Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Learner agency and academic engagement in AI-supported higher education: The roles of e-learning autonomy and self-efficacy

Pari Irai

jnrjparii@gmail.com

Massey University

Allan Cheng Chieh Lu

National Taiwan Normal University

Xiaoyuan Wu

Yiwu Industrial & Commercial College

Article

Keywords: academic engagement, artificial intelligence, e-learning autonomy, higher education, learning self-efficacy, learner agency, self-determination theory

Posted Date: November 24th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11193021/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Learner agency and academic engagement in AI-supported higher education: The roles of e-learning autonomy and self-efficacy

Short title

Learner agency in AI-supported higher education

Authors and affiliations

Pari Irai[1]*, Allan Cheng Chieh Lu[2], and Xiaoyuan Wu[3]

[1] School of Management, Massey University, Auckland, New Zealand

[2] Graduate Institute of International Human Resource Development, National Taiwan Normal University, Taipei, Taiwan

[3] School of Foreign Studies, Yiwu Industrial and Commercial College, Yiwu, China

***Corresponding author**

Pari Irai

School of Management, Massey University

Auckland, New Zealand

Email: jnrjparii@gmail.com

ORCID: 0000-0002-7104-0259

Co-author email addresses

Allan Cheng Chieh Lu: allanlu71429@ntnu.edu.tw

Xiaoyuan Wu: xiaoyuan@ywicc.edu.cn

Abstract

The increasing availability of artificial intelligence (AI) tools to university students raises important questions regarding learners' responsibility for their work and sustained engagement when assistance is easily accessible. This study investigated the relationships among e-learning autonomy, learning self-efficacy, and academic engagement within an AI-supported higher education environment. A cross-sectional online survey of 223 undergraduate students employed adapted measures to assess perceived capacity for self-directed learning, confidence in personal abilities, and participation in academic activities without excessive dependence on AI assistance. Regression-based mediation analysis indicated that e-learning autonomy was positively associated with both learning self-efficacy and academic engagement. Learning self-efficacy was also positively associated with engagement and showed a significant positive indirect association between autonomy and engagement, alongside a significant direct association. These results highlight autonomy and self-efficacy as interconnected learner resources linked to academic engagement in contexts where AI assistance is present. The findings advance understanding of the human dimensions of AI-supported higher education and underscore the need for institutions to address both AI access and the cultivation of students' ownership of learning and confidence in their abilities.

Keywords: academic engagement; artificial intelligence; e-learning autonomy; higher education; learning self-efficacy; learner agency; self-determination theory

1 Introduction

Artificial intelligence (AI) is changing how university students obtain explanations, generate ideas, organise information, draft text, and respond to academic problems. Generative AI systems such as ChatGPT, Gemini, Claude, and DeepSeek have made these forms of assistance immediate and widely accessible. In response, universities have developed policies and teaching practices intended to support responsible use (Chan, 2023; McDonald et al., 2025; Moorhouse et al., 2023). Students also report benefits that include personalised support, assistance with writing and brainstorming, and easier access to explanations (Chan & Hu, 2023).

A central educational problem, however, is that while readily available AI assistance can facilitate learning, it may also diminish the learner's active role in the learning process. Students can use AI to clarify complex material and obtain feedback, but they may also delegate goal setting, information evaluation, problem solving, and task completion to the technology. As a result, visible task completion may coexist with limited intellectual effort or reduced responsibility for learning. Excessive or uncritical reliance on AI-generated content may undermine independent problem solving, promote superficial engagement, and raise concerns about academic integrity (Cotton et al., 2024; Kasneci et al., 2023). Thus, access to AI should not be conflated with effective learning or sustained engagement (Holmes & Tuomi, 2022; Heung & Chiu, 2025).

This problem requires attention because academic engagement depends on what students do with available resources. Students must continue to establish goals, select strategies, monitor understanding, evaluate information, respond to difficulty, and participate with teachers and peers. These activities require both autonomy and confidence. Students who retain responsibility for their learning may be better able to use AI as support rather than as a substitute for learning,

while students who doubt their own capabilities may be more likely to withdraw from demanding tasks or depend on externally generated answers. Understanding these learner differences is therefore necessary for designing AI-supported education that strengthens rather than displaces active participation.

The consequences of failing to address this problem are immediate. Universities may invest in AI access, policy development, and technical training without considering the personal capabilities required for productive technology use. Students may become proficient in generating academic outputs but less willing or able to evaluate information, persist through difficulty, or explain their own reasoning. Disparities in autonomy and self-efficacy may further widen the gap between students who can critically integrate AI and those who become dependent on it. Institutional responses focused solely on access or prohibition risk overlooking the learner resources necessary for AI assistance to support meaningful engagement.

Research on AI in higher education has examined institutional adoption, intelligent tutoring, automated assessment, personalised learning, academic integrity, student perceptions, and technology acceptance (Bond et al., 2024; Zawacki-Richter et al., 2019). Recent studies have begun to examine the psychological and learning processes associated with AI-supported engagement. Li and Chiu (2025), for example, found that psychological-need satisfaction mediated the relationship between teacher support and engagement with generative AI chatbots. Dong et al. (2026) reported that dimensions of the Community of Inquiry mediated the relationship between generative AI-based learning analytics and engagement, with digital literacy shaping these relationships. Hamamra et al. (2026) showed that learner autonomy in ChatGPT-supported writing depended on AI literacy, critical judgement, and students' capacity to manage assistance responsibly.

Recent research has advanced understanding of AI adoption, students' experiences with specific tools, and engagement with AI-supported activities. However, limited knowledge exists regarding how students' perceived capacity to direct digitally mediated learning relates to their confidence in their learning abilities and to broader academic, cognitive, and social engagement. Investigating these relationships contributes to the study of learner agency in higher education, particularly as academic assistance can now be readily delegated to AI.

