Humanities & Social Sciences Communications

ARTICLE

https://doi.org/10.1057/s41599-025-06292-8 OPEN

The interrelationship of key factors affecting the learning outcomes of liberal arts majors: an empirical study

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Through the deep integration of digital technologies such as large language models and knowledge graphs into pedagogy, this study explores the impact of technology use on learners' academic outcomes to inform effective application throughout the teaching process. In this study, 123 undergraduate students majoring in International Chinese Language Education were subjected to pre- and post-tests, with their learning process tracked via a SPOC platform. By integrating Adaptive Structuration Theory (AST) and the Unified Theory of Acceptance and Use of Technology (UTAUT), the analysis of comprehensive learner factors yielded key findings. Learning behavior and self-efficacy positively impacted outcomes for students with low initial skills, yet self-efficacy and pre-learning skill level themselves did not directly determine outcomes. Critically, while the breadth of technology application played a significant mediating role, its overall level of use exerted a negative moderating effect on the relationship between learning behavior and final scores. This indicates that technology acts as a double-edged sword, capable of facilitating learning processes while also potentially undermining the effectiveness of positive learning behaviors when used excessively or without strategic focus.

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Introduction

The global higher education landscape is undergoing a profound transformation, propelled by digital advancements in large language models, knowledge graphs, and the metaverse (Idris et al., 2024). This shift is central to the "new liberal arts" initiative, which calls for the deep integration of technology to reshape disciplinary systems, curricula, and pedagogical methods, aiming to cultivate talent for the digital era (Penprase, 2021). Accordingly, the educational sector is leveraging these technologies to optimize resources, innovate teaching practices, and enhance academic quality and the student experience (Li and Huang, 2025; Wu, 2024). However, a significant challenge impedes this transformation. Research indicates that while humanities and social sciences students often possess strong digital ethics and awareness, they frequently lack the corresponding digital knowledge and technical skills (Kim, 2022). This gap between aptitude and application critically hampers the effective integration of technology into liberal arts education (Seol, 2025). Therefore, a systematic analysis of technology's specific impact on the learning outcomes of liberal arts students—particularly those with low initial technical proficiency—has become an urgent priority.

Current scholarly approaches to this issue remain limited. Many studies focus singularly on technology adoption or isolated psychological factors, such as self-efficacy, overlooking the dynamic interrelationships among key variables, including technology use, learning behaviors, and psychological traits, throughout the learning process. Crucially, there is a scarcity of empirical research that explicates how technology application mediates the learning journey, moving beyond correlation to explain the underlying mechanisms of impact.

To address these gaps, this study introduces an integrated theoretical framework combining Adaptive Structuration Theory (AST) and the Unified Theory of Acceptance and Use of Technology (UTAUT). This framework facilitates a holistic analysis of how technology is appropriated and structured by learners (AST) within the context of their acceptance motivations and behavioral intentions (UTAUT). The study aims to elucidate the mechanism through which these factors interact to influence learning outcomes, with a specific focus on the mediating role of technology application. The findings are expected to contribute to the theoretical understanding of technology-mediated learning in liberal arts and offer practical insights for designing effective, inclusive digital learning environments.

Literature review

The use of technology in liberal arts education. Technology is no longer merely an auxiliary tool but is profoundly reshaping the content, methods, and experiential dimensions of education. Existing research, however, has often focused on macro-level analyses of evolutionary trajectories or discussions of generic application cases, such as the personalized learning system (Tapalova and Zhiyenbayeva, 2022) or the data-driven teaching mechanisms (Raza, 2025), lacking in-depth analysis of the specific epistemological foundations and pedagogical characteristics of liberal arts disciplines.

Within liberal arts pedagogy, technology opens new pathways for cultivating core competencies while presenting unique challenges. Digital humanities technologies—such as text mining, social network analysis, and GIS—enable students to reveal deep patterns and connections within texts through visualization (D Hirsch, 2012). Collaborative platforms and generative AI tools are reshaping writing processes by providing real-time feedback and effectively mitigating writing anxiety (Dwivedi et al., 2023; Hynninen, 2018). Similarly, virtual and augmented reality enhance the understanding of historical and cultural contexts through immersive experiences (Parong and Mayer, 2021). Nevertheless, liberal arts students face a critical dilemma: a misalignment between their digital literacy and humanistic literacy. This is manifested in weak technical operational (Smith and Storrs, 2023) and data skills (Vodă et al., 2022), the potential erosion of humanistic spirit by technological rationality leading to superficial learning and degradation of critical thinking (Higgins et al., 2012), and new academic ethical challenges posed by the widespread use of generative AI (Al-Kfairy et al., 2024). This context underscores that simply applying technology is insufficient; a critical examination of how it integrates with the goals of liberal education is imperative.

Research on the influence of technology on learning outcomes. A substantial body of research suggests that technology has a dual effect on learning (Antoninis et al., 2023; Hughes et al., 2025). While digital technologies expand access to resources and enhance interactive experiences, they can also lead to attention fragmentation and increased cognitive load (Heflin et al., 2017). This duality is particularly pronounced among liberal arts students. Although they often possess a strong sense of digital responsibility, their practical technology application skills are frequently inadequate (Choi, 2016), making them more susceptible to the negative impacts of "ineffective technology integration"(Seemiller and Grace, 2017).

