Article

Volume 15, Issue 3 (2026), pp. 283-302
Journal of Interdisciplinary Studies in Education
ISSN: 2166-2681Print 2690-0408 Online | https://ojed.org/jise
https://doi.org/10.32674/2p8kkj40

Preparing Students for AI-Powered Learning: The Mediating Power of Self-Efficacy between Holistic Engagement and Digital Readiness

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ABSTRACT

Integrating digital platforms and generative AI into higher education requires an understanding of the psychological factors that influence student adaptation. In this study, 338 students were surveyed to explore how engagement (emotional, behavioral, and cognitive), self-efficacy, and digital readiness interact, using adapted scales and structural equation modeling (SEM). The results indicate that engagement strongly affects digital readiness ($\beta = .55$, $p < .001$) and self-efficacy ($\beta = .83$, $p < .001$). Self-efficacy predicts readiness ($\beta = .31$, $p < .001$) and mediates the relationship between engagement and readiness ($\beta = .25$). In the GenAI era, self-confidence is as crucial as technical skills for digital adaptation in education. The study recommends frameworks such as the Agile Pedagogy to increase confidence and support adaptation.

Keywords: Agile Pedagogy, Digital Readiness, GenAI Tools, Self-Efficacy, Student Engagement

INTRODUCTION

Higher education has undergone significant changes because of the extensive use of GenAI tools (Bahroun et al., 2023). In a modern hybrid learning environment, student performance is influenced by their ability to interact effectively with digital tools (Chuaphun & Samanchuen, 2024). To bridge the gap between theory and practice, several researchers have argued that integrating AI into learner-centered frameworks is crucial for improving the quality of teaching and learning (Mahmood, 2025). This study highlights the role of GenAI in shaping teaching methods and stresses the need for ongoing research in educational psychology and digital systems as GenAI rapidly advances (Singh & Paiva, 2025).

In an AI-powered education model, it is vital to include psychological factors such as student engagement, self-efficacy, and digital readiness (Tsai et al., 2011; Huang, 2022; Woreta et al., 2025). Although research has often examined these separately (Hong & Kim, 2018), gaps remain in studies of GenAI adoption. First, there is a notable lack of research on the multidimensional nature of student engagement (Fredricks et al., 2004; Reevie, 2012). The behavioral, emotional, and cognitive dimensions of engagement must be studied to understand their impact on digital readiness. Second, explaining how engagement drives meaningful use of GenAI through self-efficacy offers new insights (Hidayat-Ur-Rehman, 2024). Integrating engagement, self-efficacy, and digital readiness into a structural model offers a novel approach to bridging research gaps.

The findings from this investigation offer vital empirical insights that support the development of agile pedagogy as a cohesive framework for educational institutions. Here, we applied agile pedagogy, a flexible teaching method characterized by iterative learning, short sprints, and feedback loops. Agile pedagogy fosters improvement through peer feedback and quick responses to students. In the GenAI era, it enhances students' digital skills, aiding their navigation and effective use of emerging technologies.

LITERATURE REVIEW

Student Engagement in the Age of Generative AI

Student engagement is the level of dedication and interest that students invest in their education (Reeve, 2012; Fredricks et al., 2004). Regardless of whether an AI tutor or a human teacher is involved, the concept of engagement extends beyond simple attendance to the responsibility students take for learning (Kulkarni et al., 2025). Behavioral, emotional, and cognitive engagement are the three distinct and interconnected dimensions of engagement.

Behavioral engagement involves active participation and commitment, which are associated with the innovative use of technology in academic settings (Appleton et al., 2006; Henrie et al., 2015). For example, prompting, refining, and cocreating with GenAI tools provides an opportunity for students to explore how innovatively they can use these tools (Guo et al., 2016; Liu and Zhong, 2025; OECD, 2026)Furthermore, the importance of GenAI lies in its ability to enhance interactivity through personalized responses, which is crucial for creativity and strengthening problem-solving skills (Eltayeb, 2025).

