INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN PROGRESSIVE EDUCATION & DEVELOPMENT

OPEN ACCESS JOURNAL

Vol 15, Issue 3, (2026) E-ISSN: 2226-6348

Determinants of Twenty-First-Century Competency Development in the Age of Artificial Intelligence: The Mediating Role of Student Engagement among Chinese University Students

Luo Nanqiao, Amelia Alias, Khairul Azhar Jamaludin

Faculty of Education, Centre for Shaping Advanced and Professional Education, Universiti Kebangsaan Malaysia

Corresponding Author Email: amelia.alias@ukm.edu.my

DOI Link: http://dx.doi.org/10.6007/IJARPED/v15-i3/28538

Published Online: 06 August 2026

Abstract

The rapid diffusion of artificial intelligence (AI) into higher education has intensified concern over how universities can cultivate the twenty-first-century competencies, namely critical thinking, creativity, collaboration, and communication, that graduates increasingly require. This study examined how five antecedents, namely AI literacy, perceived teacher support, academic self-efficacy, growth mindset, and facilitating conditions, relate to these competencies among Chinese university students, and the extent to which student engagement mediates these relationships. Integrating Social Cognitive Theory, Self-Determination Theory, and the unified theory of acceptance and use of technology within a presage-process-product logic, the study tested sixteen hypotheses using partial least squares structural equation modelling on cross-sectional survey data from 400 undergraduates. The measurement model demonstrated satisfactory reliability and validity, and the structural model explained 49.1% of the variance in student engagement and 58.4% in twenty-first-century competencies. Eleven hypotheses were supported. AI literacy, perceived teacher support, academic self-efficacy, and growth mindset each predicted engagement; engagement predicted competencies; and engagement mediated the effects of all four antecedents, fully mediating perceived teacher support and growth mindset. Facilitating conditions showed no significant association with either engagement or competencies. The findings position student engagement as the common behavioural pathway through which personal and social antecedents are converted into competency, and they suggest that institutional strategy should prioritise the cultivation of AI literacy and supportive teaching over the provision of technological infrastructure alone.

Keywords: Artificial Intelligence Literacy, Student Engagement, Twenty-First-Century Competencies, Higher Education, Partial Least Squares Structural Equation Modelling

Introduction

Artificial intelligence (AI) has rapidly permeated global higher education. What started as a peripheral digital utility is now an expected component of university students' information-seeking, writing, editing, and brainstorming (Thornhill-Miller et al., 2023). The impact of AI goes beyond tools to influence the competencies that higher education is expected to impart. Competencies for the future of work and education that are most valued by employers and policy-makers worldwide involve the so-called Four Cs: critical thinking, creativity, collaboration, and communication, rather than just accumulating information that AI systems could access quickly (Thornhill-Miller et al., 2023; World Economic Forum, 2025).

China's AI initiatives in higher education are arguably one of the most ambitious state-led effort in the world with programs spanning from the New Generation Artificial Intelligence Development Plan (State Council of the People's Republic of China, 2017) to the integration of AI into university education (Ministry of Education of the People's Republic of China, 2018; Yang & Peters, 2026). China's larger education system is the largest in the world with over 48 million university students and around 12 million graduate each year to a highly competitive labor market (Ministry of Education of the People's Republic of China, 2024). Chinese university students are regularly using domestic and foreign AI tools for educational support, and the conditions for AI-based learning are developing rapidly.

However, access and availability do not guarantee competency development. An increasing body of evidence suggests that if AI tools are used without consideration and critically, it might have a negative impact on the very skills that are intended to be supported (Gerlich, 2025; Chan & Hu, 2023). The decisive question is therefore not whether students encounter AI, but under what conditions that encounter builds rather than diminishes competency, and through what mechanism personal, social, and technological factors translate into competency development.

Three gaps in the existing literature motivate the present study. First, the determinants of competency, such as AI literacy, teacher support, self-efficacy, mindset, and enabling conditions, have largely been examined in isolation rather than within a single, integrated model, making their relative contributions difficult to compare. Second, the mechanism that links these determinants to competency outcomes is under-theorised and under-tested; in particular, the role of student engagement as a mediating process has rarely been examined directly. Third, there is limited Chinese-specific, theory-integrated evidence, analysed with rigorous variance-based methods, on the development of the Four-C competency cluster among university students.

Accordingly, this study develops and tests an integrated model in which five antecedents, namely AI literacy, perceived teacher support, academic self-efficacy, growth mindset, and facilitating conditions, relate to twenty-first-century competencies both directly and indirectly through student engagement. Drawing on Social Cognitive Theory, Self-Determination Theory, and the unified theory of acceptance and use of technology, integrated through a presage-process-product logic, the study addresses four research questions: whether each antecedent is associated with student engagement; whether engagement is associated with twenty-first-century competencies; whether each antecedent is directly associated with those competencies; and whether engagement mediates these relationships. By answering these questions with data from 400 Chinese undergraduates and partial least squares structural equation modelling (PLS-SEM), the study offers an empirically grounded account of how competency develops in the age of AI, with implications for theory, institutional practice, and education policy.