The present study examines associations among e-learning autonomy, learning self-efficacy, and academic engagement within an educational context where AI tools are accessible. E-learning autonomy is defined as students' perceived ability to plan, monitor, and direct their learning while maintaining responsibility for decisions that might otherwise be delegated to AI. Learning self-efficacy denotes confidence in managing academic demands without excessive reliance on AI assistance. Academic engagement encompasses academic activity, cognitive involvement, and social participation with instructors and peers. Notably, the study focuses on relationships among these learner resources rather than measuring the effects of any specific AI tool.

Self-determination theory (SDT) and self-efficacy theory provide complementary frameworks for understanding the proposed relationships. SDT emphasises volition and perceived effectiveness as central to motivated functioning, while self-efficacy theory explains how beliefs about capability are associated with effort, persistence, and participation (Bandura, 1997; Deci & Ryan, 2000; Ryan & Deci, 2020). The focal constructs in this study are informed by these perspectives but do not constitute direct measures of SDT need satisfaction. This distinction is elaborated in the theoretical framework.

The study uses data collected at a single point in time and therefore examines statistical associations rather than temporal or causal effects. Within an AI-supported higher education context, the study addresses the following research questions:

RQ1: What is the association between e-learning autonomy and learning self-efficacy?

RQ2: What is the association between learning self-efficacy and academic engagement after accounting for e-learning autonomy and demographic covariates?

RQ3: To what extent is e-learning autonomy associated with academic engagement directly and indirectly through learning self-efficacy?

2 Theoretical framework and hypothesis development

2.1 Self-determination theory and self-efficacy theory

SDT explains how social and learning environments support motivation and effective functioning through the satisfaction of three basic psychological needs: autonomy, competence, and relatedness (Deci & Ryan, 2000; Ryan & Deci, 2020). Autonomy refers to the experience of acting with volition and personal endorsement. Competence involves feeling effective in interactions with the environment, and relatedness pertains to connection with and support from others. In higher education, learning conditions that fulfill these needs can promote purposeful participation and persistence.

The constructs examined in this study should not be treated as direct indicators of psychological-need satisfaction. E-learning autonomy refers to students' perceived capacity to direct and assume responsibility for digitally mediated learning. In the administered questionnaire, this responsibility was defined in terms of decisions that students could otherwise delegate to AI. The construct therefore represents an autonomy-related dimension of learner

agency rather than autonomy-need satisfaction itself. Similarly, learning self-efficacy is associated with perceived competence but remains conceptually distinct from competence-need satisfaction. It reflects students' beliefs in their ability to organize and execute the actions required for successful learning (Bandura, 1997). Relatedness was not included as a separate explanatory construct as it fell outside the operational definition within the present study context. The engagement measure incorporates participation with teachers and peers, but these dimensions describe involvement in academic relationships rather than satisfaction of the psychological need for relatedness. Preserving these distinctions prevents related constructs from being treated as interchangeable.

Self-efficacy theory complements SDT by explaining how capability beliefs shape students' choices, effort, persistence, and responses to challenges (Bandura, 1997). Students with higher learning self-efficacy are more likely to attempt demanding tasks, maintain effort, employ effective strategies, and recover from setbacks. Mastery experiences are particularly important because successful performance demonstrates that a learner can manage similar demands in the future. These perspectives support a model in which students who retain greater responsibility for AI-supported learning also report stronger confidence in their own learning capabilities, which is associated with increased academic engagement. The model does not assume that AI access produces autonomy or self-efficacy, but rather examines how these learner resources are related within an environment where AI assistance is available.

2.2 E-learning autonomy and learning self-efficacy

Learner autonomy refers to the capacity to take responsibility for decisions related to learning. Within digitally mediated environments, e-learning autonomy encompasses planning, goal setting, resource and strategy selection, progress monitoring, and responding to challenges

(Firat, 2016). Although it overlaps with self-regulated learning, the two constructs are distinct. Autonomy highlights ownership of learning decisions, while self-regulated learning focuses more specifically on the cognitive, motivational, and behavioural processes through which learning is managed (Zimmerman, 2002).

The integration of AI tools introduces additional decision points within digitally mediated learning. Learners must determine when to seek assistance, how to formulate effective queries, assess the accuracy and relevance of generated content, and decide how to incorporate this material into their own work. In this context, autonomy does not entail rejecting AI assistance or engaging in solitary learning. Rather, it involves the intentional use of available support while maintaining responsibility for comprehension, evaluation, and completion of academic tasks.

E-learning autonomy is expected to be positively associated with learning self-efficacy because directing one's own learning can foster mastery experiences. Learners who set goals, select strategies, monitor progress, and address difficulties may interpret successful outcomes as evidence of their competence. Repeated management of academic demands can further strengthen confidence in overcoming future challenges (Bandura, 1997). In ChatGPT-supported university learning, Hamamra et al. (2026) described learner autonomy as a mediated capacity reliant on critical regulation of AI assistance. Zhao and Qin (2021) also found that perceived teacher autonomy support was positively correlated with university students' self-efficacy. Although teacher autonomy support differs from students' own e-learning autonomy, the finding supports a connection between autonomy-related learning conditions and efficacy beliefs. Based on this theoretical reasoning and related empirical evidence, the following hypothesis is proposed: H1: E-learning autonomy is positively associated with learning self-efficacy.

2.3 Learning self-efficacy and academic engagement

Learning self-efficacy refers to confidence in learning effectively, completing academic tasks, maintaining effort, coping with challenges, and achieving learning objectives (Bandura, 1997). In the present study, the adapted items emphasised confidence in performing these activities without extensive reliance on AI. This construct is distinct from technical confidence in operating AI systems. For example, a student may be proficient in using an AI tool yet remain uncertain about understanding complex material or completing demanding work independently.

Academic engagement refers to students' active investment and participation in their studies. Consistent with the Higher Education Student Engagement Scale, this study examined academic activity, cognitive engagement, social engagement with teachers, and social engagement with peers (Zhoc et al., 2019). The adapted items assessed whether students maintained these forms of participation without excessive reliance on AI. Engagement is therefore distinct from the frequency or duration of AI use. Frequent interaction with an AI system does not necessarily indicate effort, deep processing, collaboration, or participation in academic relationships.