Emotional engagement is characterized by curiosity and enjoyment in the learning process. Previous research has demonstrated that customization is essential for fostering a sense of belonging and increasing interest in learning (Bond et al., 2020), which are crucial for enhancing emotional engagement. Without such personalization, learners may feel disconnected, undermining their motivation and overall engagement. Building on this, GenAI technology responses are personalized and delivered in real time, making the learning process more emotionally engaging (Nguyen et al., 2024; Subramanian Iyer, 2024). Additionally, customization promotes a sense of belonging and fosters curiosity about learning, thus increasing emotional involvement and strengthening students' confidence in their academic ability.

Cognitive engagement refers to students' willingness to invest mental energy and engage in learning processes to comprehend content (Fredricks et al., 2004; Appleton et al., 2006). The examination of complex topics by GenAI challenges students with adaptive assignments that require problem solving and the development of new information rather than simple memories (Liu et al., 2022; Eltayeb, 2025). GenAI has the potential to significantly enhance higher-order thinking skills, which are essential for advanced learning (Subramanian Iyer, 2024). Engaging in these cognitively demanding interactions will allow students to develop their subject expertise (Shao & Wang, 2026; Wang, 2026).

Self-Efficacy

Academic self-efficacy, defined as an individual's belief in his or her capacity to address future challenges, is fundamental to students' success in learning (Bandura, 1997). The traditional use of technology in education is supported by individuals' confidence in their own skills; likewise, students' approaches to evaluating GenAI outputs are significantly influenced by their self-efficacy beliefs (Schunk & DiBenedetto, 2020). Students with strong self-efficacy tend to trust their critical thinking and analytical skills when they assess AI-generated results and form independent judgments (Alhur et al., 2025).

Consequently, self-efficacy transforms general engagement into purposeful GenAI utilization.

Digital Readiness

Digital readiness includes an individual's technical skills, ethical awareness, critical thinking, and adaptability to successfully leverage the digital environment (van de Werfhorst et al., 2022). A digitally prepared student is familiar with GenAI tools and can evaluate AI-generated content (Zawacki-Richter et al., 2022; Holmes et al., 2019). These students are likely to utilize technology as a collaborative learning tool without any bias. Although many students believe that they are technically skilled (Stadler et al., 2024), few possess the deeper skills required for responsible, ethical, and mindful GenAI deployment. Digital readiness is the fundamental literacy required for student progress in technology-enhanced learning (Maryani et al., 2023).

Theoretical Framework and Hypothesis Development

This research is anchored in Bandura's social cognitive theory (SCT) (Bandura, 1997), which defines self-efficacy as a person's belief in his or her ability to overcome challenges on the way to success. As technology paves the way for students by providing learning support, self-efficacy improves through meaningful engagement with technology in digital education (Fredricks et al., 2004), thereby enhancing digital readiness (Parkes et al., 2015).

Despite its importance, the role of self-efficacy in bridging engagement and digital readiness has not been extensively explored (Wolverton et al., 2020; Ergun & Adibatmaz, 2020). The present study provides a clear conceptualization of behavioral and psychological components by explicitly modeling self-efficacy as the mediator through which engagement is converted into digital readiness (Hu et al., 2025). The following hypotheses are derived from the theoretical background, linking student behavior and confidence to digital adaptation:

H_1: Holistic engagement positively influences digital readiness.

H_2: Holistic engagement positively influences self-efficacy.

H_3: Self-efficacy positively influences digital readiness

H_4: Self-efficacy positively mediates the relationship between holistic engagement and digital readiness.

METHODOLOGY

Research Design and Context

To empirically test the paradigm, this study employs a quantitative, cross-sectional survey method (Creswell, 2015). However, cross-sectional data reveal these relationships in a snapshot and do not establish temporal causality (Hair et al., 2019); this approach is essential for analyzing the structural linkages in the model.

The study was conducted at an Indian university during a structured short-term interdisciplinary workshop. The program deliberately used agile pedagogy by adapting project management principles to the learning context (Cubric, 2013). During the learning sprint, the students were instructed to use GenAI tools to complete writing tasks. Peer review cycles served as sprint reviews, and students iteratively revised each other's completed tasks. They subsequently provided feedback to improve the completion of the next task when using the GenAI assistant. There was no restriction on providing feedback because we wanted students to use their full creativity to criticize AI-generated content and reform their peers' prompts or questions.