Literature Review

Twenty-First-Century Competencies and Student Engagement

Twenty-first-century skills refer to the transferable, higher-order skills that are necessary for work, learning, and citizenship in a world that is increasingly complex and technology-driven. A commonly adopted conceptualization is the Four-C model, which includes: critical thinking, creativity, collaboration and communication (Battelle for Kids, 2019). Although it may lack conceptual precision, its four skills remain valuable as they are the least automatable and the most highly desired in today's graduate labor market (Thornhill-Miller et al., 2023; Romero, 2026). In this study, the Four-C model was conceptualized as a cluster of skills, and no emphasis was placed on any single one of them.

Student engagement is frequently conceptualized as the proximal behavioral process in which the educational process is enacted. Following the influential tripartite conceptualisation of Fredricks et al. (2004), engagement comprises behavioural engagement (effort, participation, and persistence), emotional engagement (interest, enjoyment, and belonging), and cognitive engagement (deep processing and self-regulation). Since skills and competencies are not necessarily acquired by virtue of students' attributes, but rather through active, meaningful, and intentional participation in educational activities, student engagement is considered in this study as the mechanism that connects the antecedents and student skills and competencies. A growing body of higher education research also conceptualizes student engagement as a mediator linking antecedents—motivational and technological—and educational outcomes (An et al., 2024; Li et al., 2023; Peng et al., 2026).

Theoretical Framework

To better understand the process of competency development in AI-based learning environment, this study adopted and integrated three theories. Social Cognitive Theory (Bandura, 1986, 1997) posits that personal agency and self-efficacy beliefs direct and regulate the effort, endurance, and goal setting involved in engagement and competency. In a similar manner, Self-Determination Theory (Deci & Ryan, 1985; Ryan & Deci, 2000, 2020) maintains that need-satisfying, need-supportive social contexts, especially supportive teaching, fuel engagement in learners by meeting their need for competence, autonomy, and relatedness. The unified theory of acceptance and use of technology, in its extended form (Venkatesh et al., 2003, 2012), contributes the construct of facilitating conditions, the perceived resources and support that enable technology use.

These theories are integrated through the presage-process-product (3P) logic, which has been applied productively to AI-and-learning research in higher education (Lu et al., 2025). In this framing, the five antecedents constitute presage factors that students bring to, or encounter in, the learning environment; student engagement constitutes the process through which those factors operate; and twenty-first-century competencies constitute the product. The 3P logic thus provides a coherent rationale for positioning engagement as the mediating mechanism and for expecting that the influence of presage antecedents on competency will be carried, wholly or partly, through engagement.

Hypothesis Development

Drawing on these theories and on recent empirical evidence, the study advances sixteen hypotheses. The first set concerns the antecedents of engagement. AI literacy, the capacity to understand, use, critically evaluate, and ethically apply AI, is expected to foster engagement by enabling students to use AI tools in ways that deepen rather than bypass learning (Lu et al., 2025; Jia & Tu, 2024). Perceived teacher support is expected to energise engagement consistent with Self-Determination Theory and with meta-analytic and Chinese evidence (Tao et al., 2022; Gong & Xu, 2024). Academic self-efficacy is expected to drive the effort and persistence that constitute engagement (Bandura, 1997; Wang & Zhang, 2024). Growth mindset is expected to relate positively, though more modestly, to engagement, consistent with evidence that mindset effects are genuine but small (Sisk et al., 2018; Macnamara & Burgoyne, 2023). Facilitating conditions are expected to support engagement by reducing barriers to AI-based learning (Venkatesh et al., 2012). These expectations yield H1 to H5, each positing a positive association between an antecedent and student engagement.

The second hypothesis concerns the engagement-competency link: student engagement is expected to be positively associated with twenty-first-century competencies (H6), consistent with the view of engagement as the proximal pathway to higher-order learning outcomes (Fredricks et al., 2004). The third set concerns the direct associations between each antecedent and competencies, over and above engagement (H7 to H11), reflecting the possibility that some antecedents, such as the critical-evaluative dimension of AI literacy and the agentic quality of self-efficacy, contribute directly to competency as well as indirectly (Shahzad et al., 2024; Wang, Sun, & Chen, 2023). The final set concerns mediation: student engagement is expected to mediate the relationship between each antecedent and competencies (H12 to H16). Figure 1 presents the hypothesised model.