Furthermore, the impact of technology exhibits significant disciplinary variation. In fields like engineering and medicine (Kyaw et al., 2019), technology integration has been shown to significantly enhance learning outcomes, improving capabilities in areas such as engineering design (Bhogayata et al., 2025) and the effective use of online learning management tools (Back et al., 2016; Broadbent and Poon, 2015). In contrast, the digital literacy foundation of humanities and social sciences students remains relatively fragile (Vodă et al., 2022). As Kim (2022) notes, while considered sufficient, liberal arts students' digital literacy is in a state of crisis based on a fragile foundation. Technology can support liberal arts learning in dimensions such as information processing, writing expression, critical thinking, and learning motivation (Dehghanzadeh and Jafaraghaee, 2018; Parong and Mayer, 2021), but its underlying mechanisms of action have not been thoroughly revealed (Sergis and Sampson, 2017).

More importantly, learners' psychological and cognitive mechanisms introduce high complexity into technology interventions. For instance, applying a meta-cognitive calibration paradigm, Talsma et al. (2019) challenged the simplistic view of self-efficacy as a self-fulfilling prophecy. They found that over-efficaciousness predicted poorer subsequent academic performance, suggesting potential negative impacts on self-regulation, and indicating that the relationship between self-efficacy and learning outcomes is not linear but is profoundly influenced by calibration levels.

The present study and research questions. Despite the rise of generative AI (e.g., ChatGPT) expanding the boundaries of human-machine collaboration in teaching (Dwivedi et al., 2023), the deep integration mechanism between such technologies and liberal arts education remains underexplored. Existing studies predominantly focus on technology adoption behavior (Selwyn, 2010), failing to systematically reveal the intrinsic connections between the depth of technology use, psychological mechanisms, and learning behaviors among liberal arts students.

To address these conceptual and empirical challenges, this study is grounded in an integrated framework of Adaptive

Structuration Theory (AST) (DeSanctis and Poole, 1994) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). It seeks to move beyond siloed approaches by investigating the following core questions: Therefore, the following research questions would be answered:

(1) How does the depth and nature of technology use specifically affect the learning outcomes of liberal arts students?
(2) How do personal factors (e.g., self-efficacy, prior skills) and learning behaviors interact with technology use to influence these outcomes within a blended learning environment?

By examining these interrelationships, particularly the mediating role of technology use, this research aims to provide strategic guidance for the effective and critical integration of technology in liberal arts education.

Theoretical framework and hypothesis

Beyond the core frameworks of the AST and UTAUT theories, this study incorporates the law of diminishing marginal returns (Dwivedi, 2009) and the theory of knowledge depth and breadth (Alexander, 2003) as critical supplementary lenses and boundary conditions. The former posits that the marginal benefits of technological investment may decrease as students' initial skill levels rise, thereby introducing a critical perspective for effect analysis. The latter expands the evaluative dimensions of learning outcomes by emphasizing that technology application should foster both the expansion of knowledge breadth and the deepening of conceptual understanding.

Guided by the law of diminishing marginal returns, the theory of knowledge depth and breadth, and Bandura's (1997) self-efficacy theory, this study posits that students' initial skill levels fundamentally shape the function of technology in learning. For learners with higher initial skills, additional technological investment may yield progressively smaller gains in perceived competence, as the challenges posed by educational technologies often fail to exceed their existing proficiency, thereby offering limited mastery experiences—a critical source of self-efficacy (Chen et al., 2004). This reasoning suggests a negative association between initial skills and self-efficacy (H1). In contrast, students with lower initial skills are more likely to benefit from the compensatory role of technology, which offers scaffolding mechanisms—such as adaptive feedback and content replay—to address foundational gaps (Jing et al., 2025). Consequently, technology use may attenuate the predictive power of initial skills on self-efficacy, effectively masking their influence (H2). Simultaneously, within the framework of Adaptive Structuration Theory (AST), students with higher initial skills are hypothesized to appropriate technological structures and resources more effectively, leading to superior final performance outcomes (H3). Hypothesis1-3 are as follows.

H1: A negative correlation exists between students' initial skills and their self-efficacy.

H2: Technology use masks the effect of initial skills on self-efficacy.

H3: Initial skill level positively affects students' final learning scores.

Bandura's self-efficacy theory highlights that individuals who believe in their own capabilities are more likely to adopt positive learning behaviors, such as sustained engagement, active participation, and diligent practice, which in turn enhance academic performance. Within the AST framework, learning behaviors can be further shaped by the technological environment, as tools and resources provided by educational technologies not only stimulate motivation but also alter the efficiency and effectiveness of behaviors. Thus, learning behaviors are expected to mediate the influence of self-efficacy on final performance (H4) (Pintrich and De Groot, 1990; Wang et al., 2025), while technology use is expected to moderate the strength of the relationship between learning behaviors and outcomes by amplifying effective strategies and buffering weaker ones (H5) (Bernacki et al., 2011). Hypothesis 4-5 are as follows.