Participants and Procedures

A structured online survey (Google Forms) was circulated via QR codes and WhatsApp to collect quantitative data. Of the 353 responses, 338 formed the final valid sample after data cleaning. Participant anonymity was strictly maintained, and entries with incorrect attention-check questions were excluded to ensure data integrity and mitigate self-reporting bias. To ensure data relevance, purposive convenience sampling was employed, and inclusion required the active use of GenAI within the workshop. Participation was voluntary and confidential, and informed consent was obtained in compliance with ethical procedures.

Instruments and Measures

The variables were measured using items adapted from well-known theories that fit technology-mediated learning. In accordance with the guidelines of Henrie et al. (2015), holistic engagement was measured using behavioral, emotional, and cognitive elements (Fredricks et al., 2004). Similarly, the digital readiness scale was modified from Hong and Kim (2018), and the self-efficacy scale was adapted from Bruning et al. (2013) to gauge confidence in AI-assisted learning. Before the main data collection, a pilot study was conducted with 90 students to validate the adapted instrument (refer to the annexure).

Data Analysis

Two phases of data analysis were conducted using SPSS (v. 23) and AMOS (v. 24). Descriptive statistics and Cronbach's alpha were computed to assess the data distribution and internal consistency. Second, confirmatory factor analysis (CFA) was used to validate the measurement model (checking factor loadings and discriminant validity via the HTMT). Structural equation modeling (SEM) was used to simultaneously estimate direct and indirect relationships. Model fit was evaluated using standard criteria for goodness-of-fit and badnessof-fit (e.g., CFI/TLI > .90, RMSEA < .08), and statistical significance was assessed at $p < .05$.

RESULTS

Table 1 summarizes the demographic characteristics and genetic AI usage patterns of the study participants ($N = 338$), including distributions by sex, age group, and field of study.

Table 1: Demographic Information

Gender	N (338)	Percentage
Male	205	61%
Female	133	39%
Age Group		
18-24	213	63%
24-30	102	30%
30-36	18	5%
36 or above	5	2%
[a]Field of Study		
Non-STEM	234	70%
STEM	104	30%
Frequency of using AI tools		
Very Often	99	29%
Often	138	41%
Occasionally	79	23%
Rarely	22	7%
Primary Purpose of GenAI Writing Tools Usage		
Writing Assignments	155	46%
Generating ideas for content writing	74	22%
Creating Presentations	46	13%
Grammatical error checking of academic writings	47	14%
Other	16	5%
[b]Mostly Used GenAI Tool		
ChatGPT	272	53%
Gemini	46	9%
Meta AI	39	7%
Claude	25	5%
Other GenAI tools	133	26%

Note. [a]In the field of study, non-STEM includes Management, Commerce, Law, and Education, and STEM includes Science, Technology, Engineering, Medical, and Psychology. [b]This item allowed for multiple responses; percentages reflect the proportion of total responses (N responses = 515), not the total number of participants. "Other GenAI tools" included Presentation AI, Grammarly, Canva, Copilot, Scribbr, Runway ML, QuillBot, Midjourney, Llama, Framer AI, Adobe Firefly, and ChatPDF.

Reliability and Measurement Model assessment

Confirmatory factor analysis (CFA) was performed to assess the measurement model. Factor loadings were examined against the .60 threshold to ensure strong construct validity (Chin, 1998). To improve the convergent validity of the constructs, item SE6 (λ = .55) from self-efficacy and item DR5 (λ = .61) from digital readiness were dropped. The removal of SE6 aligns with that of Ng et al. (2021), suggesting that participants perceived ethical considerations as a distinct dimension and not an element of self-efficacy. Similarly, DR5 was excluded because foundational IT literacy is considered a separate domain from the competencies required for GenAI-mediated writing (Gunzler et al., 2013).

