Research in Learning Technology
Vol. 34, 2026

ORIGINAL RESEARCH ARTICLE

Bridging technical and emotional skill gaps: AI-enhanced adaptive learning and emotional intelligence in project management education

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Received: 8 July 2025; Revised: 11 October 2025; Accepted: 23 January 2026; Published: 24 February 2026

This study explores how Artificial Intelligence (AI)-enhanced adaptive learning supports technical competencies and emotional intelligence (EI) development in project management education. Using a mixed-methods design, it integrates Partial Least Squares Structural Equation Modeling (PLS-SEM) with thematic analysis to examine how intelligent learning systems influence conceptual mastery, engagement, and interpersonal skills. Findings show that AI-enhanced features, such as real-time feedback, simulations, and reflective prompts, enhance understanding of project management concepts while fostering EI capacities such as empathy, collaboration, and conflict resolution. Participants emphasised the importance of prompt engineering for personalisation, alongside concerns about bias, transparency, and ethical data use. Grounded in constructivist, experiential, and connectivism theories, the study proposes an illustrative framework for adaptive systems integrating cognitive and socio-emotional learning. The findings highlight AI's potential to develop the hybrid skill sets essential for project leadership while calling for responsible, inclusive, and ethically governed implementation in higher education.

Keywords: AI-enhanced learning; adaptive learning platforms; emotional intelligence; project management education; educational technology

Introduction

Artificial Intelligence (AI) is reshaping higher education through personalised learning, adaptive feedback, and intelligent tutoring, with significant improvements projected in accessibility and data-driven instruction (Holmes et al., 2019). In project management education, AI-enhanced platforms offer new opportunities to build both technical proficiency and soft skills such as leadership and teamwork (Akavova et al., 2023).

Emotional Intelligence (EI) is equally vital for project success, supporting team cohesion, conflict resolution, and adaptability in complex environments (Clarke, 2010b; Goleman, 1995). Yet EI remains inconsistently addressed in project management curricula, often relegated to general leadership courses without structured opportunities for development (Lambrechts et al., 2013).

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Citation: Research in Learning Technology 2026, **34**: 3625 - http://dx.doi.org/10.25304/rlt.v34.3625
(page number not for citation purpose)

AI-enhanced platforms simulate real-world dynamics, offering feedback and safe spaces to practice empathy, aligning technical and interpersonal skill development with industry needs (Chetry, 2024). This study extends that potential by examining how adaptive AI instruction can bridge technical and interpersonal skill development – an underexplored dimension in project management education. While prior research has examined AI's role in enhancing cognitive outcomes, few studies explore its capacity to support affective and interpersonal learning. Using a mixed-methods approach, this research proposes an exploratory framework that integrates AI-enhanced adaptive learning with EI development.

Although situated within the Canadian higher-education context, the findings contribute to global discussions on how adaptive AI technologies can promote inclusive and emotionally responsive learning environments. The study extends models of experiential and connective learning to include affective adaptation and offers data-driven insights for designing emotionally aware AI systems in management education.

Research aim and scope

This study explores how AI-enhanced adaptive learning platforms can support the development of both technical and EI skills in project management education. It focuses on higher education contexts where personalised, inclusive instruction is increasingly prioritised. By investigating learner and educator perceptions, this research aims to generate an illustrative framework for integrating AI into curricula that prepare students for the complex interpersonal and technical demands of the profession.

Research objectives

This research investigates three key objectives:

1. Explore the role of adaptive learning platforms in personalising project management education and addressing learner skill gaps through feedback, simulations, and AI-enhanced assessments.
2. Examine the potential for AI-supported EI development by identifying key inte rpersonal competencies, such as empathy, conflict resolution, and reflective leadership, which could be practiced through intelligent simulations.
3. Provide actionable recommendations for integrating AI into higher education curricula to enhance technical mastery, EI, and workplace readiness.

Research questions

1. How do participants perceive the integration of AI-enhanced adaptive learning platforms in enhancing EI and project management skill development, specifically in aligning theoretical knowledge with real-world practice in higher education?
2. What potential benefits and challenges do stakeholders perceive in implementing AI-enhanced tools within project management curricula, and how do they believe these tools could affect students' preparedness for industry standards and evolving demands?

Significance of the study

This study contributes to both educational theory and applied practice by investigating the convergence of adaptive AI technologies and EI development. It addresses critical gaps in traditional project management education and aligns with current demands for agile, reflective, and collaborative professionals. Findings offer practical insights for curriculum designers, educators, and institutions aiming to implement inclusive, technologically enhanced teaching strategies that foster comprehensive skill development.

Literature review

AI-enhanced adaptive learning

AI continues to transform higher education through adaptive learning environments that personalise instruction based on learner behaviour and performance data (Bearman et al., 2022; (Crompton & Burke, 2023, p. 2). Most studies examine how AI-enhanced platforms improve learning efficiency and cognitive mastery by identifying learners' pace, preferences, and knowledge gaps to recommend targeted resources (Akavova et al., 2023; Holmes et al., 2019; Mampota et al., 2023). Features such as text-to-speech, transcription, and translation also enhance accessibility for students with disabilities and multilingual backgrounds (Kanont et. al., 2024; Park, 2024).

Although these studies show gains in technical skills, they often overlook emotional and interpersonal learning. The prevailing focus on measurable outcomes has framed AI primarily as a cognitive enhancer, offering limited insight into how adaptive systems might also cultivate empathy, collaboration, and reflective learning (Klímová et al., 2023, p. 1; Razia et al., 2022; Zhang, 2024, p. 3).