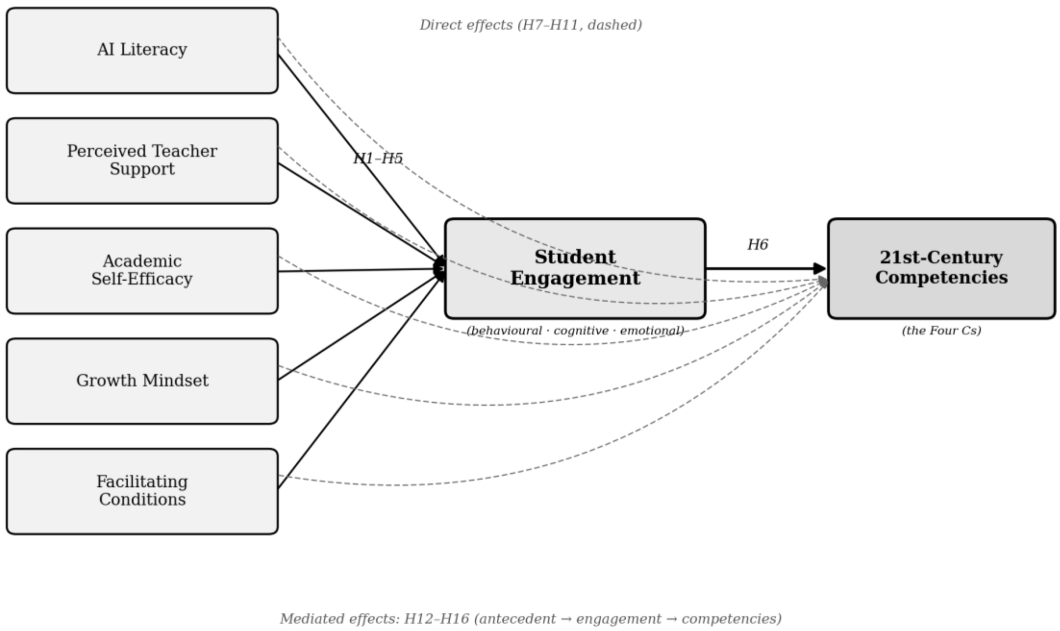

Figure 1. Hypothesised research model.

Methodology

Research Design

The study adopted a quantitative, cross-sectional survey design and analysed the data using partial least squares structural equation modelling (PLS-SEM). PLS-SEM was selected because the model is complex, involving a mediator and multiple antecedents; because the analysis is oriented towards explaining and predicting the target constructs; and because the method accommodates non-normal data and latent constructs measured reflectively (Hair et al., 2019, 2022). Consistent with the cross-sectional design, all relationships are interpreted as associational rather than causal.

Population, Sample, and Procedure

The target population comprised Chinese undergraduate students. Using a multistage sampling procedure, an anonymous self-administered questionnaire was distributed, yielding 400 returns. The first 50 responses were used as a pilot sample to assess the reliability of the instrument ; as the pilot confirmed that the instrument was reliable and required no modification, data collection continued with the same instrument and these cases were retained as part of the main sample. After screening for incomplete responses, out-of-range values, and straight-line (zero-variance) response patterns, the main analytic sample comprised 400 complete and valid cases with no missing values. This sample size exceeds the recommendation of Krejcie and Morgan (1970) for large populations and comfortably satisfies the PLS-SEM ten-times rule (Hair et al., 2022), under which the most complex construct in the model would require only 60 cases. The realised sample fell short of the initial target of 500, owing to voluntary non-response and an end-of-semester data-collection window; nonetheless, it remained adequately powered for the planned analysis.

Instrument

The questionnaire comprised a demographic section and 35 items measuring the seven constructs on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), with five items per construct. All multi-item measures were adapted from previously published and validated instruments: AI literacy from scales developed for college populations (Ma & Chen, 2024; Wang, Rau, & Yuan, 2023); perceived teacher support from the emotional and instrumental support scale of Federici and Skaalvik (2014); academic self-efficacy from the New General Self-Efficacy Scale (Chen et al., 2001); growth mindset from the implicit theories of intelligence tradition (Dweck, 1999; Dweck et al., 1995); facilitating conditions from the UTAUT2 construct (Venkatesh et al., 2012); student engagement from the tripartite model (Fredricks et al., 2004; Li et al., 2023); and twenty-first-century competencies from Four-C instruments (Panthumas et al., 2024; Battelle for Kids, 2019). Items were rendered into Chinese through a translation and back-translation procedure (Brislin, 1970), and content validity was reviewed by subject-matter experts (Lawshe, 1975). Table 1 summarises the constructs and their sources.

Table 1
Operationalisation of the study constructs.

Construct	Code	Dimensions	No. of items	Source scale (adapted)	Representative item
AI literacy	AIL	Awareness; use & application; evaluation; ethics	5	Ma & Chen (2024); Wang, Rau, & Yuan (2023)	"I can critically evaluate the accuracy and reliability of the content produced by AI tools."
Perceived teacher support	PTS	Emotional support; instrumental support	5	Federici & Skaalvik (2014)	"My teachers are willing to help me whenever I have difficulties with my studies."
Academic self-efficacy	ASE	Unidimensional (academic capability belief)	5	Chen, Gully, & Eden (2001)	"When facing difficult academic tasks, I am certain that I will accomplish them."
Growth mindset	GM	Incremental (growth) belief about ability	5	Dweck (1999); Dweck, Chiu, & Hong (1995)	"I believe my abilities can be developed with effort and good strategies."
Facilitating conditions	FC	Unidimensional (perceived enabling resources)	5	Venkatesh, Thong, & Xu (2012)	"I have the resources necessary to use AI tools for my learning."
Student engagement	SE	Behavioural; emotional; cognitive	5	Fredricks, Blumenfeld, & Paris (2004); Li et al. (2023)	"When I study, I try to understand the material deeply rather than just memorise it."
21st-century competencies	TCC	Critical thinking; creativity; collaboration; communication	5	Panthumas, Zaw, & Kittipichai (2024); Thornhill-Miller et al. (2023)	"I can analyse a problem from several different perspectives before reaching a conclusion."

