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Harnessing AI in education for sustainable development: The interplay of AI-supported blended learning, student self-regulation, and cognitive load

Nessrin Shaya [A]
Rawan Abukhait [B]
Muhammad Nisar Khattak [C]
Cheng Cheng [D]

[A] *Education Department, Ajman University, United Arab Emirates*
[B] *College of Business, Ajman University, United Arab Emirates*
[C] *College of Business, Ajman University, United Arab Emirates*
[D] *Business School, King's College London, United Kingdom*

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Correspondence

Cheng.3.cheng@kcl.ac.uk [D]

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Abstract

Although blended learning (BL) represents a transformative educational model, it is unclear how digital transformation (DT) shapes the dynamics of BL, particularly through the integration of artificial intelligence (AI), in higher education. This study examines how artificial intelligence–supported self-regulated learning (AI-SRL), informed by cognitive load theory and AI-driven pedagogy, can enhance BL models to promote equitable, inclusive education and advance sustainable development within the context of ongoing DT. Three hundred and ten higher-education students in the United Arab Emirates (UAE) who participated in BL courses completed an online survey. In addition, 11 faculty members and academic leaders were interviewed. The findings show that the use of AI mediates the relationship between DT and students' behavioural and academic outcomes – namely, procrastination, heuristic processing, and academic achievement. DT increases the adoption of AI to improve academic performance while simultaneously increasing procrastination and reliance on heuristic (surface-level) processing. AI-SRL mitigates these negative outcomes, reducing procrastination and heuristic processing. Furthermore, AI-integrated pedagogy empowers students to harness the benefits of AI-enhanced DT to improve academic performance while minimising adverse cognitive and behavioural effects. This study provides a nuanced understanding of BL in higher education, showing that the use of AI helps shape student experiences and outcomes.

Introduction

According to the United Nations Sustainable Development Goals (SDGs), all learners should be equipped with the skills, competencies, and knowledge to support sustainable development (United Nations, 2023). Specifically, education should promote sustainable lifestyles, respect for human rights, peace, gender equality, global citizenship, non-violence, and the appreciation of cultural diversity (United Nations Educational, Scientific and Cultural Organization [UNESCO], 2023). This endeavour requires the use of various forms of technology, including artificial intelligence (AI), which offers data-driven solutions that may help to reduce poverty, to take appropriate climate-related action, and to manage resources sustainably (Vinuesa et al., 2020). However, the advantages of using AI must be considered alongside issues including algorithmic bias, digital inequality, and the environmental footprint of AI tools (Yarlaggada, 2025). Hence, there is a need for appropriate policies that govern the use of AI to ensure it contributes responsibly to sustainability goals. Education serves as a key pillar in this context: education systems must be inclusive, accessible, and participatory to empower individuals to act as global citizens and to contribute to sustainable development (Shaya et al., 2025). Moreover, ethnic diversity and systemic inequality at the policy, institutional, and individual levels have a great influence on the educational experiences of minority populations (Fleming, 2019). Hence, educational approaches must ensure that students achieve academic success while retaining the desire to continue learning throughout their lives, with a focus on equity, social justice, and intercultural awareness.

In this context, blended learning (BL) offers a flexible, inclusive, and resource-efficient approach to education. It combines face-to-face and online modes of learning, reducing the need for physical infrastructure and travel, thereby lowering carbon emissions and operational costs (Means et al., 2013). However, constant and persistent inequalities have been exposed following the digital transformation, presented in the form of a multifaceted digital divide with unequal access to digital technologies, tools, devices, internet connectivity and digital literacy that can halt the effectiveness of blended learning for many populations (World Bank, 2021). Additionally, the rapid, often forced adoption of technology may overwhelm educators and institutions, who are either underprepared, already experiencing burnout or undertrained (UNESCO Global Education Monitoring report, 2023).