Emotional intelligence in project management education

In project management education, EI underpins leadership, teamwork, and communication effectiveness (Afshari & Ghamkhar, 2023; Soliman et al., 2023). However, most instructional approaches rely on self-reflection or instructor-led activities with limited technological integration. Existing research predominantly frames EI as a fixed personal attribute rather than a skill that can be intentionally cultivated through feedback-rich, adaptive environments (Boyatzis & Saatcioglu, 2008; Clarke, 2006; Clarke, 2010b). This lack of attention to technology-mediated EI development represents a significant gap in project management education research.

Theoretical foundations

This study draws on Experiential Learning Theory (Kolb, 1984), Scaffolding Theory (Vygotsky, 1978), and Connectivism (Siemens, 2005) to explain how AI can mediate cognitive and affective learning. Experiential learning emphasises cycles of action and reflection that AI can simulate through adaptive feedback and scenario-based engagement. Scaffolding theory positions AI as an intelligent support system that adjusts guidance to learner needs, fostering self-regulation and emotional awareness. Connectivism views AI as a networked node in the learning ecosystem, enabling dynamic interaction between human and technological agents.

Together, these frameworks support a holistic understanding of learning where cognitive and emotional growth occur in tandem, providing a conceptual basis for exploring AI as a facilitator of both reflection and empathy in project-based education.

Integrating AI and EI

Combining AI's data-driven adaptability with EI's interpersonal focus enables more holistic learning experiences (Verma & Bhalla, 2024; Clarke, 2010a). Adaptive platforms, equipped with sentiment analysis or artificial empathy tools, can simulate collaborative dynamics and provide real-time feedback on communication and leadership behaviours (Cui & Liu, 2022; Wang & Liu, 2023, pp. 11–12). These capabilities are especially valuable in project management education, where learners must navigate both technical decision-making and human interaction.

However, empirical evidence on this integration remains scarce. Existing work tends to prioritise system performance over affective outcomes, limiting understanding of how learners develop emotional competencies through AI-mediated environments. Ethical concerns, such as data privacy, bias, and over-reliance on automation, also require greater attention to ensure transparency and inclusivity in emotionally adaptive learning systems (Klímová et al., 2023, p. 1).

Gaps and contribution

Current literature reveals three main gaps. Firstly, the dominance of cognitive metrics has overshadowed research on affective learning and emotional development in AI-enhanced contexts. Secondly, few studies have examined these dynamics within project management education, where EI is central to leadership and collaboration. Thirdly, most empirical evidence derives from non-Canadian settings, highlighting the need for context-specific exploration that considers digital infrastructure and institutional culture. This study addresses these gaps by:

1. Investigating how AI-enhanced adaptive learning supports both cognitive and emotional development in project management education.
2. Introducing an exploratory, context-specific framework for EI development through adaptive systems in Canadian higher education.
3. Contributing to international debates on the ethical and inclusive use of AI by offering empirical insights into benefits, limitations, and implementation challenges.

By critically synthesising existing literature and articulating this multilevel contribution, the study positions AI-enhanced learning as both a cognitive and socio-emotional process.

Methodology

This study employed a mixed-methods design to examine how AI-enhanced adaptive learning supports both technical and EI development in project management education. Integrating quantitative and qualitative approaches enabled a comprehensive understanding of learner experiences while ensuring ethical compliance, methodological transparency, and reflexivity.

Quantitative strand: Survey design and analysis

The quantitative phase used an online survey to gather structured insights into participants' familiarity with AI-enhanced tools, their perceived impact on learning outcomes, and their potential for enhancing both technical and interpersonal competencies. A total of 261 responses were collected, of which 152 were complete and included in the final analysis, yielding a response rate of 58.2%.

A combination of purposive, convenience, and snowball sampling was employed to recruit participants. The survey was distributed via academic mailing lists, LinkedIn, and the Project Management Institute (PMI) network. Respondents included students and faculty from Canadian institutions involved in project management education.

Data were analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM) via SmartPLS 4.0. This method was chosen for its flexibility in modeling complex relationships among latent constructs in exploratory research. The model tested relationships between key variables, including adaptive learning features, EI development, and perceived readiness for industry. Validity and reliability thresholds were met across constructs, and all hypothesised paths were significant.

Qualitative strand: Interviews and thematic analysis

To enrich the survey findings, eight semi-structured interviews were conducted with participants across undergraduate, graduate, and instructional roles in project management education. A purposive sampling strategy ensured diversity in perspective and experience. Interviews explored reflections on adaptive learning, AI-supported feedback, and the emotional dimensions of collaborative project work.

Data collection continued until thematic saturation was reached – that is, no new insights emerged – consistent with qualitative research standards for small, homogeneous samples (Guest et al., 2020; Mason, 2010, p. 2). All interviews were transcribed and analysed using Braun and Clarke's (2006) six-phase thematic analysis, supported by NVivo 14. Codes were developed inductively and organised into five overarching themes aligned with survey findings, enabling strong methodological triangulation. This integrated design provided statistical depth and contextual richness, offering a robust foundation for analysing how AI-enhanced platforms support holistic learning outcomes in project management education.

Ethical considerations

Ethical approval was granted by the Yorkville University Research Ethics Board (Approval Code: 20250310). All participants received detailed information about the study and provided electronic informed consent prior to participation. Participation was voluntary, with the right to withdraw at any time without penalty.

Data confidentiality was strictly maintained: interview recordings were stored on encrypted devices, transcripts anonymized, and survey data secured on university servers. Only the research team had access to identifiable materials.