Self-efficacy theory predicts a positive association between learning self-efficacy and engagement. Students who believe they can learn effectively are more likely to approach demanding tasks, persist after setbacks, and adapt their strategies when necessary. Stronger efficacy beliefs also support cognitive engagement, as confident students are more willing to work through complex material instead of avoiding it or relying on superficial approaches. Linnenbrink and Pintrich (2003) similarly argued that self-efficacy shapes behavioural, cognitive, and motivational engagement through students' choices, effort, persistence, and strategy use.

Learning self-efficacy may also facilitate social engagement. Students who believe they can manage academic demands are more likely to communicate ideas, ask questions, seek assistance, and participate in collaborative learning. In contrast, students with lower confidence may withdraw from these interactions due to concerns about revealing difficulties. Oriol-Granado et al. (2017) reported a positive relationship between academic self-efficacy and engagement within a model linking autonomy-supportive conditions, personal resources, engagement, and performance.

AI assistance does not eliminate the need for confidence in personal learning capabilities. Students must continue to evaluate information, integrate it with prior knowledge, persist when generated responses are inadequate, and engage in interpersonal learning. Students with stronger learning self-efficacy may therefore be better prepared to use AI support without disengaging from the intellectual and social work required for meaningful learning. This reasoning leads to the following hypothesis: H2: Learning self-efficacy is positively associated with academic engagement.

2.4 The indirect association through learning self-efficacy

The preceding arguments suggest that learning self-efficacy may statistically explain part of the association between e-learning autonomy and academic engagement. Students who take greater responsibility for AI-supported learning are more likely to set goals, select strategies, monitor progress, and address difficulty. Successful management of these activities can enhance confidence in learning capabilities. Increased efficacy beliefs are then associated with greater effort, persistence, cognitive investment, and participation with teachers and peers. Similar evidence has been reported in other higher education contexts. Zhao and Qin (2021) found that self-efficacy mediated the relationship between perceived teacher autonomy support and deep

learning. Li and Chiu (2025) found that psychological-need satisfaction explained the relationship between teacher support and engagement with generative AI chatbots. Dong et al. (2026) showed that the relationship between generative AI-based learning analytics and student engagement depended on intermediary learning processes and digital literacy. Although these studies investigate different antecedents and mechanisms, they collectively highlight the importance of learner resources in linking technology-related conditions with engagement.

A significant indirect association in the present study would not establish that autonomy temporally produces self-efficacy or that self-efficacy subsequently causes engagement. Rather, it would indicate that the observed relationships align with the proposed theoretical sequence. Longitudinal or experimental research is required to test temporal ordering and causal mediation. Accordingly, the following hypothesis is proposed: H3: E-learning autonomy is positively associated with academic engagement indirectly through learning self-efficacy. The hypothesised direct and indirect associations among e-learning autonomy, learning self-efficacy, and academic engagement are presented in Figure 1.

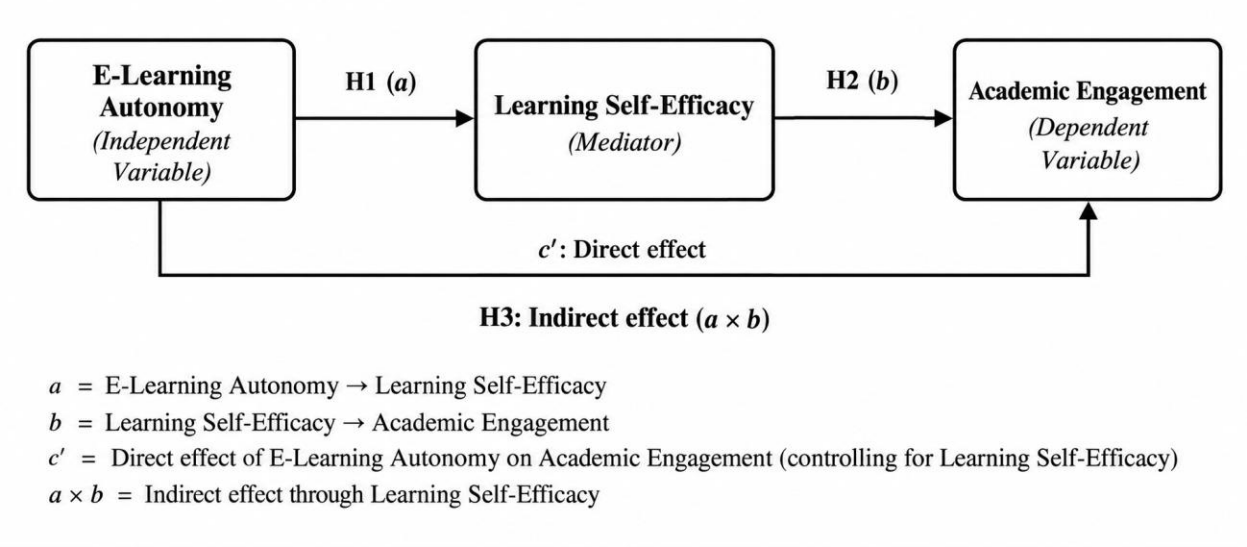


Figure 1. Conceptual model of the proposed associations among e-learning autonomy, learning self-efficacy, and academic engagement.

3 Method

3.1 Research design and context

A quantitative cross-sectional survey was employed to examine associations among e-learning autonomy, learning self-efficacy, and academic engagement among undergraduate students at a higher education institution in eastern China. Data collection occurred at a single point in time, which enabled testing of the proposed direct and indirect statistical relationships but did not establish temporal order or causality.