Data Analysis

Analysis followed the standard two-stage PLS-SEM procedure (Hair et al., 2022). The reflective measurement model was assessed first, through indicator loadings, internal consistency reliability (Cronbach's alpha, rho_A, and composite reliability), convergent validity (average variance extracted), and discriminant validity (the heterotrait-monotrait ratio (Henseler et al., 2015) and the Fornell-Larcker criterion (Fornell & Larcker, 1981)). Common method bias was examined using Harman's single-factor test (Podsakoff et al., 2003) and the full collinearity approach of Kock (2015). The structural model was then assessed through collinearity diagnostics, path coefficients, the coefficient of determination (R-squared), effect size (f-squared), and predictive relevance (Q-squared). The significance of path coefficients and specific indirect effects was established using bootstrapping with 5,000 subsamples, and mediation was classified following Zhao et al. (2010) and Nitzl et al. (2016).

Results

Respondent Profile and Descriptive Statistics

The 400 respondents in the main sample were closely balanced by gender and were diverse across year of study, disciplinary field, institution type, and experience with AI tools. Descriptive statistics for the seven constructs are reported in Table 2. Construct means clustered near the mid-point of the five-point scale (2.98 to 3.02), with comparable standard deviations (0.82 to 0.85). All skewness values fell between -0.07 and 0.12 and all kurtosis values between -0.63 and -0.31, well within the thresholds of plus or minus 1 and plus or minus 2 respectively, indicating approximately symmetric, near-normal univariate distributions and sufficient variance for variance-based estimation.

Table 2
Descriptive statistics of the constructs (N = 400).

Construct (code)	Items	M	SD	Skewness	Kurtosis
AI literacy (AIL)	5	3.004	0.835	0.099	-0.619
Perceived teacher support (PTS)	5	3.021	0.828	-0.001	-0.311
Academic self-efficacy (ASE)	5	2.990	0.849	0.073	-0.551
Growth mindset (GM)	5	2.984	0.826	0.118	-0.552
Facilitating conditions (FC)	5	3.000	0.823	-0.067	-0.307
Student engagement (SE)	5	3.005	0.818	-0.021	-0.376
21st-century competencies (TCC)	5	3.004	0.848	0.068	-0.626

Measurement Model

A pilot study (n = 50) returned Cronbach's alpha coefficients between 0.843 and 0.902 for all constructs, indicating that no items required modification. In the main sample, the measurement model met all assessment criteria, as reported in Table 3. All 35 indicators loaded at or above the 0.708 threshold, with loadings ranging from 0.79 to 0.87. Internal consistency was strong across constructs: Cronbach's alpha ranged from 0.878 to 0.899, rho_A from 0.878 to 0.899, and composite reliability from 0.911 to 0.925, all within the acceptable 0.70-to-0.95 band. Convergent validity was satisfied, with the average variance extracted (AVE) of every construct exceeding 0.50 (range 0.672 to 0.712).

Table 3
Indicator loadings, reliability, and convergent validity.

Construct	Indicator	Loading	alpha	rho_A	CR	AVE
AI literacy	AIL1	0.823	0.890	0.890	0.919	0.695
	AIL2	0.837				
	AIL3	0.839				
	AIL4	0.842				
	AIL5	0.827				
Perceived teacher support	PTS1	0.834	0.891	0.891	0.920	0.696
	PTS2	0.869				
	PTS3	0.810				
	PTS4	0.827				
	PTS5	0.831				
Academic self-efficacy	ASE1	0.842	0.899	0.899	0.925	0.712
	ASE2	0.852				
	ASE3	0.839				
	ASE4	0.849				
	ASE5	0.837				
Growth mindset	GMI1	0.787	0.878	0.878	0.911	0.672
	GMI2	0.828				
	GMI3	0.834				
	GMI4	0.831				
	GMI5	0.816				
Facilitating conditions	FC1	0.821	0.889	0.889	0.918	0.692
	FC2	0.832				
	FC3	0.831				
	FC4	0.835				
	FC5	0.839				
Student engagement	SE1	0.832	0.879	0.879	0.912	0.674
	SE2	0.818				
	SE3	0.808				
	SE4	0.811				
	SE5	0.835				
21st-century competencies	TCC1	0.832	0.890	0.890	0.919	0.694
	TCC2	0.819				
	TCC3	0.848				
	TCC4	0.825				
	TCC5	0.841				

Discriminant validity was confirmed by two criteria. All heterotrait-monotrait (HTMT) ratios were below the conservative 0.85 threshold, the largest being 0.755, and the Fornell-

Larcker criterion was satisfied, with the square root of each construct's AVE exceeding its correlations with all other constructs (Table 4).

Table 4
Discriminant validity (Fornell-Larcker criterion).