These procedures ensured compliance with Yorkville University's research ethics standards and adhered to the Tri-Council Policy Statement (TCPS 2) principles of respect for persons, welfare, and justice.

Results

This section presents findings from both quantitative and qualitative analyses, outlining participant demographics, PLS-SEM results, and themes from interviews. Table 1 summarises reliability and validity indicators (α, CR, AVE) for each construct. The analysis examined how AI-enhanced learning influences technical skills, EI, and perceived project readiness.

Quantitative findings

Demographic profile

A total of 152 participants completed the survey. Their demographic data are summarised in Table 2. Most participants were male (56.6%), while females comprised 43.4%. Regarding age, most participants were between 25 and 34 years old (28.9%), followed by those in the 35–44 age range (23.7%). The 18–24 age group comprised 18.4%, while 22.4% were aged 45–54, and 6.6% were 55 or older. The roles of the participants were almost evenly split between educators (46.7%) and students (53.3%). For educational backgrounds, nearly half of the participants were graduates (48%), while 32.9% had postgraduate education, and 19.1% were undergraduates. When asked about their familiarity with project management education, the majority reported being somewhat familiar (51.3%) or very familiar (44.7%), with a small percentage (3.9%) stating they were not familiar. Finally, most participants had used AI-enhanced adaptive learning platforms before (74.3%), while 25.7% had not.

Table 1. Convergent validity and reliability.

Constructs	Items	Loading	(α)	CR	AVE
AI-enhanced adaptive learning (AEAL)	AEAL1	0.715	0.862	0.871	0.508
	AEAL2	0.697			
	AEAL3	0.762			
	AEAL4	0.623			
	AEAL5	0.731			
	AEAL6	0.700			
	AEAL7	0.741			
	AEAL8	0.723			
Emotional intelligence development (EID)	EID1	0.845	0.835	0.843	0.669
	EID2	0.792			
	EID3	0.830			
	EID4	0.803			
Project Management Education Outcomes (PMEO)	PMEO1	0.824	0.778	0.781	0.692
	PMEO2	0.821			
	PMEO3	0.851			
Perceived challenges (PC)	PC1	0.906	0.943	0.959	0.814
	PC2	0.897			
	PC3	0.879			
	PC4	0.902			
	PC5	0.925			

Source: Results obtained from PLS-SEM.

Citation: Research in Learning Technology 2026, **34**: 3625 - http://dx.doi.org/10.25304/rlt.v34.3625

Table 2. Demographic profile of participants.

	Categories	*N*	*N* (%)
What is your gender?	Female	66	43.4
	Male	86	56.6
What age range do you best fall into?	18–24	28	18.4
	25–34	44	28.9
	35–44	36	23.7
	45–54	34	22.4
	55+	10	6.6
What is your role?	Educator	71	46.7
	Student	81	53.3
What is your level of education?	Graduate	73	48.0
	Postgraduate	50	32.9
	Undergraduate	29	19.1
How familiar are you with project management education?	Not familiar	6	3.9
	Somewhat familiar	78	51.3
	Very familiar	68	44.7
Have you used any AI-enhanced adaptive learning platforms before?	No	39	25.7
	Yes	113	74.3

Structural equation modeling

Structural Equation Modeling (SEM) was used to examine the relationships among adaptive learning, EI, and project management education outcomes. This method accounts for measurement error while modeling both direct and indirect effects among latent constructs (Henseler et al., 2009).

Given the non-normal distribution of the data, as indicated by descriptive statistics and confirmed through Cramer–von Mises tests, PLS-SEM was selected (Guenther et al., 2023). This variance-based approach is well-suited for exploratory studies and performs robustly with non-normal data, making it a preferred method in education, business, and social science research (Hair et al., 2022).

The structural model assessed the following hypotheses:

- **H1:** AI-enhanced adaptive learning positively influences emotional intelligence development.
- **H2:** Emotional intelligence development positively impacts project management education outcomes.
- **H3:** AI-enhanced adaptive learning has a direct positive effect on project management education outcomes.
- **H4:** Perceived challenges negatively moderate the relationships between AI-enhanced adaptive learning, EI development, and project management education outcomes.

Measurement model evaluation

The first step comprises a measurement model that analyses the observed variables' measurement properties. The measurement model is visually presented in Figure 1.

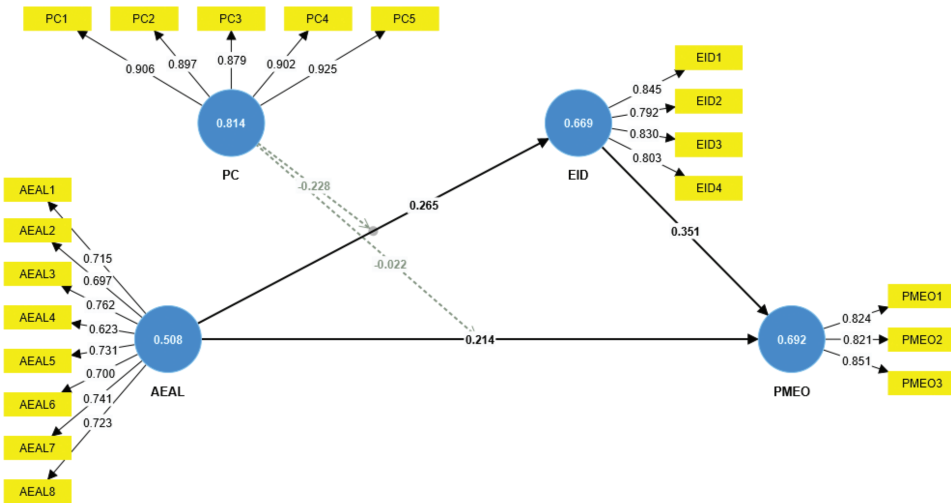

Figure 1. Measurement model.