Although the BL approach is not new to universities in the UAE, it was adopted relatively late. The COVID-19 pandemic served as a catalyst for this adoption, as institutions were compelled to transition quickly to fully online instruction. Since the end of the pandemic, there has been substantial heterogeneity in BL in universities across the UAE. While some have completely eliminated BL in favour of on-campus education, others have retained BL for selected courses, and a few have transitioned back to face-to-face delivery but later reintroduced BL for specific courses or programmes (Shaya et al., 2025). Notably, even before the COVID-19 pandemic, the BL initiative led by the Center for Excellence in Teaching and Learning during the 2016–2017 academic year signalled that public universities in the UAE were active in formalising BL. Since then, several courses have been systematically designed, reviewed, and granted official approval for delivery using the BL model in the UAE (Al-Mekhlafi et al., 2025). The approach combines the intentional use of face-to-face instruction and technology-mediated learning activities that enhance flexibility, learner autonomy, and active engagement (Garrison & Vaughan, 2008; Graham, 2013). It has been developed within a structured regulatory and quality assurance environment shaped by the UAE Ministry of Education. The inspection frameworks distinguish between face-to-face, online, and BL modes and require institutions to establish approved policies for each. At present, the national framework does not set a minimum requirement for BL. Nevertheless, many institutional policies consider 25% online delivery as the minimum threshold for classifying a course as blended. Specific programme design guided by accreditation and quality standards. Over the past decade, universities have increasingly experimented with different blended configurations.

How AI is integrated into BL courses in UAE higher education

As institutions in the UAE aim at offering high-quality education at reduced costs within an equitable and inclusive approach, reconsidering the common education strategies has become a must (Ayob et al., 2022). At the same time, an increased demand for technologically competent employees by current and future job markets, coupled with nationwide implementation of AI curriculum across all government schools since 2025, covering topics like algorithms, data and ethics (EPC, 2025), shows that AI integration into Blended Learning meets the national priorities for digital transformation (DT) and allows delivering education in an inclusive and innovative way. The report indicates that about 94% of UAE students use AI tools and technologies in their studies (Sircar, 2025). Currently, AI is incorporated to complement teaching rather than as a replacement for instruction. Consistent with international guidance, this integration mainly involves generative and analytics-driven AI tools that can provide adaptive feedback and assist students with academic writing, research skill development, and learning analytics (OECD, 2025; UNESCO, 2023). During the online phases of BL courses, students often use AI-enabled platforms to s-

-ummarise readings, to generate study guides, to brainstorm ideas, and to receive formative feedback on drafts; at the same time, they must verify the AI-generated content and reflect on how the use of AI has affected their learning (EDUCAUSE, 2023; UNESCO, 2023). These practices are particularly salient in the BL context, which requires students to study independently and to regulate their learning across modalities. According to empirical research from the UAE, students primarily use AI to improve their comprehension, efficiency, reflective learning, research and time management (Khadragy et al., 2024). This is especially important in BL courses that involve synchronous learning, where students are required to demonstrate greater autonomy in their learning. Instructors also use AI tools to assess how students are engaging with the material, allowing them to identify learning gaps and to provide timely and individualised feedback. This information also allows courses to be redesigned, a process that often involves multiple stages and discussions (OECD, 2025). Importantly, faculty members in the UAE are quite cautious and ethical in their adoption of AI, especially when they use it to evaluate student work (Khadragy et al., 2024), which is in line with international literature (Mah & Grob, 2024). The goal is to maintain complete transparency and academic integrity. Hence, AI detection systems are currently used for Arabic content, separately from English-content platforms, which have not proved to be meaningful.