H4: Learning behavior mediates the effect of self-efficacy on final score.

H5: Technology use moderates the effect of learning behavior on final score.

According to the Self-efficacy Theory and the Unified Theory of Acceptance and Use of Technology (UTAUT), students with stronger self-efficacy are more confident in adopting and mastering new technologies, which increases their likelihood of using them effectively (Compeau and Higgins, 1995; Yan and Zhang, 2024). Effective technology use, in turn, facilitates higher quality learning processes, enabling students to achieve better outcomes. Thus, technology use is not only an outcome of self-efficacy but also a mechanism through which self-efficacy translates into improved academic performance (Dai et al., 2024). Hypothesis 6-7 are as follows.

H6: Technology use is positively correlated with self-efficacy.

H7: Technology use mediates the effect of self-efficacy on the final score.

Based on the above theories and hypotheses, this study proposes the research model as shown in Fig. 1. This model covers the path from self-efficacy and learning behavior to final grades, to accurately test mediating (indirect) effects rather than simply testing the direct effects between every two variables. Therefore, no explicit direct effect hypothesis was proposed regarding the variables of learning behavior, final grades, and technology use.

Methods

Participants. This study recruited 123 participants from two intact classes within the International Chinese Language Education major at a university. The participants were aged between 19 and 20 years. Reflecting the gender imbalance common in liberal arts disciplines, the sample consisted of significantly more female than male participants. This gender distribution is consistent with the widespread phenomenon of horizontal gender segregation in global higher education (Bailey and Graves, 2016; Charles and Bradley, 2009). Since gender differences are not the main concern of this study, the sample does not affect the main conclusion of this study.

Design. A self-report questionnaire was developed utilizing a five-point Likert scale to measure students' self-efficacy, initial skill levels, and technology use—the latter specifically

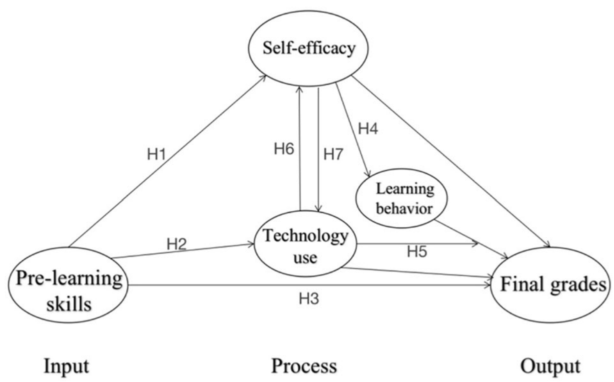

Fig. 1 Learning Process Model for Liberal Arts Students.

encompassing the use of the learning platform (SPOC), knowledge graphs, and the large language model integrated within the platform. Technology use was conceptualized along two dimensions: breadth (the variety of these tools used) and depth (the intensity and sophistication of their use), adapting established scales from prior research. To ensure reliability, validity, and content validity, all scale items were adapted from previously validated instruments published in authoritative journals (Elmalı et al., 2020; Gallego-Arrufat et al., 2019; Karahanna et al., 2006). Minor modifications were made to the item wordings to better fit the specific context of this study (see Appendix A, Table A1).

Data collection procedures. This study was conducted within the context of a regular course that adopted a blended learning model, integrating online instruction via the Chaoxing Learning Platform with traditional offline classroom teaching. Data collection occurred at two time points: (1) a pre-test survey was administered at the beginning of the semester to capture baseline initial skills, and (2) a post-test survey was conducted at the end of the semester to assess changes in self-efficacy. In addition to the survey data, behavioral data were collected throughout the semester via the Chaoxing Learning Platform. These process metrics (detailed in Table 1) included assignment grades, video watching time, discussion frequency, and in-class activity. To enable direct comparison across all measures, these heterogeneous data types were standardized and converted to a common five-point scale.

Analysis. This study utilized SPSS 26.0 and its accompanying Process plugin for statistical analysis. The reliability and validity of the questionnaire were assessed using SPSS. Hypothesis testing was conducted as follows: direct effects were examined through regression analysis, mediation effects were tested using the Process plugin (Model 4, specialized for testing indirect/mediating pathways), and moderation effects were analyzed with the Process plugin (Model 1, designed for examining interaction/conditional relationships).

Results

Reliability and validity. In this paper, reliability was evaluated by Cronbach's Alpha (CA) and combined reliability (CR), and validity was tested by mean variance extraction value (AVE) and factor loading (Fornell and Larcker, 1981; Hsu and Lin, 2008). CA values for all variables range from 0.882 to 0.975, and CR values are between 0.883 and 0.975, both exceeding the recommended thresholds. This indicates high internal consistency within each construct and exemplary reliability. AVE values span from 0.687 to 0.846, all surpassing the 0.5 benchmark, demonstrating strong convergent validity, and indirectly reflecting high reliability (see Appendix A, Table A2).

The core of validity testing lies in evaluating the convergent validity and discriminant validity of variables. Aggregation validity is mainly evaluated by examining factor loadings and average extracted variance (AVE) values. Specifically, when the factor loadings of all variables are above 0.7 and the AVE values exceed 0.5, it can be determined that these variables have strong convergent validity (Jiang et al., 2002) (see Appendix A, Table A3).