	AIL	PTS	ASE	GM	FC	SE	TCC
AIL	0.834						
PTS	0.043	0.834					
ASE	-0.034	-0.069	0.844				
GM	-0.006	-0.012	-0.017	0.819			
FC	-0.007	0.010	-0.027	0.015	0.832		
SE	0.505	0.451	0.145	0.104	0.021	0.821	
TCC	0.516	0.253	0.370	0.050	-0.009	0.668	0.833

Common method bias was not a concern. Harman's single-factor test attributed only 23.08% of the total variance to the largest single factor, well below the 50% threshold, and all full-collinearity variance inflation factors ranged from 1.008 to 2.436, comfortably below the 3.3 criterion (Kock, 2015).

Structural Model and Hypothesis Tests

Inner-model collinearity was negligible (all variance inflation factors below 2.0). The model demonstrated substantial explanatory power: the five antecedents jointly accounted for 49.1% of the variance in student engagement (R-squared = 0.491), and the antecedents together with engagement accounted for 58.4% of the variance in twenty-first-century competencies (R-squared = 0.584). Predictive relevance was confirmed, with Q-squared values of 0.331 for engagement and 0.405 for competencies, both well above zero.

Table 5 reports the direct path coefficients. Four of the five antecedents were significant positive predictors of engagement: AI literacy (beta = 0.494, $p < .001$), perceived teacher support (beta = 0.444, $p < .001$), academic self-efficacy (beta = 0.195, $p < .001$), and growth mindset (beta = 0.115, $p < .001$), supporting H1 to H4. Facilitating conditions did not predict engagement (beta = 0.023, $p = .493$), so H5 was not supported. Student engagement was the strongest predictor of competencies (beta = 0.438, $p < .001$), supporting H6. Among the direct antecedent-to-competency paths, AI literacy (beta = 0.302, $p < .001$) and academic self-efficacy (beta = 0.321, $p < .001$) were significant, supporting H7 and H9, whereas perceived teacher support (beta = 0.065, $p = .069$), growth mindset (beta = 0.013, $p = .706$), and facilitating conditions (beta = -0.009, $p = .797$) were not, so H8, H10, and H11 were not supported.

Table 5
Structural model: direct path coefficients and hypothesis tests.

Hyp.	Path	beta	SE	t	p	95% CI	Decision
H1	AIL → SE	0.494	0.033	14.95	< .001	[0.429, 0.556]	Supported
H2	PTS → SE	0.444	0.036	12.50	< .001	[0.373, 0.512]	Supported
H3	ASE → SE	0.195	0.035	5.53	< .001	[0.123, 0.262]	Supported
H4	GM → SE	0.115	0.034	3.35	< .001	[0.048, 0.181]	Supported
H5	FC → SE	0.023	0.034	0.69	.493	[-0.041, 0.090]	Not supported
H6	SE → TCC	0.438	0.042	10.42	< .001	[0.356, 0.518]	Supported
H7	AIL → TCC	0.302	0.039	7.79	< .001	[0.225, 0.377]	Supported
H8	PTS → TCC	0.065	0.036	1.82	.069	[-0.005, 0.136]	Not supported
H9	ASE → TCC	0.321	0.035	9.21	< .001	[0.252, 0.388]	Supported
H10	GM → TCC	0.013	0.033	0.38	.706	[-0.051, 0.078]	Not supported
H11	FC → TCC	-0.009	0.034	-0.26	.797	[-0.076, 0.057]	Not supported

Mediation Analysis

The specific indirect effects are shown in Table 6. In total, student engagement served to mediate four of the five relationships with antecedents and competency. The indirect effects of AI literacy (0.216, $p < .001$), perceived teacher support (0.195, $p < .001$), academic self-efficacy (0.085, $p < .001$), and growth mindset (0.050, $p = .002$) were significant, supporting H12 through H15, while the indirect effect for facilitating conditions was not (0.010, $p = .499$), indicating H16 was not supported. This pattern of mediation has theoretical implications. In the cases of AI literacy and academic self-efficacy, both the indirect effects and the direct effects are significant and are consistent in sign, showing the occurrence of (partial) mediation. In the instances of growth mindset and perceived teacher support, the indirect effect is significant, while the direct effect is not, implying (indirect-only) full mediation. This means that the link to competency occurs entirely through engagement for these constructs. Of the sixteen hypotheses put forth, eleven were supported.

Table 6
Mediation analysis: specific indirect effects.

Hyp.	Indirect path	Indirect effect	SE	t	p	95% CI	Mediation type	Decision
H12	AIL → SE → TCC	0.216	0.025	8.51	< .001	[0.168, 0.267]	Complementary (partial)	Supported
H13	PTS → SE → TCC	0.195	0.024	8.15	< .001	[0.149, 0.243]	Full (indirect-only)	Supported
H14	ASE → SE → TCC	0.085	0.017	5.02	< .001	[0.052, 0.119]	Complementary (partial)	Supported
H15	GM → SE → TCC	0.050	0.016	3.19	.002	[0.021, 0.082]	Full (indirect-only)	Supported
H16	FC → SE → TCC	0.010	0.015	0.68	.499	[-0.018, 0.041]	No mediation	Not supported

Discussion

The findings provide a clear and theoretically-consistent narrative of how twenty-first century competencies arise in an AI-enabled learning setting. The main result is that student engagement was the common behavioral conduit through which the antecedents connected to competency. Engagement was the best individual predictor of competency and also mediated four of the five antecedent effects, validating both the core proposition and the presage-process-product construct underpinning the study.