UAE universities have implemented strong digital infrastructure and institutional policies, ensuring that students and teachers are aware of the specific guidelines for artificial intelligence usage (AIU). Consistent with international recommendations, universities increasingly adopt artificial intelligence–integrated pedagogy (AIP), allowing AIU based on clearly defined boundaries rather than its prohibition (OECD, 2025; UNESCO, 2023). In addition, many UAE universities offer professional development initiatives, including AI-focused teacher incubator programmes, to ensure that AI is integrated in an appropriate manner (Al-Mekhalifi et al., 2025). This allows AI to be integrated into BL courses in a personalised way that facilitates self-regulated learning (SRL) while ensuring the face-to-face sessions remain the central component of the courses. Learners differ in the way they apply self-regulated learning strategies, through setting goals and objectives, planning and engaging in appropriate strategies to achieve these objectives, such as effective management of time and resources (Broadbent et al., 2022). They undergo critical reflection to monitor and adjust these strategies towards achieving objectives, persist in facing challenges and apply help-seeking behaviours. Students frequently use generative AI platforms such as ChatGPT to generate ideas, to clarify concepts, and to draft assignments. Furthermore, Studiosity is an AI-supported feedback tool that assists students with writing and problem-solving tasks (Studiosity, 2024). NotebookLM helps faculty and students to synthesise course materials and support inquiry-based learning (NYUAD, n.d.). Nearpod and Padlet facilitate interactive activities and formative assessment across the online and face-to-face components of BL courses. Taken together, UAE universities have implemented AI tools to enhance learning while maintaining the central role of the instructor.

Knowledge gap

The use of AI in education has been widely explored, particularly regarding how it can help tutor students, provide predictive analytics, assess assignments, and make learning platforms more adaptive. However, the majority of this research has focused only on fully online environments or has been conducted in controlled experiments, not BL courses (Crompton & Burke, 2023; Zawacki-Richter et al., 2019; Wu et al., 2025). Moreover, this research has mostly been performed in the context of Western or East Asian higher education systems. UAE universities represent one of the world's most aggressive adopters of AI-driven educational technologies under national DT strategies. The UAE has a unique socio-institutional context with strong state-led digital policies, a multicultural student population, and hybrid instructional models; hence, AI adoption and outcomes may be quite different compared to the previously studied environments. Consequently, these published findings cannot be generalised to the UAE.

Methodologically, much of the existing research has relied on short-term experimental interventions, self-reported perceptions of the usefulness of AI, or single-variable outcome measures such as satisfaction or achievement. There is a lack of integrative models that simultaneously examine institutional DT, actual AIU behaviours, pedagogical design, and student cognitive–behavioural outcomes within a unified structural framework. Moreover, prior work has rarely incorporated moderated-mediation approaches to explain *how* and *under what conditions* AI influences learning outcomes, so it is difficult to understand the mechanisms through which AI exerts beneficial or detrimental effects in BL. From a practical perspective, researchers have tended to frame AI as a technological tool rather than as a pedagogically embedded system. It is unclear how AIP and artificial intelligence–supported self-regulated learning (AI-SRL) shape the consequences of AIU (Faza & Lestari, 2025). There is equivocal evidence regarding the outcomes of AI tools: although it has led to performance gains (Chen et al., 2022; Ifenthaler & Schumacher, 2023), it is possible that excessive exposure to digital technologies in blended and online contexts can lead to poor engagement with the material, overreliance and procrastination (Agrawal & Krishna, 2024; Broadbent & Lodge, 2021; Broadbent et al., 2022; Tomasik et al., 2020). The lack of research describing how the adoption of AI tools connects to self-regulation and instructional design (Wu et al., 2025) makes it difficult to implement AI responsibly in BL. The present study addresses these contextual, methodological, and practical gaps by examining how institutional DL translates into AIU in BL within the UAE, and how this usage influences procrastination, heuristic processing, and academic performance. Importantly, this study introduces AI-SRL and AIP as moderating mechanisms. Specifically, this study addresses four research questions: (1) what is the effect of institutional DT on the adoption and extent of AIU in BL contexts? (2) How does the use of AI influence students' tendencies towards procrastination, heuristic processing, and academic performance? (3) What are the underlying mechanisms through which AIU mediates the DT–student learning outcomes nexus in BL environments? (4) To what extent do AI-SRL and AIP moderate the DT and learning outcomes nexus?