Its quality is assessed based on reliability, convergent validity, and discriminant validity.

Reliability and convergent validity

Reliability and convergent validity were assessed through factor loadings, Cronbach's alpha (α), composite reliability (CR), and average variance extracted (AVE), following SEM guidelines (Hair et al., 2022; Henseler et al., 2009). Most items exceeded the 0.70 loading threshold; two (AEAL2, AEAL4) fell slightly below but were retained as their constructs maintained acceptable AVE values (>0.50). No items fell below the exclusion threshold of 0.40.

As shown in Table 1, all constructs met the 0.70 criteria for Cronbach's alpha and CR, confirming internal consistency. Convergent validity was further supported by AVE values exceeding 0.50 for all constructs.

Although a small number of items exhibited slightly lower factor loadings (e.g. 0.55–0.60), they were retained due to their theoretical alignment with the latent constructs of EI and adaptive learning. Following recommendations by Hair et al. (2021), items with conceptual significance and internal consistency within their dimensions were preserved to maintain construct validity rather than removed solely on statistical grounds.

Discriminant validity

Discriminant validity was assessed using the Heterotrait–Monotrait (HTMT) ratio (Henseler et al., 2015) and the Fornell-Larcker criterion (Fornell & Larcker, 1981). An HTMT value below 0.90 indicates adequate discriminant validity, while the Fornell-Larcker approach requires that the square root of each construct's AVE exceeds its correlations with other constructs. As shown in Tables 3 and 4, all HTMT values were below 0.90, and the diagonal values in Table 4 (square roots of AVE) were greater than the corresponding inter-construct correlations. These results confirm

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Table 3. **HTMT** correlations.

	AEAL	EID	PC	PMEO
AI-enhanced adaptive learning (AEAL)				
Emotional intelligence development (EID)	0.362			
Perceived challenges (PC)	0.113	0.2		
Project Management Education Outcomes (PMEO)	0.415	0.57	0.326	

Source: Results obtained from PLS-SEM.

Table 4. Fornell-Larcker Criterion.

	AEAL	EID	PC	PMEO
AI-enhanced adaptive learning (AEAL)	**0.713**			
Emotional intelligence development (EID)	0.323	**0.818**		
Perceived challenges (PC)	-0.098	-0.183	**0.902**	
Project Management Education Outcomes (PMEO)	0.351	0.465	-0.288	**0.832**

Source: Results obtained from PLS-SEM.

that the measurement model meets the criteria for discriminant validity and is suitable for structural analysis.

Structural model

To evaluate the significance of the hypothesised relationships, PLS estimation was conducted using 5000 bootstrapped samples. Figure 2 displays the model's explanatory power, with R^2 values of 0.187 for EI development and 0.301 for project management education outcomes. These values indicate that the model explains approximately 18.7% of the variance in EI development and 30.1% in education outcomes.

As detailed in Table 5, all three hypotheses were supported. Hypothesis 1, proposing that AI-enhanced adaptive learning positively influences EI development, showed a significant effect ($\beta = 0.265$, $p < 0.001$). Hypothesis 2, which tested the impact of EI development on project management outcomes, also revealed a strong, statistically significant relationship ($\beta = 0.351$, $p < 0.001$). Finally, Hypothesis 3, which examined the direct effect of AI-enhanced learning on project management outcomes, was supported as well ($\beta = 0.214$, $p = 0.003$).

Moderation analysis

The moderation analyses for Hypothesis 4 yielded mixed results, suggesting that perceived challenges may influence, but not uniformly constrain, the relationship between AI-enhanced adaptive learning, EI development, and educational outcomes. The negative moderating effect was statistically weak ($\beta = –0.228$, $p = 0.002$), yet qualitative data revealed persistent concerns about equity, ethical transparency, and digital readiness as barriers to AI integration.

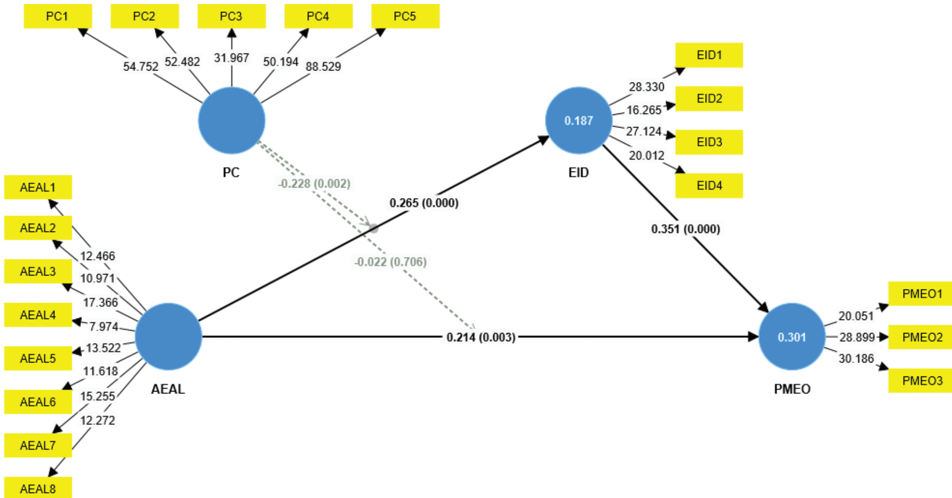

Figure 2. Structural model.