The questionnaire contextualized the focal constructs within an educational environment in which AI tools were available for learning and academic activities. The term AI was used broadly, without limiting participants to a specific tool or to generative AI alone. The study therefore did not estimate the effect of any particular system. Instead, it assessed students' perceived capacity to retain direction, confidence, and engagement when AI assistance was available. Frequency, duration, and specific purposes of AI use were not measured as behavioural variables.

3.2 Participants and data collection

Participants were undergraduate students enrolled at the higher education institution. A voluntary-response sampling approach was used because participation depended on students choosing to complete an online questionnaire distributed via university communication channels. Survey invitations were sent to 250 eligible students. Of these, 223 students completed the questionnaire between 22 and 28 May 2025, resulting in a response rate of 89.2%.

Prior to accessing the questionnaire, prospective participants received information outlining the study's purpose, participation requirements, voluntary nature, confidentiality protections, and intended use of responses. Electronic informed consent was obtained before participation commenced. Participants retained the right to discontinue at any point before submitting the questionnaire. The questionnaire did not request participant names. Survey responses and platform metadata were managed confidentially, and inadvertently entered identifying text and identifying platform metadata were removed from the shared dataset.

The final analytical sample included 223 participants who provided complete data for e-learning autonomy, learning self-efficacy, and academic engagement. Valid age data were available for 221 participants, ranging from 18 to 22 years. One nonnumeric and one implausible age response were excluded from the demographic analysis. Therefore, the age distribution in Table 1 is based on 221 valid responses, while the main analyses utilised the full sample of 223 participants.

Ethical approval was granted before data collection through a formal letter issued by the institution's ethics committee. Although the committee did not assign an approval or reference number, all study procedures were conducted in accordance with the institution's ethical requirements. Participation was voluntary, electronic informed consent was obtained from all participants, and the confidentiality of their responses was maintained throughout the study.

3.3 Questionnaire development and measures

The present analysis drew on demographic variables and three measures from a broader questionnaire: e-learning autonomy, learning self-efficacy, and academic engagement. Established measures of these constructs were adapted to reflect learning in contexts where AI tools are available. These adaptations assessed students' ability to direct, manage, and sustain

their learning without excessive reliance on AI assistance while preserving the conceptual focus of the original instruments.

The original English-language measures were translated into Chinese for administration. A Chinese-language expert reviewed the translated questionnaire for clarity, linguistic appropriateness, consistency with the source constructs, and suitability for the local higher education context. The review also ensured that references to AI retained the intended meaning of the original measures. The expert's feedback was incorporated prior to data collection.

E-learning autonomy was assessed with the 10-item e-Learning Autonomy Scale developed by Firat (2016). This scale evaluates students' ability to manage and take responsibility for their learning in digital environments. The items were adapted to specifically address planning, monitoring, decision making, strategy selection, and goal setting in contexts where AI assistance was available. Responses were recorded on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Five e-learning autonomy items with weak factor loadings (LA2, LA3, LA5, LA8, and LA9) were removed following confirmatory factor analysis (CFA). These excluded items were negatively worded and reflected limited responsibility or passive acceptance of AI guidance. The final instrument included LA1, LA4, LA6, LA7, and LA10. Mean scores were calculated, with higher scores indicating greater perceived autonomy in AI-supported learning.

Learning self-efficacy was measured using the 10-item Student Self-Efficacy Scale developed by Rowbotham and Schmitz (2013). This scale evaluates students' confidence in completing academic tasks, acquiring relevant knowledge and skills, maintaining motivation, and managing academic challenges. The items were adapted to clarify that confidence concerned students' own learning capabilities rather than technical proficiency in using AI. Responses were

collected using the original four-point scale: 1 (not at all true), 2 (hardly true), 3 (moderately true), and 4 (exactly true). All ten items were retained following CFA. The mean of the item scores was calculated to generate the learning self-efficacy score, with higher values reflecting greater confidence in managing academic learning.

Academic engagement was assessed using 16 items from the Higher Education Student Engagement Scale developed by Zhoc et al. (2019). These items encompassed four dimensions: academic engagement, cognitive engagement, social engagement with teachers, and social engagement with peers. Affective engagement was excluded, as the study specifically examined students' academic, cognitive, and social involvement in learning. Several items were adapted to assess whether students maintained participation and intellectual investment without excessive reliance on AI. Responses were collected using a five-point scale from 1 (strongly disagree) to 5 (strongly agree). CFA resulted in the removal of academic engagement items AE3 and AE4 due to weak factor loadings. The final instrument comprised 14 items: two academic engagement items and four items for each of the remaining three dimensions. Dimension scores were calculated by averaging the retained items within each dimension. The overall engagement index was then calculated as the mean of the four-dimension scores, giving each dimension equal weight. Higher scores indicated greater academic, cognitive, and social engagement. The overall index was treated as an observed composite rather than a validated higher-order latent construct.

3.4 Data analysis

Data analysis proceeded in four stages. First, the dataset was assessed for completeness, coding errors, inconsistencies, and implausible demographic values. No item-level responses were missing for e-learning autonomy, learning self-efficacy, or academic engagement. One nonnumeric age response and one implausible age value were excluded from the demographic

age profile. In the available mediation analysis, the nonnumeric response had been coded as 0 and the implausible recorded value of 98 had been retained; consequently, the model included all 223 participants. Because the analysis could not be re-estimated, the sensitivity of the findings to alternative treatment of these two records could not be assessed.

CFA was conducted using Mplus version 7.4 to evaluate the measurement structure of the adapted instruments. Although the hypothesised mediation model included three principal variables–e-learning autonomy, learning self-efficacy, and an overall engagement index–the CFA operationalised engagement as four distinct first-order dimensions. The measurement model therefore comprised six correlated first-order factors: e-learning autonomy, learning self-efficacy, academic engagement, cognitive engagement, social engagement with teachers, and social engagement with peers. Item responses were treated as continuous indicators, and the model was estimated using maximum likelihood. Model fit was assessed using chi-square, comparative fit index (CFI), Tucker–Lewis index (TLI), root mean square error of approximation (RMSEA), and standardised root mean square residual (SRMR). CFI and TLI values approaching or exceeding .90, and RMSEA and SRMR values below .08, were collectively interpreted as indicating acceptable fit (Kline, 2016).