Heuristic processing refers to a mode of cognitive processing characterised by fast, intuitive, and effort-minimising judgments that rely on mental shortcuts rather than systematic analysis (Evans & Stanovich, 2013; Kahneman, 2011). Academic procrastination is defined as the voluntary delay of intended academic tasks despite expecting negative consequences (Klingsieck, 2013; Steel, 2007). AIP describe instructional approaches that intentionally integrate AI to support learning processes, such as scaffolding, feedback, personalisation, and metacognitive regulation, rather than merely automating content delivery or assessment (Holmes et al., 2019; UNESCO, 2021). AI-SRL refers to the ability of learners to plan, monitor, and evaluate their learning processes while strategically employing AI tools as cognitive, metacognitive, and motivational supports (Azevedo et al., 2017; Holmes et al., 2019; Faza & Lestari, 2025; Zimmerman, 2011). To be effective, AI-SRL must emphasise intentional, ethical, and reflective use of AI so that it improves the self-regulatory capacities of learners without leading to dependence on AI or passive heuristic processing (Faza & Lestari, 2025). Students are increasingly using ChatGPT, Grammarly, Quizlet, and other AI-enhanced learning management systems as part of their SRL, namely goal setting, strategic planning, monitoring of understanding, feedback-based revision, and reflective learning. In addition, Studiosity provides on-demand, AI-mediated feedback to support performance monitoring, strategic revision, and reflective learning for writing and problem-solving tasks. Academic performance is commonly operationalised as students' achievement in assessed tasks designed to measure learning outcomes within a course (Yorke, 2003). It is especially important to examine heuristic processing, procrastination, academic performance, and AIP within BL contexts because the BL approach fundamentally reshapes how students engage cognitively, temporally, and pedagogically with learning tasks. Compared to courses that only involve face-to-face sessions, BL requires learners to take greater responsibility regarding self-regulation and time management (Broadbent & Poon, 2015; Zimmerman, 2011). Thus, there is an increased likelihood of heuristic processing: students may come to depend on AI-generated cues and shortcuts to reduce cognitive effort, favouring fast, intuitive decision-making over deeper analytic processing (Evans & Stanovich, 2013; Kahneman, 2011). Moreover, the greater flexibility associated with BL may promote procrastination, especially when students believe they can rely on AI tools to complete their assignments effectively (Klingsieck, 2013; Steel, 2007). These dynamics can affect academic performance: unregulated technology use can undermine the quality of learning, while well-scaffolded digital support can enhance outcomes (Broadbent & Poon, 2015; Credé et al., 2015). Therefore, it is necessary to investigate these constructs together to uncover the mechanisms through which AI influences learning in blended environments. This information can also help develop AIP that intentionally promotes metacognitive awareness, sustained engagement, and responsible AIU rather than surface-level performance gains (Holmes et al., 2019; UNESCO, 2020).

Theoretical and conceptual framework

This paper argues that BL supported by AI tools is instrumental in advancing sustainable development through equitable and inclusive education. However, there are concerns about the effectiveness of such approaches, especially regarding potential negative impacts on student outcomes. In response, this study argues that AI-SRL combined with AIP can mitigate these challenges. Two lenses can help understand how students engage with AI: SR-

-L and cognitive load theory.