Table 5. Hypothesis testing and path coefficients.

Hypothesis	Relationships	β	*T*	*P*	Result
H1	AEAL → EID	0.265	3.762	<0.001	Supported
H2	EID → PMEO	0.351	4.088	<0.001	Supported
H3	AEAL → PMEO	0.214	2.992	0.003	Supported
H4a	AEAL x PC → EID	–0.228	3.133	0.002	Supported
H4b	AEAL x PC → PMEO	–0.022	0.377	0.706	Not supported

Source: Results obtained from PLS-SEM.

This divergence highlights the contextual and experiential nature of adopting AI tools in higher education. Rather than definitive evidence of moderation, the findings suggest a complex interplay among technological affordances, institutional readiness, and user trust (Figures 3–4), which is consistent with prior studies on socio-technical contingencies in AI adoption (Bearman et al., 2022; Holmes et al., 2019).

Qualitative analysis

To complement the survey findings, a triangulated thematic analysis was conducted using semi-structured interviews (n = 8) and open-ended survey responses (n = 152). Guided by Braun and Clarke's (2006) six-phase framework, this analysis inductively identified recurring patterns in participant experiences with AI-enhanced adaptive learning and EI development.

Reflexive journaling documented coding decisions and evolving interpretations, while peer debriefing sessions challenged initial assumptions and strengthened analytic credibility. These practices enhanced transparency and helped to mitigate potential bias arising from the researcher's dual role as educator and investigator.

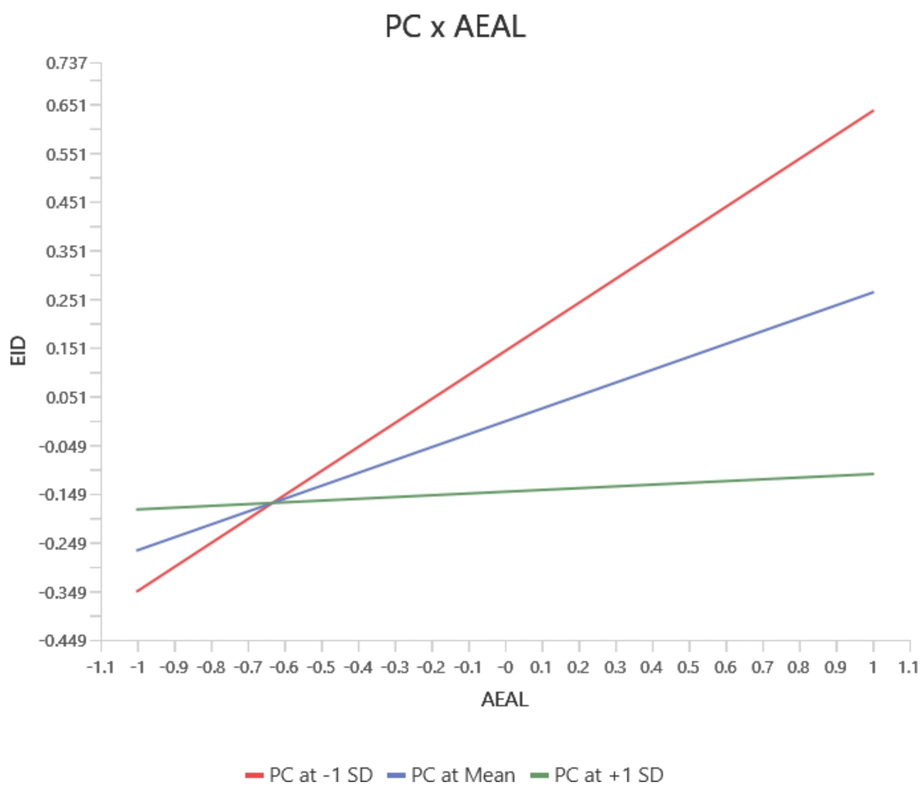

Figure 3. Interaction plot of the impact of PC x AEAL on EID.

Data analysis procedure

The qualitative strand employed Braun and Clarke's (2006) six-phase thematic analysis to explore participants' experiences with AI-enhanced adaptive learning and EI development in project management education. Open-ended survey responses and interview transcripts were transcribed, manually coded in Microsoft Word, and organised in NVivo 14.

Initial codes captured recurring ideas about personalisation, emotional engagement, and learning outcomes. These were refined into themes through iterative review for coherence and alignment with the research questions. Although a single researcher conducted the coding, reflexive memoing and multiple rounds of verification ensured analytic rigour and transparency.

Emergent themes

Five key themes were identified and are discussed next, with anonymised quotes illustrating participants' experiences.