Item retention was determined based on standardised factor loadings, overall model fit, item wording, and conceptual relevance. Seven items with the weakest loadings were removed: AE3 and AE4 from academic engagement, and LA2, LA3, LA5, LA8, and LA9 from e-learning autonomy. The model was re-estimated using the 29 retained items. Composite reliability (CR) and average variance extracted (AVE) were calculated from the final standardised factor loadings, using reference thresholds of at least .70 for CR and .50 for AVE.

E-learning autonomy was calculated as the mean of the five retained items, and learning self-efficacy was calculated as the mean of all ten items. Engagement scores were first calculated within each dimension: academic engagement used two retained items, while cognitive engagement, social engagement with teachers, and social engagement with peers each used four items. The overall engagement index was calculated as the mean of these four dimension scores. Each dimension therefore contributed equally to the index, despite differences in the number of retained items. IBM SPSS Statistics version 23 was used for data screening, composite score calculation, descriptive statistics, and correlation analysis.

The hypothesised indirect association was tested using the PROCESS macro version 4.2 for IBM SPSS Statistics, employing Model 4 with 5,000 bootstrap samples (Hayes, 2022). E-learning autonomy was specified as the predictor, learning self-efficacy as the mediator, and the observed academic engagement index as the outcome. Gender, age, and year of study were included as covariates. Gender was coded as 0 for male and 1 for female. Year of study was treated as an ordinal variable coded as 1 for first year, 2 for second year, and 3 for third year. Indirect associations were considered statistically significant if the 95% bootstrap confidence intervals did not include zero.

4 Results

4.1 Measurement model

The final correlated six-factor measurement model exhibited acceptable fit: $\chi^2(333) = 745.59$, $p < .001$, CFI = .930, TLI = .915, RMSEA = .075, 90% CI [.067, .082], and SRMR = .049. All retained indicators loaded positively and significantly onto their respective first-order factors, with standardised factor loadings ranging from .672 to .948. As reported in Table 2 in

Appendix B, CR values ranged from .819 to .959, and AVE values ranged from .578 to .854. These results supported the reliability and convergent validity of the six first-order factors evaluated in the CFA.

For the subsequent correlation and mediation analyses, an observed overall engagement index was calculated as the mean of the four engagement dimension scores. This approach gave equal weight to academic engagement, cognitive engagement, social engagement with teachers, and social engagement with peers. A higher-order engagement factor was not tested; therefore, the overall index should be understood as an observed composite rather than a validated higher-order latent construct. The mediation analysis included e-learning autonomy as the predictor, learning self-efficacy as the mediator, and the overall engagement index as the outcome.

4.2 Descriptive statistics and correlations

Table 3 presents the means, standard deviations, and Pearson correlations among the study variables. Mean scores were 3.63 (SD = 0.66) for e-learning autonomy, 3.08 (SD = 0.43) for learning self-efficacy, and 3.60 (SD = 0.59) for overall academic engagement. E-learning autonomy was positively correlated with learning self-efficacy ($r = .606$, $p < .001$) and engagement ($r = .717$, $p < .001$). Learning self-efficacy was also positively correlated with engagement ($r = .632$, $p < .001$). Gender and year of study were not significantly correlated with the three focal constructs.

Table 3. Descriptive statistics and correlations among the study variables

Variable	M	SD	1	2	3	4	5
1. Gender	0.60	0.49	—				
2. Year of study	1.51	0.69	.186**	—			
3. E-learning autonomy	3.63	0.66	.006	−.002	—		
4. Learning self-efficacy	3.08	0.43	.010	.042	.606***	—	
5. Overall academic engagement	3.60	0.59	.005	−.015	.717***	.632***	—

Note. N = 223. Gender was coded 0 = male and 1 = female. Year of study was coded 1 = first year, 2 = second year, and 3 = third year. Learning self-efficacy used a four-point response scale; e-learning autonomy and engagement used five-point response scales. Overall academic engagement was calculated as the mean of the four engagement dimension scores. **p < .01. ***p < .001.

4.3 Hypothesis testing and mediation analysis

E-learning autonomy was positively associated with learning self-efficacy (B = 0.396, SE = 0.035, t = 11.32, p < .001, 95% CI [0.327, 0.464]), supporting H1. The mediator model, which included gender, age, and year of study as covariates, accounted for 37.1% of the variance in learning self-efficacy (R^2 = .371).

Learning self-efficacy was positively associated with overall academic engagement after accounting for e-learning autonomy and the demographic covariates (B = 0.438, SE = 0.077, t = 5.71, p < .001, 95% CI [0.287, 0.589]), supporting H2. The outcome model accounted for 57.9% of the variance in engagement (R^2 = .579).

None of the demographic covariates demonstrated significant associations with learning self-efficacy or academic engagement. Age was not significantly related to learning self-efficacy (B = 0.004, SE = 0.004, p = .399) or academic engagement (B = −0.004, SE = 0.005, p = .474).

The total association between e-learning autonomy and academic engagement was significant significant (B = 0.639, SE = 0.042, t = 15.10, p < .001, 95% CI [0.556, 0.723]). After learning self-efficacy was included in the model, the direct association remained significant (B = 0.466, SE = 0.050, t = 9.35, p < .001, 95% CI [0.368, 0.564]).

The indirect association via learning self-efficacy was also significant (B = 0.173, BootSE = 0.038, 95% bootstrap CI [0.104, 0.253]), supporting H3. The significant direct and indirect associations suggests that learning self-efficacy statistically accounted for part, but not all, of the relationship between e-learning autonomy and academic engagement. However, as all variables were measured concurrently, these results do not establish causal mediation. The mediation results, including the direct, indirect, and total associations, are summarised in Table 4.