SRL is conceptualised as a motivational and metacognitive force that drives learners to actively engage in specific learning activities. It is increasingly recognised as a foundational competence for lifelong learning in higher education (Roth et al., 2013). Zimmerman's (2011) SRL cyclical model includes three main phases – forethought, performance, and self-reflection – that drive the goal setting, progress tracking, and adaptive behavioural strategies of learners. There is a strong link between SRL and academic success (Sitzmann & Ely, 2011), particularly for learners who are capable of navigating challenges independently and adapting to diverse learning environments (Peverly et al., 2003). The introduction of generative AI is a critical inflection point within this context: although it can optimise SRL through real-time, individualised feedback and support, learners may become disengaged when they begin to rely passively on the technology. Most prior SRL-focused educational research has explored how learners develop and apply SRL strategies within traditional or digitally mediated environments. This study expands the theoretical scope of SRL by examining its evolution in AI-enhanced learning contexts. Specifically, it focuses on AI-SRL, a form of SRL that is supported, scaffolded, and potentially transformed by generative AI technologies such as ChatGPT. Generative AI tools provide an immediate, adaptive, and individualised environment that may stimulate learners' SRL more effectively than conventional educational technologies. Hence, AI-SRL has the potential to significantly enhance student engagement, support deeper learning, and mitigate some of the unintended consequences as a result of AI's extensive use. Despite its potential, there has been limited insight into how AI-SRL influences the interaction between AIU and student learning outcomes. There is a notable gap in explaining how AIU mediates the effects of institutional DT initiatives on student behaviours such as procrastination, heuristic processing, and academic achievement.

Cognitive load theory (CLT) (Sweller, 1994, 2019) represents another valuable lens to interpret how the interactions between AI usage, AIP, and AI-SRL affect student outcomes. CLT posits that learning is restricted by the limited capacity of the working memory, so instructional design is critical in the process of knowledge construction (Sweller, 1988; Sweller et al., 2011). Hence, accumulated knowledge in the long-term memory presents as a critical factor that can explain differences between learners, hence confirming the importance of crafting learning experiences (Sweller, 2019), particularly in BL where extraneous cognitive load magnifies and the need for self-regulation is far more pronounced. Within this context, AI-supported learning tools can either augment or impede cognitive processing, depending on how the learning experience is designed and pedagogically integrated. By shaping the balance between intrinsic, extraneous, and germane cognitive loads, these elements determine whether AI operates as a cognitive scaffold or a burden. As such, instructional design should focus on reducing unnecessary mental efforts such as distractions or poorly designed materials, while optimising mental efforts dedicated to processing, constructing and integrating new information into existing knowledge, thereby improving retention of information (Chen et al., 2020; Sweller, 2019). Furthermore, there has been limited research on the role of AIP. The literature tends to identify AI primarily as a technological tool, but it fails to discuss the pedagogical frameworks that are necessary to integrate AI effectively into BL. There is a need to examine how AIP can shape the relationship between DT and AI adoption and, more importantly, how AIP influences the indirect effects of DT on student outcomes via AIU. The present study bridges these gaps by exploring the causal, mediating, moderating, and moderated-mediation relationships between DT, AIU, AIP, and AI-SRL in shaping student learning outcomes.

Literature review

Scholars have recently started to focus on AI in BL settings rather than online-only learning environments. Chen et al. (2020) report that blended science, technology, engineering, and mathematics (STEM) courses with AI-driven adaptive feedback systems, which guide students through independent study, improve student performance considerably. Similarly, Ifenthaler and Schumacher (2023) find that in BL at the university level, an AI-driven learning analytics dashboard is more effective than when teacher feedback is provided during face-to-face classes. On the other hand, Park and Doo (2024) ascertain that while AI may contribute positively to students' learning outcomes in blended contexts, its effectiveness largely depends on pedagogical integration. The present study represents a timely attempt to show that the pedagogical framework and students' self-regulatory behaviours are the main components that underscore the impact of AI in BL courses.