Theme 1: AI as a cognitive scaffold for concept mastery

Participants described AI tools as cognitive supports that simplified complex content and enhanced retention. Platforms such as ChatGPT and Microsoft Copilot helped to

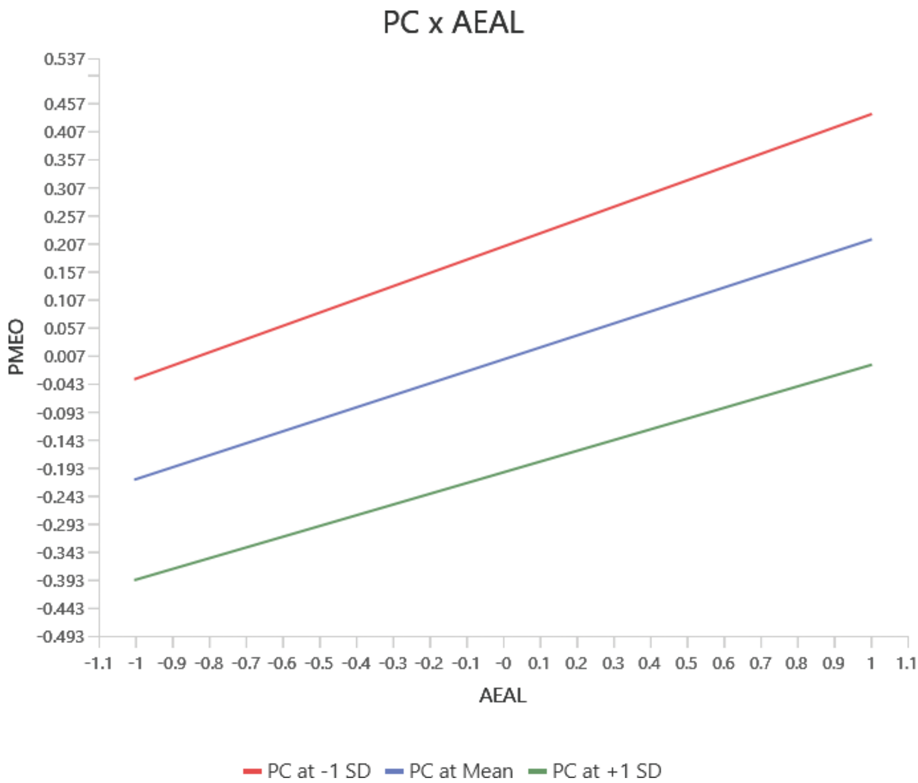

Figure 4. Interaction plot of the impact of PC x AEAL on PMEO.

break down theories, prepare for certification exams, and generate memory aids. One participant shared, 'I used AI to generate rhymes and breakdowns for Certified Associate in Project Management (CAPM®) exam prep – it made the content easier to remember'.

These accounts echoed survey responses highlighting the value of *bite-sized lessons*, *step-by-step walkthroughs*, and adaptive practice. Prior research (Holmes et al., 2019; Mampota et al., 2023) similarly emphasises microlearning and responsive pacing. AI was viewed not as a content repository but as an interactive instructional aid fostering comprehension and confidence through repetition and analogy.

Theme 2: Personalization through prompting and learner agency

Meaningful personalisation depended on user input. While adaptive tools can tailor content, their effectiveness hinges on learner engagement. As one participant observed, 'Personalization? It's about how you prompt it. If you're vague, you get vague'.

Survey data supported this, showing higher satisfaction among users employing detailed prompts. These findings align with Akavova et al. (2023) and Popenici and Kerr (2017), who argue that adaptive learning is co-constructed. This theme highlights the importance of *prompt literacy* and learner agency in realising AI's potential.

Theme 3: Simulating emotional intelligence development

Participants saw potential for AI to support EI development, particularly in team-based simulations. One suggested, 'AI should give you feedback like, your team member quit – why did that happen? That would help us learn emotional consequences'.

They valued emotionally responsive scenarios modeling conflict, empathy, and regulation. Survey results reinforced this interest, identifying scenario-based, emotionally aware feedback as desirable. These insights support Goleman's (1995) view that EI is teachable and highlight the value of low-risk, simulated environments for developing interpersonal competence in technical programs.

Theme 4: Bridging theory and practice through adaptivity

Participants often found a gap between classroom instruction and real-world project dynamics. Some criticised rigid simulations where different inputs yielded the same results: 'Even if I changed how I allocated work, the simulation result was always the same'.

They advocated for adaptive simulations that vary outcomes based on learner decisions. Supported by Holmes et al. (2019) and Chetry (2024), this theme frames AI as a *virtual apprenticeship* offering real-time, context-sensitive feedback and fostering decision-making aligned with professional practice.

Theme 5: Addressing cultural and emotional nuance in AI

Concerns were raised about AI's ability to interpret emotional and cultural nuance, especially in diverse classrooms. One participant stated, 'Facial recognition and emotion detection have systemic biases, especially for racialized folks', while another added, 'It's hard to feel AI understands cultural nuance'.

Survey data echoed these issues, calling for emotionally intelligent systems that are inclusive and responsive to multicultural dynamics. These findings reinforce (Reiss, 2021, p. 11) caution about marginalisation in emotional AI and emphasise the need for ethical, culturally adaptive design.

Summary of findings

The framework emerging from this study is presented as an illustrative and exploratory model, not a prescriptive or validated design. Table 6 integrates quantitative (SEM) and qualitative findings, while Figure 5 presents the illustrative framework demonstrating how AI-enhanced adaptive learning can foster EI through iterative cycles of reflection, feedback, and adaptive engagement. Situated within the Canadian higher-education context, the framework's primary contribution lies in conceptualising how adaptive systems mediate both cognitive and emotional learning processes. It offers a context-specific foundation for future research, inviting cross-disciplinary testing and refinement to assess its transferability and practical relevance in diverse educational environments.

Discussion

This study examined how AI-enhanced adaptive learning shapes technical and EI development in project management education. Table 6 synthesises quantitative

Table 6. Integration of quantitative and qualitative findings.