The primary method for distinguishing validity is to examine whether the square root of the AVE of each variable is significantly greater than the correlation coefficient between those variables and other variables. Additionally, discriminant validity can also be validated by comparing the factor loadings of variables on their respective factors with other factors. Ideally, the AVE square root of all variables should be significantly higher

Table 1 Process data.

Variable	Dimension	Specific Content	Numerical Value (average)
Initial skills	Technical Knowledge, (TK)	Same as the technical knowledge items in Table A1	2.29
	Technical Security, (TS)	Same as the technical knowledge items in Table A1	2.98
	Technical Capability, (TC)	Same as the technical knowledge items in Table A1	2.93
Learning Behavior	Homework Grades	The grades of students' regular homework	4.33
	Video Duration	The duration of student video learning	3.78
	Discussion Frequency	The number of times students participate in discussions on online platforms	2.99
	Classroom Engagement	Student check-in and classroom participation frequency	3.5
Post-learning skills	Self-efficacy TK	Significant improvement in pre- and post-test questionnaires	1.52
	TS		1.08
	TC		1.00
	Final Course Grades	Student exam scores	4.25

Table 2 Correlation coefficient matrix of main variables.

Correlation Coefficient

	Initial skills	Learning Behavior	Technology Use	Final Grades	Self-efficacy
Initial skills	1				
Learning Behavior	−0.081	1			
Technology Use	0.259**	0.131	1		
Final Grades	−0.140	0.752**	0.132	1	
Self-efficacy	−0.814**	0.231*	0.212*	0.287**	1

*$p < 0.05$, **$p < 0.01$.

Table 3 Correlation coefficient matrix.

	M	SD	Initial skills	Self-efficacy	Technology Use	SPOC	KG	GPT
Initial skills	2.73	0.78	1					
Self-efficacy	1.20	0.83	−0.814**	1				
Technology Use	3.73	0.62	0.259**	0.212*	1			
SPOC	4.07	0.53	0.210*	0.160	0.690**	1		
KG	3.58	0.87	0.213*	0.202*	0.936**	0.549**	1	
GPT	3.56	0.78	0.236**	0.170	0.864**	0.347**	0.734**	1

*$p < 0.05$, **$p < 0.01$.

Table 4 Mediation model for technical use -1.

Variable	Self-efficacy		SPOC		KG		GPT	
	β	t	β	t	β	t	β	t
Initial skills	−0.865**	−15.399	0.142*	2.358	0.238*	2.402	0.235**	2.668
R^2	0.662		0.044		0.046		0.056	
F	237.143		5.559		5.769		7.118	

*$p < 0.05$, **$p < 0.01$.

Table 5 Mediation model for technical use -2.

	Self-efficacy		
	β		t
Initial skills	−0.997**		−26.169
SPOC	0.334**		5.095
KG	0.110*		2.010
GPT	0.248**		4.511
R^2		0.860180.833	
F			

*$p < 0.05$, **$p < 0.01$.

than their correlation coefficients with other variables, and the loadings of each variable on its main factor should be significantly greater than the cross-loadings on other factors. This result implies good discriminability among the variables, thus demonstrating high discriminant validity (see Appendix A, Table A4).

Pre-learning skill. This study first conducted a correlation analysis on the main variables, exploring the relationship between final grades, initial skills, technology use, learning behavior, and self-efficacy. Discovering some significant correlations: initial skills are positively correlated with technology use and negatively correlated with self-efficacy; learning behavior is positively correlated with final grades and self-efficacy, as shown in Table 2.

In the research hypothesis, H1 proposed a negative correlation between initial skills and self-efficacy, and the results of data analysis showed a negative correlation between the two. The H1 hypothesis is valid. The H3 hypothesis suggests a correlation between initial skills and final grades. However, the test results indicate that there is no significant correlation between the two; therefore, the H3 hypothesis is not supported. The hypothesis proposed by H6 that the use of technology is positively correlated with self-efficacy has been verified, thereby validating H6.

To verify the mediating effect of technology use on the impact of initial skills on self-efficacy, a bias-corrected non-parametric bootstrap approach was employed, and Model 4 of the PROCESS macro program in SPSS (Model 4 is a simple mediation model) was used to test the mediating effect. Firstly, descriptive statistics and correlation analysis were conducted on each variable, as shown in Table 3.

Following the validation of H1, it was determined that initial skills are positively correlated with technology use (SPOC, KG, GPT). When both initial skills and technology use are included in the regression equation, initial skills significantly and positively influence technology use, which in turn can significantly predict final grades, as shown in Tables 4–6.

According to the judgment method of Wen and Ye (2014) on mediating effects and suppressing effects, the research results show that the indirect effects of technology use on pre-learning skill to self-efficacy are 0.047 (SPOC), 0.026 (KG), and 0.058 (GPT), respectively. The 95% confidence interval of the point estimate value does not include 0, indicating significance. Only the SPOC effect is significant, with the 95% confidence interval of

Table 6 Total effect, direct effect, and mediating effect.