Table 2: Loadings, Reliability, and Convergent Validity

Constructs	Items	Loadings(λ)	Alpha (α)	CR	AVE
Holistic Engagement (HE)	CE	.893	.858	.925	.803
	BE	.881			
	EE	.916			
Cognitive Engagement (CE)	CE1	.742	.811	.814	.522
	CE2	.719			
	CE3	.686			
	CE4	.744			
Behavioral Engagement (BE)	BE1	.703	.778	.782	.474
	BE2	.695			
	BE3	.731			
	BE4	.621			
Emotional Engagement (EE)	EE1	.798	.859	.856	.597
	EE2	.733			
	EE3	.745			
	EE4	.814			
Digital Readiness (DR)	DR1	.774	.804	.800	.502
	DR2	.779			
	DR3	.627			
	DR4	.641			
Self-Efficacy (SE)	SE1	.762	.846	.855	.543
	SE2	.800			
	SE3	.819			
	SE4	.606			
	SE5	.676			

Note. CMIN = 451.841; df = 170; p< = .0001; Cmin/df = 2.658; CFI = .92; GFI = .89; RMSEA = .07; TLI = .93; SRMR = .047.

Internal consistency was obtained through Cronbach's alpha (α) values, which ranged from .77 to .86. In the final model, high internal consistency was observed, and the values exceeded the benchmark of .70 (Nunnally, 1978), indicating satisfactory reliability across all the constructs. Composite reliability

(CR) values exceed the .70 threshold, ranging from .78 to .92 (Hair et al., 2019). All the constructs had AVE values greater than .50 for convergent validity, except for behavioral engagement (.47). Nonetheless, this construct was retained in accordance with the standard set by Fornell and Larcker (1981), which states that convergent validity is still sufficient if the AVE is less than .50 but composite reliability is greater than .60.

The HTMT ratio, as shown in Table 3, was used to evaluate discriminant validity; all the HTMT values fell below the conservative cutoff of .85 (Henseler et al., 2015). The ratio between behavioral and cognitive engagement (.84) approaches the .85 threshold, indicating that discriminant validity is marginal in some cases, according to the study. Theoretically, this marginal overlap is explained by the constructs being related aspects of the same broad "Holistic Engagement" framework, which is a limitation of multidimensional measurement.

Table 3: Heterotrait–Monotrait (HTMT) Ratio

	SE	DR	BE	EE	CE
SE					
DR	.727				
BE	.675	.663			
EE	.810	.716	.827		
CE	.761	.664	.837	.786	

Table 4: Structural Model Assessment

	Path	Effect Type	β	Supported	Effect Size
H1	Engagement → Digital Readiness	Direct	.554***	Yes	Large
H2	Engagement → Self-Efficacy	Direct	.831***	Yes	Large
H3	Self-Efficacy → Digital Readiness	Direct	.306***	Yes	Medium
H4	Engagement → Self-Efficacy → Digital Readiness	Indirect (Mediation)	.254***	Yes	Medium

Note. ***$p < .001$

The structural model demonstrates strong predictive power, with all proposed hypotheses being statistically significant (ρ < .001). Holistic engagement had a significant positive effect on self-efficacy (β = .83) and a direct effect on digital readiness (β = .55). Digital readiness was positively influenced by self-efficacy to a moderate degree (β = .31).

The model explains 61% of the variance in digital readiness ($R^2 = .61$) and 70% of the variance in self-efficacy ($R^2 = .70$). These R^2 values are regarded as significant by Cohen (Cohen, 1988), suggesting that the proposed model is very successful at predicting students' digital readiness.

Bootstrapping analysis (5,000 samples, 95% CI) confirmed a significant indirect effect of engagement on digital readiness through self-efficacy ($\beta_{indirect} = .25$, 95% CI [.04, .45]). The direct path from engagement to readiness was still statistically significant ($\beta = .55$), indicating partial mediation.

The variance accounted for (VAF) was computed to evaluate the practical significance. Engagement had an overall impact of .80 (.55 + .25) on digital readiness. Approximately 31% of the overall effect is attributable to the indirect effect (.25), suggesting that although active participation directly develops digital skills, increasing students' psychological confidence (self-efficacy) accounts for nearly one-third of digital readiness.