Table 4. Results of the mediation analysis

Hypothesis and path	B	SE	t	p	95% CI	Result
H1: E-learning autonomy → learning self-efficacy	0.396	0.035	11.32	< .001	[0.327, 0.464]	Supported
H2: Learning self-efficacy → overall academic engagement	0.438	0.077	5.71	< .001	[0.287, 0.589]	Supported
Direct association, c′	0.466	0.050	9.35	< .001	[0.368, 0.564]	Significant
Total association, c	0.639	0.042	15.10	< .001	[0.556, 0.723]	Significant
H3: Indirect association through learning self-efficacy	0.173	0.038[1]	—	—	[0.104, 0.253]	Supported

Note. N = 223. Unstandardised coefficients are reported. Estimates were adjusted for gender, age, and year of study. [1]Bootstrapped standard error. CI = confidence interval. The indirect association was estimated using 5,000 bootstrap samples and evaluated using a 95% percentile bootstrap confidence interval.

5 Discussion

This study examined how e-learning autonomy, learning self-efficacy, and academic engagement were related in an AI-supported higher education context. Students who reported greater capacity to direct and manage learning without excessive AI dependence also reported stronger confidence in their own learning capabilities and higher engagement. Learning self-efficacy remained positively associated with engagement after autonomy and demographic

covariates were considered, and it statistically accounted for part of the autonomy–engagement association. These findings answer the three research questions and support the corresponding hypotheses. They describe relationships among learner resources in an AI-supported environment; they do not show that AI use increased or decreased autonomy, self-efficacy, or engagement.

The positive association between e-learning autonomy and learning self-efficacy answers RQ1 and supports H1. Students who reported greater capacity to plan, monitor, and control learning in the presence of AI also expressed more confidence in managing academic demands without depending heavily on the technology. One possible interpretation is that taking responsibility for learning gives students opportunities to develop confidence through managing academic tasks. The survey cannot establish whether such experiences occurred or whether greater confidence instead preceded students' reported autonomy. This interpretation is consistent with Bandura's (1997) account of mastery experience and with SDT's emphasis on volition and effective functioning (Ryan & Deci, 2020).

The AI-related wording gives this association particular relevance. The retained autonomy items focused on planning, performance monitoring, control, strategy development, and goal setting without surrendering these functions to AI. The result therefore suggests that learner agency in AI-supported education is closely connected with confidence in one's own capacity to learn. This interpretation complements Hamamra et al. (2026), who described autonomy in ChatGPT-supported writing as a mediated capacity requiring critical management of AI assistance. Nevertheless, the relationship may operate in both directions. Students with stronger self-efficacy may be more willing to exercise autonomy, while autonomous action may reinforce efficacy.

The positive correlation between learning self-efficacy and engagement, after accounting for e-learning autonomy and demographic covariates, answers RQ2 and supports H2. Students who were more confident that they could learn, persist, and achieve without extensive AI assistance also reported stronger academic, cognitive, and social involvement. This finding is consistent with research connecting efficacy beliefs with effort, persistence, strategy use, and active participation (Linnenbrink & Pintrich, 2003; Oriol-Granado et al., 2017). Confidence in one's own learning remains important when AI can supply rapid explanations or outputs because students must still judge quality, integrate information, respond when assistance is inadequate, and participate with teachers and peers.

RQ3 concerned the direct and indirect associations between autonomy and engagement. The positive indirect association supports H3 and is consistent with the proposed sequence in which students who retain responsibility for learning report stronger efficacy beliefs, which are associated with greater engagement. The remaining direct association shows that self-efficacy did not account for the entire relationship. Other learner and contextual factors may connect autonomy with engagement, including motivation, self-regulated learning strategies, AI literacy, teacher support, peer support, and task design. Previous studies have likewise shown that psychological-need satisfaction, digital literacy, and learning presence help explain differences in AI-supported engagement (Dong et al., 2026; Li & Chiu, 2025).

The findings extend the human-centred study of educational technology by identifying autonomy and self-efficacy as connected but distinct resources. E-learning autonomy concerns who directs learning decisions; learning self-efficacy concerns whether students believe they can manage the demands that follow from those decisions. Their joint association with engagement

suggests that providing AI access without supporting students' ownership and confidence gives an incomplete account of technology-enhanced learning.

6 Implications

6.1 Theoretical implications

The study brings e-learning autonomy, learning self-efficacy, and multidimensional engagement into a single model situated in AI-supported higher education. The primary theoretical contribution is the demonstration of associations among these distinct learner resources when academic assistance is accessible. The observed significant indirect association aligns with the hypothesised role of self-efficacy in mediating the relationship between autonomy and engagement. However, as all constructs were measured concurrently, the study cannot confirm self-efficacy as a causal pathway between autonomy and engagement.

The findings also clarify the appropriate use of SDT in this model. E-learning autonomy and learning self-efficacy are related to the ideas of autonomy and competence, but the measures do not assess satisfaction of the corresponding psychological needs. The results therefore support an SDT-informed account of learner agency rather than a direct test of the full need-satisfaction process. Self-efficacy theory provides the more specific explanation for why confidence is associated with effort and participation. Future studies could measure autonomy-need, competence-need, and relatedness-need satisfaction alongside the present constructs to examine their empirical distinctions.

6.2 Practical implications

Universities should complement AI access and technical training with learning designs that preserve student responsibility. Instructors can provide meaningful choices within clearly

structured tasks, require students to explain how they reached conclusions, and ask them to evaluate rather than merely reproduce AI-generated material. Activities that require goal setting, progress monitoring, source verification, and reflection on AI-assisted decisions can make autonomy observable in the learning process.

Learning self-efficacy can be supported through progressively demanding tasks, timely feedback, modelling of effective learning strategies, and opportunities to revise work after identifying weaknesses. These practices can help students experience mastery while keeping AI in a supporting role. Clear guidance on acceptable AI use and instruction in evaluating generated information can complement these approaches (Chan, 2023; Chan & Hu, 2023).