Quantitative SEM findings	Corresponding qualitative themes	Plain-language educational implications
AI-enhanced adaptive learning positively predicts EI development (H1 supported)	Learners described greater self-awareness and empathy when feedback was personalized.	Adaptive systems can be designed to prompt reflection and emotional regulation.
EI development predicts stronger project management outcomes (H2 supported)	Participants linked interpersonal awareness with better teamwork and communication.	Embedding EI feedback loops may strengthen collaboration skills.
AI-enhanced learning directly influences educational outcomes (H3 supported)	Students valued real-time feedback that improved both technical and relational competence.	Educators should integrate AI feedback that addresses cognitive and emotional goals.
Perceived challenges moderate these relationships weakly (H4 partly supported)	Interviews highlighted ethical and equity concerns about AI over-reliance.	Institutions must accompany AI adoption with digital-ethics training and support.

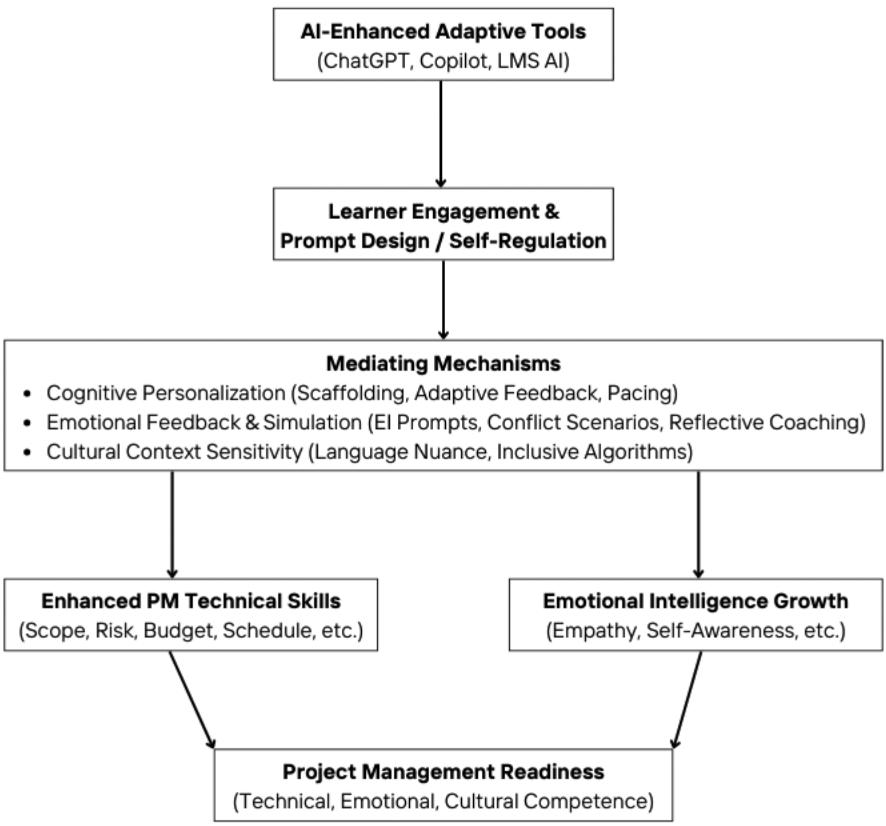

Figure 5. Illustrative framework of AI-enhanced adaptive learning for emotional intelligence and project management.

(SEM) and qualitative findings, linking statistical relationships with participants lived experiences. Collectively, the results highlight AI's pedagogical potential while highlighting contextual and ethical considerations for educators.

Interpretation of findings

Participants viewed AI as a cognitive scaffold, particularly for mastering complex, high-stakes content such as project management methodologies and certification preparation. This aligns with Holmes et al. (2019), who found that adaptive learning enhances comprehension through real-time feedback and segmented instruction. Qualitative data also suggested that AI serves not only as an information source but as a responsive, supplemental tutor.

A key nuance concerned personalisation, where effective adaptation depends as much on learner agency and prompt literacy as on system design. Participants noted that precise, iterative input was essential for meaningful, context-sensitive feedback, supporting Akavova et al. (2023), who describe adaptive learning as a co-constructed process shaped by both digital fluency and algorithmic design.

Insights on EI development, traditionally viewed as a human domain, were especially salient. While some questioned AI's ability to interpret emotions authentically, others valued simulations that model conflict, deliver emotionally responsive feedback, and prompt reflection. These environments create low-risk spaces for developing self-awareness and empathy, echoing Goleman's (1995) framework and recent work on emotionally intelligent AI agents.

Participants also emphasised the need to bridge the theory–practice gap, preferring adaptive systems that mirror real-world complexity over rigid simulations. Dynamic, decision-responsive environments translated theory into practice, aligning with Chetry's (2024) concept of AI as a virtual apprenticeship.

Finally, participants highlighted AI's limitations in recognising cultural and emotional nuance. Concerns about bias in emotion-recognition technologies prompted calls for more inclusive and culturally sensitive design practices, echoing (Reiss, 2021, p. 9) ethical cautions regarding emotionally adaptive systems in diverse educational contexts.

Thematic integration

The integration of quantitative and qualitative findings presents a coherent narrative: AI-enhanced adaptive learning supports both technical skill development and EI in project management education. PLS-SEM results confirmed relationships among adaptive learning, emotional competencies, and learning outcomes, while qualitative themes added contextual depth on personalisation and reflection. Together, the data suggest that AI can bridge cognitive and affective learning domains.

Practical and ethical implications

AI can complement traditional instruction by enhancing technical understanding and emotional maturity, provided its integration is guided by intentional design, faculty training, and ethical governance.

