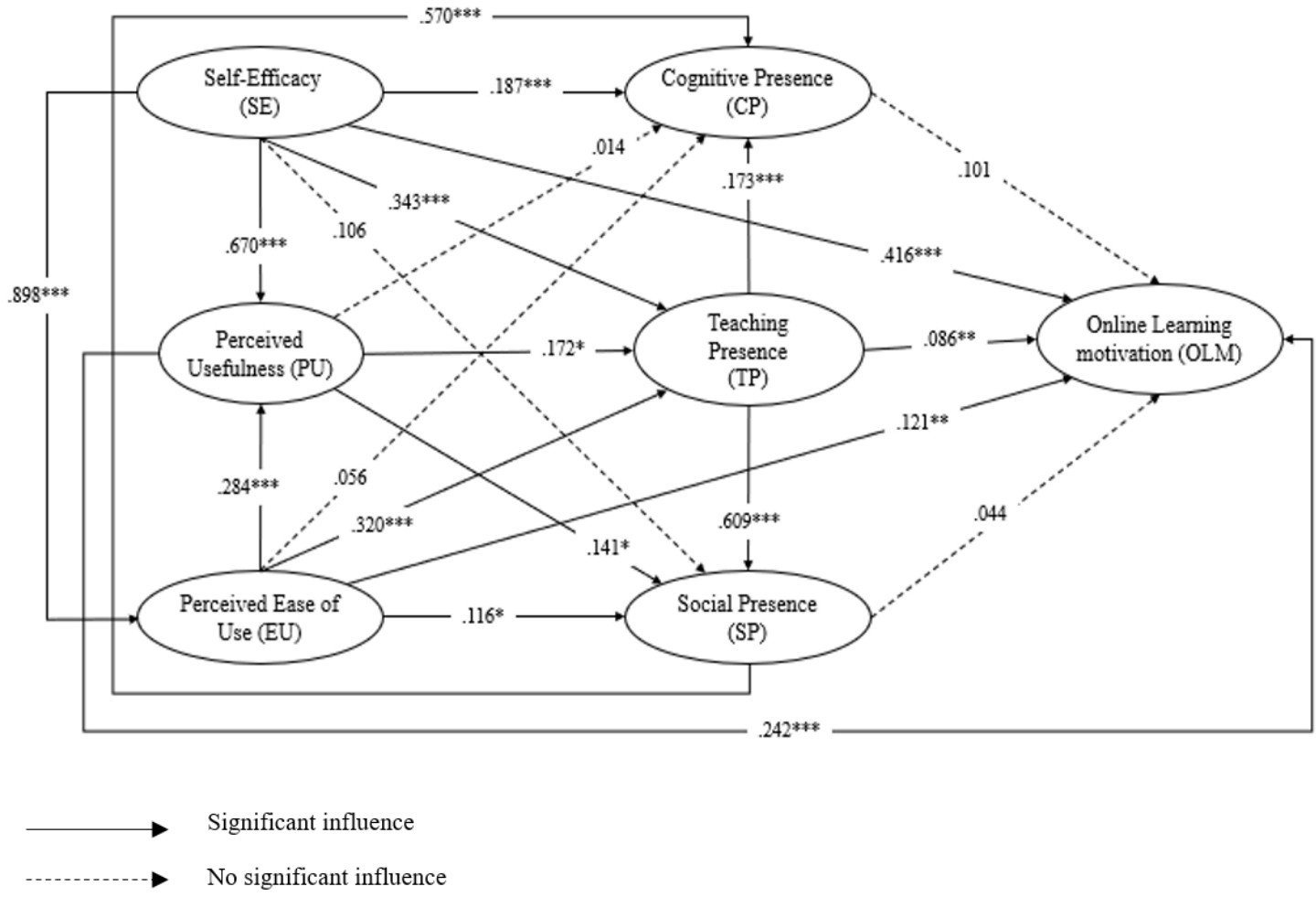

Figure 2

Parameter estimates of the general structural model