In the context of engagement antecedents, AI literacy and perceived teacher support were the strongest predictors. The high standing of AI literacy supports the argument that in the context of an AI-enabled setting, the ability to use AI in a purposeful and critical manner affects the depth of students' engagement (Lu et al., 2025; Jia & Tu, 2024). The potency of perceived teacher support fits well with the tenets of Self-Determination Theory and meta-analytic evidence of the support-engagement connection (Ryan & Deci, 2020; Tao et al., 2022). Academic self-efficacy was significant, but a relatively small predictor, in line with Social Cognitive Theory (Bandura, 1997), while growth mindset, though significant, was also a weak predictor, aligning with evidence that the effects of mindset, while real, are small and heterogeneous (Macnamara & Burgoyne, 2023; Sisk et al., 2018; Yeager & Dweck, 2020).

The mediation effects are of particular interest. Because perceived teacher support and growth mindset effects were fully mediated via engagement, their beneficial effects on competency depend on them becoming translated into engagement in the learning process. This is a crucial finding. It means that, as related to the present competency development framework, teacher support is no longer an end but rather a means of engagement that goes deeper. It also accounts for the non-significant direct effects for these antecedents. The effects for AI literacy and academic self-efficacy, on the other hand, are both indirect and direct, indicating their agentic and critical-evaluative qualities impact competency directly and beyond the role of engagement (Shahzad et al., 2024).

The most consistent unexpected finding was the null role of facilitating conditions, which failed to predict engagement or competency directly and produced no indirect effect. Several interpretations are plausible and not mutually exclusive. Theoretically, facilitating conditions in UTAUT2 were formulated to predict technology use rather than the deeper engagement and competency examined here, so their limited reach is consistent with the boundary of that construct. Contextually, the rapid and broad build-out of AI infrastructure in China may have produced uniformly high, low-variance perceptions of facilitating conditions, weakening their power to differentiate students. A degree of measurement weakness, reflected in two sub-threshold indicators, may also have contributed. These possibilities temper any strong substantive conclusion; what can be said is that, as measured here, perceived facilitating conditions did not behave as an engagement-enabling or competency-enabling resource. This result speaks directly to the policy paradox identified at the outset: the provision of access appears insufficient, in itself, to advance student-level competency.

Conclusion

This study developed and tested an integrated, engagement-mediated model of twenty-first-century competency development among Chinese university students in the age of artificial intelligence. The evidence indicates that AI literacy, perceived teacher support, academic self-efficacy, and growth mindset relate to competency largely through student engagement; that AI literacy and academic self-efficacy additionally contribute directly; and that the mere provision of facilitating conditions is, by itself, insufficient. The principal contribution is the demonstration that student engagement is the common behavioural conduit through which personal and social antecedents are converted into competency, a conclusion underscored by the full mediation of both teacher support and growth mindset.

Table 7 consolidates the principal findings of the study, setting out for each construct its association with student engagement, its direct association with twenty-first-century competencies, the indirect effect transmitted through engagement, and the conclusion that follows for theory and practice.

Table 7
Summary of the principal findings, hypothesis outcomes, and conclusions.

Construct (code)	Path to SE (H1–H5)	Path to TCC (H7–H11)	Indirect via SE (H12–H16)	Role of engagement	Principal conclusion
AI literacy (AIL)	H1: 0.494*** Supported	H7: 0.302*** Supported	H12: 0.216*** Supported	Complementary (partial)	Strongest driver of engagement and also a direct contributor; critical, purposeful AI use is a curricular priority.
Perceived teacher support (PTS)	H2: 0.444*** Supported	H8: 0.065 ns Not supported	H13: 0.195*** Supported	Full (indirect-only)	Reaches competency only by deepening engagement; support is a means to engagement rather than an end in itself.
Academic self-efficacy (ASE)	H3: 0.195*** Supported	H9: 0.321*** Supported	H14: 0.085*** Supported	Complementary (partial)	Largest direct contribution to competency, operating both directly and through engaged effort and persistence.
Growth mindset (GM)	H4: 0.115*** Supported	H10: 0.013 ns Not supported	H15: 0.050** Supported	Full (indirect-only)	A small but genuine effect, realised only when the belief is translated into engaged learning behaviour.
Facilitating conditions (FC)	H5: 0.023 ns Not supported	H11: -0.009 ns Not supported	H16: 0.010 ns Not supported	No mediation	Perceived access and infrastructure alone advanced neither engagement nor competency.
Student engagement (SE)	— (mediator)	H6: 0.438*** Supported	—	Mediating process	Strongest single predictor of competency and the common behavioural pathway from antecedents to the Four Cs.