Variable		Effect Value	Coefficient Product Test			95% confidence interval	
			SE	z	p	Lower limit	Upper limit
Direct Effect	Initial skills→ Self-efficacy	−0.997	0.038	−26.169	0.000	−1.071	−0.922
Total Effect	Initial skills→ Self-efficacy	−0.865	0.056	−15.399	0.000	−0.975	−0.755
Mediating Effect	Initial skills→ SPOC→ Self-efficacy	0.047	0.026	1.825	0.068	0.009	0.108
Mediating Effect	Initial skills→ KG→ Self-efficacy	0.026	0.026	0.994	0.320	−0.005	0.097
Mediating Effect	Initial skills→ GPT→ Self-efficacy	0.058	0.031	1.907	0.057	0.000	0.118

Table 7 Mediation model for learning behavior.

Variable	Final grades		Learning behavior		Final Grades	
	β	t	β	t	β	t
Self-efficacy	0.141**	3.298	0.161*	2.613	0.046*	1.986
Learning Behavior					0.593**	17.969
R^2	0.082		0.053		0.751	
F	10.878		6.829		181.345	

*$p < 0.05$, **$p < 0.01$.

the point estimate value ([0.009, 0.108]). In the test of the mediating effect of technology use on initial skills and self-efficacy, the coefficient c is significant. Starting with the mediating effect, subsequent testing revealed significant indirect effects, with a * b indicating a different sign from the regression coefficient c ‘. It can be inferred that the indirect effects of SPOC technology on initial skills and self-efficacy belong to the “masking effect”, accounting for 4.758%. The results indicate that the research hypothesis H2 holds.

In addition, the roles of the depth and breadth of the three technologies in the impact of initial skills on self-efficacy were verified separately, and it was found that they all have a masking effect (see Appendix B, Table B1).

Learning behavior. To verify the mediating effect of learning behavior on the impact of self-efficacy on final grades, the same method as H2 is used to test the mediating effect. The mediation model results indicate that self-efficacy ($\beta = 0.141$, $t = 3.298$, $p = 0.001$) is significantly positively correlated with final grades. When both self-efficacy and learning behavior are included in the regression equation, self-efficacy maintains a significant positive impact on learning behavior ($\beta = 0.161$, $t = 2.613$, $p = 0.001$). Furthermore, learning behavior ($\beta = 0.593$, $t = 17.969$, $p < 0.001$) significantly and positively predicts final grades, as shown in Tables 7–8.

The Bootstrap 95% CI for the mediation effect does not include 0 ([0.528, 0.658]), indicating a significant mediation effect. Given the significant positive correlation between self-efficacy and final grades, coupled with the significant mediating role of learning behavior, it can be concluded that learning behavior partially mediates the influence of self-efficacy on final grades, contributing to 67.654% of the total effect.

The mediating effect of specific learning behaviors was assessed individually, revealing that homework grades serve as a mediator in this relationship, while other behaviors did not exhibit significant mediating effects. The mediating role of homework grades accounted for 32.580% of the effect. At this point, H4 is confirmed, primarily through the mediation of the learning behavior associated with homework grades.

To explore further whether technology use moderates the impact of learning behavior on final grades, a moderation analysis was conducted using Model 1 of the PROCESS macro in SPSS. The findings are presented in Table 9.

Learning behavior has a significant positive impact on final grades in all three models. The direct effect of technology use is not significant in either Model 2 ($\beta = 0.049$, $t = 1.362$) or Model 3 ($\beta = 0.012$, $t = 0.331$). This means that technology use, by itself, does not directly affect the final score. However, the introduction of the interaction term between learning behavior and technology use significantly affects learning behavior ($\beta = -0.181$, $t = -3.824$). This suggests that technology use moderates the relationship between learning behavior and final grades. Furthermore, the value of the model shows a gradual increase from 0.744 to 0.782, implying that incorporating interaction terms explains variance in final grades better. Given the significance of the interaction term, it is concluded that technology use significantly moderates the relationship between learning behavior and final grades, thereby validating H5. Specifically, this moderation is negative, indicating that the positive influence of learning behavior on final grades may diminish with high levels of technology usage. When learning behavior affects final grades, the moderating variable (technology use) exhibits significant differences in its impact at various levels. To further elucidate the interaction between technology use and learning behavior on final grades, this study presents detailed illustrations as shown in Fig. 2.

As technology use progresses from low to high, the slope of the correlation between learning behavior and final grades diminishes. This indicates a continuous weakening in the relationship between learning behavior and final grades, demonstrating a negative moderating effect.

The specific learning behaviors—including homework grades, video duration, discussion frequency, and classroom engagement —were verified in conjunction with the use of three technologies: SPOC, KG, and GPT (see Appendix B, Table B2). Except for knowledge graphs, which do not exhibit a moderating effect on the influence of videos on final grades, all other technologies display a moderating negative effect.

The impact of technology use on learning outcomes. To verify the mediating effect of technology use on the impact of self-efficacy on final grades, the same method as H2 was used to test the mediating effect (see Appendix B, Tables B3–B5 for details).