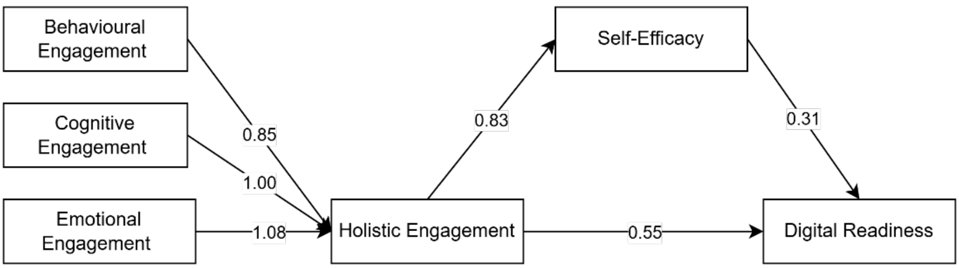

Figure 1: Path Analysis Results

DISCUSSION

All the hypotheses were supported by the structural model, which revealed that self-efficacy is a significant partial mediator and that student engagement is a strong predictor of digital readiness. The robustness of the relationships is confirmed by the model's predictive power, which explains the variance in digital readiness and self-efficacy. In particular, the relationship between engagement and self-efficacy had the strongest effect on the model.

These findings imply that holistic engagement is an antecedent that influences student success in real educational settings in the GenAI era. Students' belief in their own abilities increases when they actively engage with AI tools (behavioral), enjoy the process (emotional), and think critically about it (cognitive), as proven by a strong association with self-efficacy. Self-confidence is a key driver of full digital readiness.

The present study distinguishes itself by incorporating agile peer feedback loops to mitigate the risk of learner isolation, which is a common issue in Gen AI environments. Structured cooperation and feedback cycles help counteract individualistic learning and increase motivation (Abraham & Singaram, 2024; Tran, 2019), and social interdependence via iterative sprint functions such as social modeling. This finding reinforces individual self-efficacy, which is consistent with Bandura's (1997) view that observing peers' successful performance strengthens one's efficacy beliefs. By positioning GenAI tools as collaborative instruments, this research advances beyond individualistic adoption models to emphasize the pedagogical necessity of collective engagement to achieve digital readiness and self-efficacy (Ren et al., 2026).

IMPLICATIONS

Theoretical Implications

By validating a structural model that extends SCT, this study makes a significant contribution to the literature. The strong link between holistic engagement and self-efficacy suggests that in a technologically advanced environment, the primary source of self-efficacy stems from active mastery experiences arising from continuous cognitive, emotional, and behavioral involvement (Bandura, 1997). Additionally, the findings suggest that the iterative nature of GenAI interactions amplifies psychological self-belief (Wu, 2023). A significant theoretical contribution is the model's robust ability to explain both endogenous variables, demonstrating that the framework effectively predicts how students adapt to new learning environments (Xu et al., 2024).

While recent studies emphasize the potential of AI tools to transform higher education (Chadha, 2024), the current research offers empirical depth by examining the mechanisms behind students' digital readiness. This distinction advances the field by moving from simple linear adoption models to a more dynamic, synergistic relationship between collaborative pedagogy frameworks and the internalization of competence, as discussed by Zakir et al. (2025).

Practical and Policy Implications

Empirical findings provide specific guidance for educational practice and policy, particularly concerning the necessary transformation in instructional culture. The study's successful implementation in an agile pedagogy class confirmed its value as a scalable framework for digital transformation. This study argues that applying agile principles, emphasizing iteration and frequent feedback, directly enhances the engagement and experiences essential for building strong self-efficacy (Noguera et al., 2018). This approach shifts the instructional focus from the final outcome to the engagement process, ensuring that digital proficiency is cultivated through collaborative and reflective actions rather than the isolated use of tools. Agile concepts are positioned as an effective instructional design for preparing higher education students for the future job market (Schön et al., 2022).