The results do not justify restricting AI or assuming that independent learning requires students to avoid it. The relevant practical goal is calibrated assistance: students should be able to use AI when it supports understanding while retaining the capacity to question its outputs, make learning decisions, and complete essential cognitive work. The recommendations follow from the theoretical interpretation of the findings and require direct evaluation in future intervention studies.

7 Limitations and future research

The sample was drawn from a single university through voluntary participation, which may limit the generalisability of the findings to other institutions, disciplines, countries, or educational systems. Replication with multi-institutional and culturally diverse samples is needed to clarify the conditions under which the observed relationships apply.

The cross-sectional design limits the ability to draw conclusions regarding temporal ordering or causal mediation. Although the findings support the hypothesised statistical associations, alternative directions of association cannot be ruled out. Longitudinal and

experimental research is required to determine whether changes in autonomy precede changes in self-efficacy and engagement. The mediation analysis also retained two problematic age entries, coded as 0 and 98. The potential impact of these entries on the adjusted estimates could not be evaluated through sensitivity analysis.

All focal variables were self-reported within a single questionnaire, creating the possibility of common-source and response-style effects. Future research should combine survey responses with interviews, observations, performance measures, learning analytics, or records of AI interaction. Such evidence could distinguish perceived autonomy and engagement from observable learning behaviour.

The questionnaire employed the broad term AI rather than specifying generative AI or particular applications. It did not identify the systems used by individual students or measure the frequency, duration, or purposes of AI use. Consequently, the findings should be interpreted as relationships among learner characteristics within an AI-supported educational context, rather than as evidence of the effects of a specific AI technology. Future research should differentiate among generative AI, translation systems, recommender tools, and other AI applications, and examine how specific usage patterns relate to autonomy, self-efficacy, and engagement.

The measures were adapted for application in an AI-related context. The final confirmatory factor analysis (CFA) excluded seven items and incorporated within-factor residual covariances. The resulting measurement specification requires validation using an independent sample. Additionally, the overall engagement index was constructed as an observed composite, assigning equal weight to four engagement dimensions. A higher-order engagement factor was not tested, and the index should not be interpreted as an independently validated latent measure of overall engagement.

8 Conclusion

Effective engagement in AI-supported higher education requires attention to students' perceived ownership of learning and confidence in their abilities. The present study found that increased e-learning autonomy correlated with higher learning self-efficacy and overall academic engagement. Learning self-efficacy partially mediated the relationship between autonomy and engagement, although a significant direct association persisted. These results indicate that autonomy and self-efficacy should be considered alongside access to AI assistance when designing learning environments. Nevertheless, the study does not establish that AI use alters these learner resources or that autonomy directly causes increased engagement. Longitudinal research employing repeated measures and tracking students' AI use is required to clarify these relationships over time.

Abbreviations

AI: artificial intelligence; AVE: average variance extracted; CFA: confirmatory factor analysis; CFI: comparative fit index; CI: confidence interval; CR: composite reliability; ML: maximum likelihood; RMSEA: root mean square error of approximation; RQ: research question; SDT: self-determination theory; SPSS: Statistical Package for the Social Sciences; SRMR: standardised root mean square residual; TLI: Tucker–Lewis index.

Declarations

Ethics approval and consent to participate

This study involved human participants and followed the ethical requirements and institutional research procedures of Yiwu Industrial and Commercial College. The Ethics Committee of Yiwu Industrial and Commercial College, China, granted ethical approval before data collection, as confirmed by a formal approval letter dated 16 May 2025. The committee did not assign an approval or reference number. Participation was voluntary, with all participants providing electronic informed consent before completing the questionnaire. Participants were informed of the study's purpose, the voluntary nature of participation, the confidentiality and anonymity of their responses, and their right to withdraw before submitting the questionnaire.

Funding declaration

The authors received no funding for the conduct of this research or the preparation of the manuscript.

Data availability

The de-identified raw survey dataset, the supplied SPSS dataset and accessible Excel/CSV copies, the Chinese and English questionnaire, participant information and consent wording, and available methodological documentation are provided as supplementary materials accompanying this submission. The materials also include the Mplus input and output files, the SPSS analysis output, and readable copies. The supplied SPSS dataset retains previously saved engagement scores, whereas the latest SPSS output documents recalculated engagement scores and their associated results. This difference is identified in the accompanying documentation. The separate original PROCESS syntax file and the exact data file referenced by the Mplus input are unavailable. Identifying text and platform metadata have been excluded from the shared survey dataset to protect participant confidentiality.

References

Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., & Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. International Journal of Educational Technology in Higher Education, 21(1). https://doi.org/10.1186/s41239-023-00436-z.

Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. International Journal of Educational Technology in Higher Education, 20(1). https://doi.org/10.1186/s41239-023-00408-3.

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: Perceptions, benefits, and challenges in higher education. International Journal of Educational Technology in Higher Education, 20(1). https://doi.org/10.1186/s41239-023-00411-8.

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. Innovations in Education and Teaching International, 61(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148.

Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behaviour. Psychological Inquiry, 11(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01.

Dong, H., Chen, X., & Shen, J. (2026). Unpacking the impact mechanism of generative AI-based learning analytics technology on student learning engagement: The mediating role of community of inquiry and the moderating role of digital literacy. International Journal of

Educational Technology in Higher Education, 23(1). https://doi.org/10.1186/s41239-026-00591-z.

Firat, M. (2016). Measuring the e-learning autonomy of distance education students. Open Praxis, 8(3), 191–201. https://doi.org/10.5944/openpraxis.8.3.310.

Hamamra, B., Khlaif, Z. N., & Mahamid, N. (2026). AI literacy and mediated learner autonomy in ChatGPT-supported EFL writing: A qualitative study at a Palestinian university. International Journal of Educational Technology in Higher Education, 23, Article 19. https://doi.org/10.1186/s41239-026-00597-7.