The mediation model results suggest that self-efficacy ($\beta = 0.151$, $t = 3.525$, $p = 0.001$) is significantly and positively associated with final grades. When both self-efficacy and technology use are included in the regression equation, self-efficacy maintains a significant positive impact on learning behavior ($\beta = 0.143$, $t = 3.247$, $p = 0.002$). In contrast, technology use ($\beta = 0.054$, $t = 0.916$, $p = 0.361$) does not significantly influence final scores. Furthermore, the Bootstrap 95% CI for

Table 8 Total effect, direct effect, and mediating effect.

Self-efficacy-Final Grades	Effect Value	Coefficient Product Test			95% confidence interval		Conclusion
		SE	z	p	Lower limit	Upper limit	
Direct Effect	0.095	0.074	1.288	0.198	0.046	0.334	Partial Mediation
Total Effect	0.161	0.061	2.613	0.010	0.040	0.281	
Mediating Effect	0.593	0.033	17.969	0.000	0.528	0.658	

Table 9 Adjustment effect model test.

	Model 1		Model 2		Model 3	
	β	*t*	*β*	*t*	*β*	*t*
Learning Behavior	0.603**	16.877	0.597**	16.616	0.556**	15.743
Technology Use			0.049	1.362	0.012	0.331
Learning Behavior× Technology Use					−0.181**	−3.824
R^2	0.744		0.749		0.782	
F	284.834		144.586		114.800	

Model 1 analyzes the impact of independent variable learning behavior on the final score of the dependent variable (Model 1 does not consider moderating variables);
Model 2 incorporates moderating variable techniques based on Model 1;
Model 3 adds interaction terms between learning behavior and technology usage based on Model 2.
*$p < 0.05$, **$p < 0.01$.

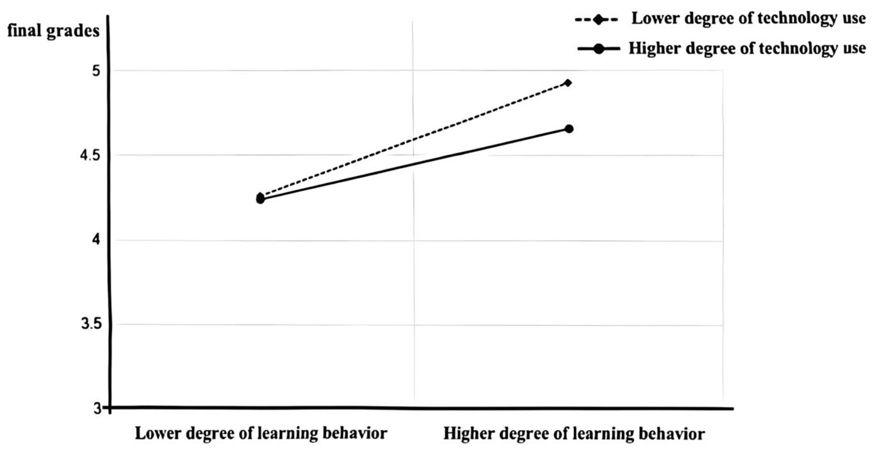

Fig. 2 The Impact of Learning Behavior and Technology Use on Final Grades. The horizontal axis represents students' learning behavior, and the vertical axis represents students' final grades.

the mediating effect spans zero ([−0.035, 0.081]), indicating that the mediating effect is not significant. Consequently, hypothesis 7, which proposes that technology use mediates the relationship between self-efficacy and final grades, is not supported.

Although the overall mediating role of technology between self-efficacy and final grades was not significant, this does not rule out the potential effects of specific technological tools or usage dimensions. Further analysis revealed that both the depth and breadth of knowledge graph (KG) usage play significant yet distinct mediating roles. Specifically, KG breadth showed a positive partial mediating effect, accounting for 40.746% of the total effect. In contrast, KG depth exerted a masking effect, representing 47.356% of the total effect, suggesting that deeper engagement with knowledge graphs may increase cognitive load and negatively influence outcomes (see Appendix B, Tables B6–B8 for details).

Moreover, both the depth and breadth of SPOC usage demonstrated significant negative moderating effects. The interaction terms "self-efficacy × SPOC breadth" ($\beta = -0.247$, $t = -2.536$) and "self-efficacy × SPOC depth" ($\beta = -0.182$, $t = -2.102$) indicate that broader and deeper use of SPOC weakens the positive relationship between self-efficacy and final performance.

Continuing to analyze the role of the depth and breadth of technology use in the impact of initial skills on technology use (see Appendix B, Table B6). The depth of technology use (SPOC, KG, GPT) plays a complete mediating role, whereas the breadth of technology use, including SPOC, KG, and GPT, serves as a partial mediator.

Here are the results of all hypotheses verification as shown in Table 10.

Discussion

Based on the comprehensive data analysis, this study yielded several key findings regarding the interplay between initial skills, self-efficacy, learning behaviors, technology use, and final academic performance among liberal arts students:

(1) The Interplay of Initial Skills, Self-Efficacy, and Technology Use.
A significant negative correlation was identified between students' initial skills and their self-efficacy. This finding

Table 10 Structural model test results.