At the policy level, these findings emphasize the need to redefine digital readiness within institutional curricula. The policy framework should prioritize resource allocation for AI-specific literacy, focusing on ethical reasoning and critical evaluation over traditional, foundational IT skills (Chiu, 2024). Given the model's cross-disciplinary predictability, digital transformation should be implemented university wide rather than being siloed within technical departments. Institutions must prioritize a readiness-first culture that incentivizes pedagogical innovation, recognizing that students' digital readiness depends as much on psychological confidence as on technical access.

Limitations and Future Research

The limitations of this research provide context for its contributions. The use of purposive convenience sampling within a particular university program and a cross-sectional survey design restricts the generalisability of causal conclusions and raises the possibility of self-report bias. Longitudinal studies to track how self-efficacy and digital readiness change over time with ongoing exposure to GenAI should be part of future research. Furthermore, conceptual overlap is suggested by the marginal discriminant validity between engagement subdimensions based on (HTMT) ratios. Furthermore, comparative research using qualitative techniques or usage data may provide objective validation of student behavior and a more thorough understanding of the elements integrated into the contemporary readiness construct. Specifically, the experimental method can be applied to further explain the role of agile techniques in the classroom.

CONCLUSION

In conclusion, this study provides solid empirical evidence that student engagement is the most effective means of improving digital readiness in AI-powered learning environments. Importantly, the study confirms that more than one-third of this beneficial impact is mediated by self-efficacy. The primary role of self-efficacy is that students with high confidence are more likely to use GenAI. These findings enable educators and organizations to strategically invest in fostering self-confidence and active engagement through agile pedagogy rather than passively adopting technology.

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Appendix

Cognitive Engagement adapted from (Appleton et al., 2006, Fredricks et al., 2004, & Henrie et al., 2015)	S.A	A	N	D	S.D
CE1: I use AI writing tools to comprehend academic data when I cannot understand it.					
CE2: I am more willing to revise and refine my drafts because AI tools provide constructive feedback.					
CE3: I use AI suggestions to improve the quality and coherence of my arguments.					
CE4: AI suggestions have enhanced my ability to learn new vocabulary and improve my writing style.					
Behavioral Engagement adapted from (Appleton et al., 2006, Fredricks et al., 2004, & Henrie et al., 2015)					
BE1: I am more consistent in completing my assignments on time.					
BE2: AI tools have increased my participation in class discussions by helping me prepare better.					
BE3: I feel more confident in writing exams after preparing with AI tools.					
BE4: I actively explore new features of AI tools to maximize their benefits.					
Emotional Engagement Adapted From (Fredricks et al., 2004, Zhang & Li., 2020, Henrie et al., 2015)					
BE1: I feel more motivated to write when using AI tools.					
BE2: AI tools help reduce my stress and anxiety related to academic writing tasks.					
BE3: I enjoy experimenting with different AI tools to improve my writing.					
BE4: The feedback provided by AI tools makes me feel more motivated to improve my writing.					
Self-Efficacy Adapted From (Bruning et al., 2013 & Mitchell et al., 2021)					
SE1: AI tools have improved my ability to structure my ideas and content clearly.					
SE2: I can easily identify and correct grammar and punctuation errors in my writing.					
SE3: My vocabulary has improved, and I can now express ideas more clearly.					

SE4: I am comfortable brainstorming and generating content from scratch.					
SE5: I can effectively write about topics that are unfamiliar or new to me.					
SE6: I am able to create plagiarism-free content using AI tools. (Item dropped)					
Digital Readiness Adapted From (Hong & Kim, 2018)					
DR1: Using AI writing tools has made me more proficient in using other digital applications.					
DR2: I am capable of using different features of AI writing tools.					
DR3: I can set up and change security options in a web browser.					
DR4: I am aware of how to properly protect intellectual property rights when using digital media content.					
DR5: I am capable of using fundamental functions of MS PowerPoint, Excel, and Word. (item dropped)					

Note: S.A = Strongly Agree; A = Agree; N = Neutral; D = Disagree; S.D = Strongly Disagree.