Hayes, A. F. (2022). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach (3rd ed.). Guilford Press.

Heung, Y. M. E., & Chiu, T. K. (2025). How ChatGPT impacts student engagement from a systematic review and meta-analysis study. Computers and Education: Artificial Intelligence, 8, 100361. https://doi.org/10.1016/j.caeai.2025.100361.

Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. European Journal of Education, 57(4), 542–570. https://doi.org/10.1111/ejed.12533.

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., . . . Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103, 102274. https://doi.org/10.1016/j.lindif.2023.102274.

Kline, R. B. (2016). Principles and practice of structural equation modeling (4th ed.). Guilford Press.

Li, Y., & Chiu, T. K. (2025). The mediating effects of needs satisfaction on the relationship between teacher support and student engagement with generative artificial intelligence chatbots from a self-determination theory perspective. Education and Information Technologies, 30(14), 20051–20070. https://doi.org/10.1007/s10639-025-13574-w.

Linnenbrink, E. A., & Pintrich, R. P. (2003). The role of self-efficacy beliefs in student engagement and learning in the classroom. Reading & Writing Quarterly, 19(2), 119–137. https://doi.org/10.1080/10573560308223.

McDonald, N., Johri, A., Ali, A., & Collier, A. H. (2025). Generative artificial intelligence in higher education: Evidence from an analysis of institutional policies and guidelines. Computers in Human Behaviour: Artificial Humans, 3, 100121. https://doi.org/10.1016/j.chbah.2025.100121.

Moorhouse, B. L., Yeo, M. A., & Wan, Y. (2023). Generative AI tools and assessment: Guidelines of the world's top-ranking universities. Computers and Education Open, 5, 100151. https://doi.org/10.1016/j.caeo.2023.100151.

Oriol-Granado, X., Mendoza-Lira, M., Covarrubias-Apablaza, C. G., & Molina-López, V. M. (2017). Positive emotions, autonomy support and academic performance of university students: The mediating role of academic engagement and self-efficacy. Revista de Psicodidáctica, 22(1), 45–53. https://doi.org/10.1387/RevPsicodidact.14280.

Rowbotham, M., & Schmitz, G. S. (2013). Development and validation of a student self-efficacy scale. Journal of Nursing & Care, 2(1), 1–6. https://doi.org/10.4172/2167-1168.1000126.

675 Ryan, R. M., & Deci, E. L. (2020). Intrinsic and extrinsic motivation from a self-determination
676 theory perspective: Definitions, theory, practices, and future directions. Contemporary
677 Educational Psychology, 61, 101860. https://doi.org/10.1016/j.cedpsych.2020.101860.

678 Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of
679 research on artificial intelligence applications in higher education: Where are the
680 educators? International Journal of Educational Technology in Higher Education, 16(1).
681 https://doi.org/10.1186/s41239-019-0171-0.

682 Zhao, J., & Qin, Y. (2021). Perceived teacher autonomy support and students' deep learning: The
683 mediating role of self-efficacy and the moderating role of perceived peer support. Frontiers
684 in Psychology, 12, 652796. https://doi.org/10.3389/fpsyg.2021.652796.

685 Zhoc, K. C. H., Webster, B. J., King, R. B., Li, J. C. H., & Chung, T. S. H. (2019). Higher
686 Education Student Engagement Scale: Development and psychometric evidence. Research
687 in Higher Education, 60(2), 219–244. https://doi.org/10.1007/s11162-018-9510-6.

688 Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. Theory Into Practice,
689 41(2), 64–70. https://doi.org/10.1207/S15430421TIP4102_2.

690

Appendix A

Table 1. Demographic profile of participants

Characteristic	Category	n	%
Gender	Male	90	40.4
	Female	133	59.6
Age (years)	18	28	12.7
	19	74	33.5
	20	80	36.2
	21	29	13.1
	22	10	4.5
Year of study	First year	134	60.1
	Second year	64	28.7
	Third year	25	11.2
Field of study	International Business	116	52.0
	Spanish Language Studies	47	21.1
	Logistics Management	18	8.1
	Information Technology	7	3.1
	Architectural and Engineering	6	2.7

Characteristic	Category	n	%
	Marketing	3	1.3
	Business English	2	0.9
	Education	2	0.9
	Accounting	1	0.4
	Aviation (Cabin Crew)	1	0.4
	Occupational Health and Safety	1	0.4
	Environmental Design	1	0.4
	Other majors	18	8.1

Note. N = 223. Percentages for gender, year of study, and field of study are based on the full sample. Age percentages exclude one nonnumeric response and one implausible value and are based on 221 valid responses. Percentages may not total exactly 100% because of rounding.

Appendix B Six-factor measurement model results

Table 2. Results of the six-factor measurement model

Construct and item	Standardised loading	CR	AVE
Academic engagement		.819	.696
AE1	.730		
AE2	.927		

Construct and item	Standardised loading	CR	AVE
Cognitive engagement		.938	.792
CE1	.852		
CE2	.935		
CE3	.910		
CE4	.859		
Social engagement with teachers		.959	.854
SET1	.889		
SET2	.920		
SET3	.939		
SET4	.948		
Social engagement with peers		.916	.732
SEP1	.942		
SEP2	.850		
SEP3	.840		
SEP4	.782		
E-learning autonomy		.887	.610

Construct and item	Standardised loading	CR	AVE
LA1	.796		
LA4	.714		
LA6	.785		
LA7	.793		
LA10	.814		
Learning self-efficacy		.932	.578
SSE1	.745		
SSE2	.754		
SSE3	.672		
SSE4	.716		
SSE5	.710		
SSE6	.769		
SSE7	.789		
SSE8	.852		
SSE9	.758		
SSE10	.821		

Note. N = 223. CR = composite reliability; AVE = average variance extracted. All standardised factor loadings were significant at $p < .001$.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- QuestionnaireItems.docx