Hypothesis	Hypothesis supported
H1: A negative correlation exists between students' initial skills and their self-efficacy.	Supported
H2: Technology use masks the effect of initial skills on self-efficacy	Supported
H3: Initial skill level positively affects students' final learning scores.	Not Supported
H4: Learning behavior mediates the effect of self-efficacy on final score.	Supported
H5: Technology use moderates the effect of learning behavior on the final score.	Supported
H6: Technology use is positively correlated with self-efficacy.	Supported
H7: Technology use mediates the effect of self-efficacy on the final score.	Not Supported

appears, at first glance, to contradict Bandura's (1997) classic assertion that successful "mastery experiences" are the foundation for building self-efficacy—which high initial skills should presumably facilitate. However, this precisely highlights the complexity of the formation mechanisms of self-efficacy. Our discovery resonates with the research of Vancouver and Kendall (2006), who pointed out that in certain learning contexts, overly high initial confidence can lead to complacency and metacognitive miscalibration, potentially undermining subsequent effort investment, thus forming a "conservative" or "calm" sense of self-efficacy. In other words, for students with high initial skills, if educational technology fails to provide new "mastery experiences" that are challenging and commensurate with their level, their self-efficacy may struggle to improve further (Chen et al., 2004).

The key innovation of this study lies in identifying the "masking effect" of technology use within this relationship. This finding significantly deepens our understanding of the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), shifting the focus from technology adoption to its consequences. The depth and breadth of technology application acted as an "equalizer": For low-skilled students, it provided crucial scaffolding and personalized support. This was key to addressing their confidence deficit, as it created small, achievable successes that directly build self-efficacy—a process central to Zimmerman's (2000) theory of mastery experiences. Concurrently, technology might also alleviate performance pressure for high-skilled students by reducing task difficulty or altering assessment criteria, causing their self-assessment to rely solely on narrow initial skill advantages. Therefore, the value of technology lies not only in improving overall performance but also in its ability to modulate initial differences among learners, offering a new empirical perspective on technology's role in promoting educational equity.

(2) The Mediating Role of Learning Behavior.

Path analysis indicated that initial skills had no direct effect on final scores, while self-efficacy and learning behaviors were stable and significant positive predictors of academic achievement. This result strongly supports the self-regulated learning model pioneered by Pintrich and De Groot (1990), which clearly outlines the causal chain of "motivation (self-efficacy) → learning strategies and behaviors (e.g., deep cognitive strategies, effort management) → academic achievement."

More importantly, by verifying the significant mediating role of learning behavior between self-efficacy and final scores, this study reveals the specific mechanism through which intrinsic motivation translates into academic outcomes. This indicates that self-efficacy not only directly stimulates learning motivation but, more crucially, indirectly optimizes learning effectiveness by prompting students to engage in deeper learning behaviors such as more focused reading, active class participation, and meticulous assignment preparation (assignment performance being a key component of this mediating pathway). This finding fully aligns with Zimmerman's (2002) exposition on self-regulated learning: students with high self-efficacy are more inclined to set challenging goals, persist in effort, and employ effective strategies, and these positive learning behaviors are the direct drivers of achievement improvement. Consequently, our research not only reaffirms the robustness of this classic theoretical framework in technology-enhanced learning environments but also refines the understanding of this mechanism by clarifying the mediating role of learning behavior.

(3) Technology's Dual Role and Pedagogical Anchoring.

The various findings of this study collectively affirm a core principle: technology should serve "knowledge acquisition and thinking cultivation," rather than become the center of learning activities (Laurillard, 2013; Wang et al., 2025). The impact of technology on students is profoundly complex and dual-edged.

For instance, the negative moderating effect of general technology use indicates that for students, high frequency but low-quality engagement can undermine the benefits of their own positive learning behaviors. This phenomenon finds support in existing research on cognitive load and technology engagement (Sweller, 2011; Xia and Liitiäinen, 2017): students who engage in high-quantity, low-quality technology use may experience cognitive overload, where their attention is fragmented by the tools themselves rather than focused on the learning content. This often traps students in a cycle of "tool mastery," (Laurillard, 2013), disrupting the deep focus essential for liberal arts learning.

We posit that this phenomenon stems from an interplay between instructional design and student engagement. When technology is integrated without clear pedagogical goals—for instance, as a mandatory but disconnected component—it can foster passive, procedural engagement. Students may click through modules or contribute to forums primarily to complete tasks, a behavior that aligns with what Henderson et al. (2017) describe as "performative" rather than "meaningful" participation. This passive mode of use is precisely what leads to the cognitive overload and "tool mastery trap" identified in our study, as student attention is diverted from learning content to the mechanics of task completion.

Conversely, the differential effects of specific technologies highlight that the value for students lies not in the tool itself, but in how they use it to achieve learning goals (Hamilton et al., 2016; Zhou et al., 2025). For example, a Knowledge Graph (KG) can aid students in structuring knowledge, whereas poorly utilized SPOC functions may hinder their progress. This demonstrates that students' strategic choices in technology application are crucial.