For educators, the findings highlight the importance of designing adaptive learning experiences that pair cognitive scaffolding with reflective prompts fostering empathy, teamwork, and self-awareness. Embedding brief emotional-reflection checkpoints within AI-supported courses can help students connect technical decision-making with interpersonal understanding.

For institutions, aligning AI adoption with professional-development initiatives is essential. Faculty training and collaboration between technology and psychology specialists will ensure responsible interpretation of emotional-learning analytics.

For policymakers and developers, transparent and inclusive AI governance remains critical. Emotional-data collection must follow informed-consent standards and privacy regulations such as PIPEDA and GDPR, while algorithms should promote fairness, accessibility, and cultural sensitivity.

Collectively, these implications position AI-enhanced adaptive learning as a complement – not a substitute – for human judgement in cultivating both technical competence and EI.

Theoretical contributions

This study advances experiential learning, scaffolding, and connectivism by showing how AI-enhanced adaptive platforms mediate both cognitive and emotional development in project management education. Drawing on Kolb's (1984) experiential model and Goleman's (1995) EI framework, the findings show that feedback-rich simulations foster reflection and experimentation, strengthening self-awareness and regulation. Extending Vygotsky's (1978) scaffolding theory, AI functions as an adaptive mediator supporting empathy and collaboration without replacing instructors. Within Connectivism (Siemens, 2005), AI acts as a co-participant in the learner's knowledge network, emphasising agency within socio-technical ecosystems. Collectively, these insights reinforce the shift towards learner-centred, ethically governed education integrating cognitive mastery with EI, offering a conceptual model for implementing adaptive AI in higher education.

Global and equity perspectives

Although grounded in the Canadian higher-education context, these findings inform global discussions on equitable and scalable AI use in learning. The study highlights the need for adaptive systems that respect cultural and linguistic diversity while ensuring access to digital infrastructure and emotional-learning support. As AI adoption expands, principles of transparency, inclusivity, and learner agency provide transferable guidance for designing adaptive platforms that balance technical competence with EI worldwide.

Limitations and interpretive boundaries

While this study offers valuable insights into how AI-enhanced adaptive learning supports EI development in project management education, several limitations and interpretive boundaries should be acknowledged. The qualitative analysis was conducted by a single coder; although reflexive journaling and peer debriefing helped mitigate bias, the absence of multiple coders limits intercoder reliability. The study's

Citation: Research in Learning Technology 2026, **34**: 3625 - http://dx.doi.org/10.25304/rlt.v34.3625

Canadian higher-education focus provides a meaningful case for examining institutional and cultural influences on AI adoption but constrains generalisability. In addition, purposive sampling via professional networking sites such as LinkedIn effectively reached participants with relevant expertise but may have introduced self-selection bias, favouring those already interested in AI and EI. Finally, the exploratory, cross-sectional design restricts causal interpretation.

Despite these constraints, the convergence of quantitative and qualitative findings provides a credible foundation for future inquiry. Cross-cultural, collaborative, and longitudinal research could further validate and extend these results, clarifying how adaptive AI systems foster EI across diverse educational settings.

Conclusion

This exploratory mixed-methods study provides initial empirical evidence linking AI-enhanced adaptive learning with EI development in project management education. Whereas prior research separated cognitive performance from socio-emotional growth, this study shows how AI-mediated feedback integrates both. By positioning AI as a cognitive and affective learning partner, it extends experiential, scaffolding, and connectivism theories to include emotional reflection and engagement in technology-supported learning.

Findings suggest that adaptive AI tools act as personalised scaffolds that strengthen conceptual mastery, foster learner agency, and build soft skills through emotionally responsive simulations. Real-time feedback and contextual adaptation bridge theoretical instruction with professional practice, preparing students for complex project environments. Though exploratory, the study highlights AI's potential to enrich learning, advance equity, and align technical education with human-centred needs.

Implications and future research

Future research should investigate how AI-enhanced learning platforms influence long-term learner development, particularly the retention and workplace transfer of EI skills. Longitudinal studies following students from education to employment could clarify the sustained impact of emotionally intelligent simulations. Comparative research across diverse cultural and institutional contexts is also needed to evaluate AI's effectiveness in multilingual, multicultural environments and to examine faculty perceptions and institutional readiness.

Ethical issues – data privacy, algorithmic transparency, and emotional manipulation – require continuous scrutiny. As AI evolves, interdisciplinary collaboration will be essential to ensure that adaptive learning systems remain effective, ethical, inclusive, and human-centered.

Key takeaways

- AI tools can be designed not only to personalise technical learning but also to support empathy, collaboration, and reflection.
- Educators can use adaptive feedback loops to help students link analytical decisions with emotional awareness.

- Institutions should adopt clear ethical and privacy safeguards when using emotional-data analytics.
- Although based in Canada, these findings offer insights relevant to any higher-education system implementing AI-supported project-management training.

Ethical approval

Ethical approval for this study was granted by the Yorkville University Research Ethics Board (Approval Code: 20250310). All participants provided informed consent prior to participation.

Conflict of interest

The authors declare no conflict of interest. Although one author is a co-founder of Karma Coaching Insights LLP, the organisation had no role in the study design, data collection, analysis, interpretation of results, or manuscript decisions. All research activities and ethical oversight were conducted through Yorkville University.

Funding

This research was supported by the Support for Scholarly Activity Fund (SSAF) at Yorkville University**.**

Acknowledgements

The authors thank the study participants for their time and insights, which made this research possible.

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