*Note. SE = student engagement; TCC = twenty-first-century competencies. Values are standardised path coefficients from PLS-SEM with 5,000 bootstrap subsamples (N = 400); ** p < .01, *** p < .001, ns = not significant. Mediation classified following Zhao et al. (2010) and Nitzl et al. (2016). R-squared = 0.491 (SE) and 0.584 (TCC); Q-squared = 0.331 (SE) and 0.405 (TCC). Overall, eleven of the sixteen hypotheses were supported.*

The findings carry several implications. Theoretically, the study shows that integrating Social Cognitive Theory, Self-Determination Theory, and UTAUT2 within a presage-process-product logic yields a more complete account than any single tradition, while also delineating the boundary of adoption-oriented constructs in explaining developmental outcomes. For policy and institutional practice, and stated cautiously in light of the facilitating-conditions result, the findings suggest that cultivating students' AI literacy and strengthening need-supportive teaching deserve at least as much emphasis as the provision of infrastructure. For educators, the full mediation of teacher support implies that support is most valuable when deliberately deployed to deepen engagement, alongside the cultivation of self-efficacy and engaged, critical AI use.

Several limitations should be acknowledged. The cross-sectional design means that the relationships are associational and cannot establish causality; all constructs were measured by self-report from a single source; and competency was assessed as students' self-perception rather than demonstrated performance, a particular caution in an AI context. The sample, although diverse, was confined to Chinese undergraduates and fell short of the initial target, and the facilitating-conditions construct could be refined. Future research should therefore employ longitudinal and experimental designs to test causality, incorporate objective or performance-based measures of the Four-C competencies, conduct multigroup analyses across subgroups, refine the measurement of facilitating conditions, and replicate the model in other national and cultural contexts. Despite these limitations, the study offers a coherent, empirically grounded foundation for understanding, and ultimately strengthening, the development of twenty-first-century competencies in the age of artificial intelligence.

References

An, F., Xi, L., & Yu, J. (2024). The relationship between technology acceptance and self-regulated learning: The mediation roles of intrinsic motivation and learning engagement. Education and Information Technologies, 29(3), 2605–2623. https://doi.org/10.1007/s10639-023-11959-3

Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall.

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

Battelle for Kids. (2019). Framework for 21st century learning definitions. Battelle for Kids.

Brislin, R. W. (1970). Back-translation for cross-cultural research. Journal of Cross-Cultural Psychology, 1(3), 185–216. https://doi.org/10.1177/135910457000100301

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), 43. https://doi.org/10.1186/s41239-023-00411-8

Chen, G., Gully, S. M., & Eden, D. (2001). Validation of a new general self-efficacy scale. Organizational Research Methods, 4(1), 62–83. https://doi.org/10.1177/109442810141004

Deci, E. L., & Ryan, R. M. (1985). Intrinsic motivation and self-determination in human behavior. Plenum Press.

Dweck, C. S. (1999). Self-theories: Their role in motivation, personality, and development. Psychology Press.

Dweck, C. S., Chiu, C., & Hong, Y. (1995). Implicit theories and their role in judgments and reactions: A world from two perspectives. Psychological Inquiry, 6(4), 267–285. https://doi.org/10.1207/s15327965pli0604_1

Federici, R. A., & Skaalvik, E. M. (2014). Students' perceptions of emotional and instrumental teacher support: Relations with motivational and emotional responses. International Education Studies, 7(1), 21–36. https://doi.org/10.5539/ies.v7n1p21

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. Review of Educational Research, 74(1), 59–109. https://doi.org/10.3102/00346543074001059

Gerlich, M. (2025). AI tools in society: Impacts on cognitive offloading and the future of critical thinking. Societies, 15(1), 6. https://doi.org/10.3390/soc15010006

Gong, W., & Xu, C. (2024). The influence of perceived teacher support on Chinese local college students' engagement: The mediating roles of academic self-efficacy and learning motivation. SAGE Open, 14(4). https://doi.org/10.1177/21582440241293327

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). Sage.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European Business Review, 31(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Jia, X. H., & Tu, J. C. (2024). Towards a new conceptual model of AI-enhanced learning for university students: The roles of artificial intelligence capability, general self-efficacy, learning motivation, and critical thinking awareness. Systems, 12(3), 74. https://doi.org/10.3390/systems12030074

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. International Journal of e-Collaboration, 11(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. Educational and Psychological Measurement, 30(3), 607–610. https://doi.org/10.1177/001316447003000308

Lawshe, C. H. (1975). A quantitative approach to content validity. Personnel Psychology, 28(4), 563–575. https://doi.org/10.1111/j.1744-6570.1975.tb01393.x

Li, S., Kwok, S. W. H., Siu, S. C. N., Chung, J. Y. S., Lam, H. C. Y., Tsang, E. Y. M., Li, K. C., Yeung, J. W. Y., & Lam, S. C. (2023). Development of generic student engagement scale in higher education: An application on healthcare students. Nursing Open, 10(3), 1545–1555. https://doi.org/10.1002/nop2.1405