Therefore, for students, the key takeaway is the need for mindful and strategic technology use. A balanced approach that emphasizes depth and quality of engagement over sheer quantity is crucial for maximizing learning outcomes (Selwyn, 2010). This implies that students should consciously reflect on whether their technology use is directly enhancing their understanding or merely creating an illusion of productivity. By anchoring their technology use firmly to learning objectives, students can ensure it acts as a catalyst for, rather than a barrier to, the development of critical thinking and deep knowledge.

Conclusion

This study demonstrates that for liberal arts students with low initial technical proficiency, learning behavior and self-efficacy are significant positive predictors of learning outcomes. Importantly, self-efficacy and prior skill levels alone do not directly determine final academic performance; rather, it is the combination of positive learning habits and sustained self-confidence that drives success. The findings also underscore the pivotal role of technology use—particularly its depth and breadth—in mediating learning processes and improving outcomes. Technology shows great potential in bridging skill gaps and creating more equitable learning opportunities. Furthermore, self-efficacy and learning behavior serve as essential mediators between technology use and final grades, emphasizing their role as fundamental drivers in the learning process. Educators are therefore encouraged to leverage technology strategically—accounting for individual student needs and differences—to promote personalized learning, cognitive development, and deeper academic understanding. By integrating technology thoughtfully into instructional design, we can enhance its positive impact, foster student engagement, and support the continuous innovation of teaching practices in a rapidly evolving educational landscape.

This study explores the roles of learning behavior, self-efficacy, and technology use in shaping learning outcomes among liberal arts majors. Integrating the Technology Acceptance and Use Theory and the Theory of Diminishing Marginal Utility, it addresses a gap in understanding technology's role in traditional learning settings and offers a novel perspective—particularly through applying the latter theory to explain the negative correlation between initial skills and self-efficacy, an approach seldom seen in educational research.

The findings highlight the importance of technological adaptability and acceptance, providing educators with critical insights for selecting and implementing technology tools (Ifenthaler and Schweinbenz, 2013). By assessing students' readiness and skills, instructors can better tailor tools and training to enhance both technical proficiency and learning outcomes. Furthermore, this study highlights the nuanced effects of technology, emphasizing that its depth and breadth have a significant influence on the results. These insights urge educators and learners to adopt technology judiciously—focusing on meaningful integration rather than mere usage (Pischetola, 2021)—to truly support learning. Importantly, the results suggest that initial skills can be overcome through diligent effort and effective strategies, wherein sustained self-efficacy and positive learning behaviors play essential roles in achieving academic success—a finding that resonates with the principles of a growth mindset (Yeager and Dweck, 2020).

While offering valuable insights, this study is constrained by its reliance on self-reported data from a limited sample of 123 students, predominantly female, and its narrow focus on specific technologies (SPOC, KG, GPT). Consequently, the relationships among the variables discovered in this study may be more representative in a liberal arts education environment with a similar curriculum structure and a high proportion of women. Future research should encompass diverse educational contexts and geographic regions, examining a broader array of educational technology tools and incorporating additional variables such as learning environments and instructor roles. Employing longitudinal designs and experimental methods—including randomized controlled trials—would help clarify causal relationships. Specifically, future studies could compare the differences in technology usage patterns and outcomes between liberal arts and STEM students to reveal the influence of disciplinary background on the integration of technology into learning. Qualitative methods, such as interviews, should be adopted to deeply collect students' feedback on their experiences with specific technologies like SPOC, knowledge graphs (KG), or generative AI (GPT). Further research should also adopt time series analysis methods such as LSTM to model the dynamic process of technology usage, to reveal the key role of "usage persistence" in learning outcomes (Zhang et al., 2025).

Data availability

All data that support the findings of this study are included within the article (and any supplementary files).

Received: 31 January 2025; Accepted: 11 November 2025;
Published online: 25 November 2025

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Acknowledgements

This work was supported by the Key Project of Education Science Planning in Heilongjiang Province [grant numbers GJB1424018].

Author contributions

Tao Zhang conceived the presented idea. Sihang Wu and Ying Qi conducted the survey and performed the computations. Sihang Wu and Xinnan Wang verified the analytical methods and results. Tao Zhang and Sihang Wu took the lead in writing the manuscript. All authors provided critical feedback and helped shape the research, analysis, and manuscript.

Competing interests

The authors declare no competing interests.

Ethical approval

All procedures involving human participants were performed in accordance with the ethical standards of the Academic Committee (Ethics Committee) of the School of Information Management, Heilongjiang University, and with the 1964 Helsinki Declaration and its later amendments. Ethical approval was granted by this committee (Approval No. HD-CIM-2024001) on March 2, 2024.

Informed consent

Informed consent was obtained orally from all participants during the course session on March 3, 2024, prior to questionnaire distribution. Oral consent was adopted due to the format of the intensive course program and was formally documented by the instructor in the session record. Before commencing the survey, the researcher explained the study's purpose, procedures, and emphasized data anonymity, voluntary participation, and the right to withdraw without penalty. The same information was provided on the first page of the questionnaire, and participants were informed that proceeding indicated their consent to participate.

Additional information

Supplementary information The online version contains supplementary material available at https://doi.org/10.1057/s41599-025-06292-8.

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