Lu, K., Zhu, J., Pang, F., & Shadiev, R. (2025). Understanding the relationship between college students' artificial intelligence literacy and higher-order thinking skills using the 3P model: The mediating roles of behavioural engagement and peer interaction. Educational Technology Research and Development, 73(2), 693–716. https://doi.org/10.1007/s11423-024-10434-1

Ma, S. A., & Chen, Z. Z. (2024). The development and validation of the Artificial Intelligence Literacy Scale for Chinese College Students (AILS-CCS). IEEE Access, 12, 146419–146429. https://doi.org/10.1109/ACCESS.2024.3468378

Macnamara, B. N., & Burgoyne, A. P. (2023). Do growth mindset interventions impact students' academic achievement? A systematic review and meta-analysis with recommendations for best practices. Psychological Bulletin, 149(3–4), 133–173. https://doi.org/10.1037/bul0000352

Ministry of Education of the People's Republic of China. (2018). Artificial intelligence innovation action plan for institutions of higher education. Ministry of Education of the People's Republic of China.

Ministry of Education of the People's Republic of China. (2024). Statistical bulletin on national education development 2024. Ministry of Education of the People's Republic of China.

Nitzl, C., Roldán, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. Industrial Management & Data Systems, 116(9), 1849–1864. https://doi.org/10.1108/IMDS-07-2015-0302

Panthumas, S., Zaw, K., & Kittipichai, W. (2024). Validation of the 21st Century Skills Assessment Scale for public health students in Thailand: A methodological study. Journal of Educational Evaluation for Health Professions, 21, 37. https://doi.org/10.3352/jeehp.2024.21.37

Peng, C., Zhang, Z., Zhang, Z., Zhang, J., Zhang, Z., Liu, Y., Jia, R., & Xu, X. (2026). AI literacy and creativity among university students: The mediating role of learning engagement. Frontiers in Psychology, 16, 1567049. https://doi.org/10.3389/fpsyg.2025.1567049

Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Romero, M. (2026). Evaluating the evolution of critical thinking, creativity, communication and collaboration through generative AI integration in higher education. Creative Education, 17(1), 1–18. https://doi.org/10.4236/ce.2026.171001

Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. American Psychologist, 55(1), 68–78. https://doi.org/10.1037/0003-066X.55.1.68

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

Shahzad, M. F., Xu, S., & Zahid, H. (2024). Exploring the impact of generative AI-based technologies on learning performance through self-efficacy, fairness and ethics, creativity, and trust in higher education. Education and Information Technologies, 30(3), 3691–3716. https://doi.org/10.1007/s10639-024-12949-9

Sisk, V. F., Burgoyne, A. P., Sun, J., Butler, J. L., & Macnamara, B. N. (2018). To what extent and under which circumstances are growth mind-sets important to academic achievement? Two meta-analyses. Psychological Science, 29(4), 549–571. https://doi.org/10.1177/0956797617739704

State Council of the People's Republic of China. (2017). New generation artificial intelligence development plan (Guo Fa [2017] No. 35). State Council of the People's Republic of China.

Tao, Y., Meng, Y., Gao, Z., & Yang, X. (2022). Perceived teacher support, student engagement, and academic achievement: A meta-analysis. Educational Psychology, 42(4), 401–420. https://doi.org/10.1080/01443410.2022.2033168

Thornhill-Miller, B., Camarda, A., Mercier, M., Burkhardt, J.-M., Morisseau, T., Bourgeois-Bougrine, S., Vinchon, F., El Hayek, S., Augereau-Landais, M., Mourey, F., Feybesse, C., Sundquist, D., & Lubart, T. (2023). Creativity, critical thinking, communication, and collaboration: Assessment, certification, and promotion of 21st century skills for the future of work and education. Journal of Intelligence, 11(3), 54. https://doi.org/10.3390/jintelligence11030054

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. MIS Quarterly, 36(1), 157–178. https://doi.org/10.2307/41410412

Wang, B., Rau, P. L. P., & Yuan, T. (2023). Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. Behaviour & Information Technology, 42(9), 1324–1337. https://doi.org/10.1080/0144929X.2022.2072768

Wang, S., Sun, Z., & Chen, Y. (2023). Effects of higher education institutes’ artificial intelligence capability on students’ self-efficacy, creativity and learning performance. Education and Information Technologies, 28(5), 4919–4939. https://doi.org/10.1007/s10639-022-11338-4

Wang, Y., & Zhang, W. (2024). The relationship between college students’ learning engagement and academic self-efficacy: A moderated mediation model. Frontiers in Psychology, 15, 1425172. https://doi.org/10.3389/fpsyg.2024.1425172

World Economic Forum. (2025). The future of jobs report 2025. World Economic Forum.

Yang, Y., & Peters, M. A. (2026). China’s 2025 White Paper on Smart Education: Governance logic, policy design, and international relevance. International Journal of Chinese Education, 15(1). https://doi.org/10.1177/2212585X251413788

Yeager, D. S., & Dweck, C. S. (2020). What can be learned from growth mindset controversies? American Psychologist, 75(9), 1269–1284. https://doi.org/10.1037/amp0000794

Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. Journal of Consumer Research, 37(2), 197–206. https://doi.org/10.1086/651257