DT and AIU

DT in education refers to the systematic adoption of digital infrastructures, governance frameworks, and institutional strategies that enable technology-driven teaching and learning practices (U.S. Department of Education, 2023). A key outcome of DT is the capacity to adopt and scale AI applications in BL environments. Investment in data platforms, interoperable learning management systems, and digital governance allows institutions to better integrate AI tools, such as adaptive learning systems, computer-based automated assessments, and learning analytics dashboards, into routine educational practice (Almahdi et al., 2024; Del Vecchio et al., 2023; Yarlaggada, 2025). Thus, DT precedes and also facilitates AI adoption by creating the infrastructure, policies, and culture necessary for widespread and sustainable AIU. Institutions that incorporate DT initiatives report higher levels of AI adoption and broader AIU across courses compared to those with fragmented or legacy systems (OECD, 2025; Tran & Pavelková, 2024). As such, DT enhances the readiness of an institution to adopt AI, while AIU reinforces DT by reshaping pedagogical models and student engagement. Importantly, the DT–AI relationship is technological and pedagogical, and thus requires leadership, training, and integration into teaching and learning processes to yield meaningful student outcomes (Akter et al., 2024). The UAE government has promoted digitalisation strategies to accelerate DT in higher education institutions. For example, the UAE National AI Strategy 2031 emphasises upgrading digital infrastructure and fostering AI readiness in universities (Wirtschafter, 2024). As such, UAE universities are at the forefront of AI adoption. Based on empirical evidence, UAE students report high engagement with AI tools in BL and online learning; moreover, institutional digital strategies and faculty readiness significantly influence the extent of AI integration (Al-Mashaqbeh et al., 2025; Sayed et al., 2025). Therefore, this study proposes the following hypothesis:

H1. DT has a significant positive effect on AIU.

AIU and student learning outcomes

BL environments are increasingly shaped by AI, which personalises learning, provides adaptive support, and enhances student engagement and performance (Zawacki-Richter et al., 2019). Intelligent tutoring systems, virtual assistants, and automated grading tools provide timely feedback, enabling self-directed learning and improving academic outcomes (Chen et al., 2020; Hwang et al., 2020). In the UAE, which has undergone a DT, continuous AI-driven feedback is central to sustaining student motivation and academic success (UAE Ministry of Education, 2022). However, these benefits depend strongly on digital literacy, infrastructure availability, and effective pedagogy (Al-Emran et al., 2023a, 2023b; Sun et al., 2021a). The impact of AI on BL has shown mixed and inconsistent results. While a few studies in the past have shown that BL is significantly associated with better learning outcomes in STEM disciplines compared to non-STEM disciplines (Voogt et al., 2018), Wu et al.'s (2025) metanalysis results depicted a medium effect of AI on BL achievement in general, that is most pronounced at the higher education level, and the least was in primary. Moreover, there are several challenges. A major barrier in AI-supported BL is procrastination. Although certain tools such as automated reminders and personalised content delivery can mitigate procrastination, when they are overused, they may also foster dependence and reduce intrinsic motivation (Broadbent & Lodge, 2021; Tomasik et al., 2020). For example, students may passively rely on AI-generated video summaries or predictive text. When used, learners may consider themselves productive, but they do not actually engage deeply with the material (Schunk & Greene, 2022). AI tools also influence how students process information. While AI simplifies tasks through curated content, chatbots, and predictive analytics, it often encourages heuristic processing – that is, quick decision-making based on accessible cues rather than deep cognitive analysis (Bedenlier et al., 2020a; Bond et al., 2021a). This can increase efficiency, but excessive reliance on these heuristic shortcuts may weaken the evaluative and critical reasoning skills of students. Thus, it is crucial to consider the double-edged sword of AI – it can promote efficiency while potentially limiting systematic processing – when designing effective AI-supported BL systems. Nevertheless, the capacity of AI tools to provide tailored learning pathways, immediate feedback, and adaptive interventions are important components for improving academic outcomes. When integrated into structured BL systems, these technologies enhance knowledge acquisition, comprehension, and application (Chen et al., 2020 Ifenthaler & Schumacher, 2023). However, their effectiveness is moderated by factors such as students' digital competence, equity of access, and the quality of AIP (Schmid et al., 2021). Accordingly, this study proposes the following hypotheses:

H2. AIU has a significant positive effect on procrastination.

H3. AIU has a significant positive effect on heuristic processing.

H4. AIU has a significant positive effect on academic performance.

Mediating role of AIU

As mentioned, AIU plays a crucial mediating role in linking institutional DT with student outcomes in BL. Specifically, DT establishes the necessary technological infrastructure and culture, while AIU translates these capabilities into direct student experiences. For example, DT initiatives in higher education often result in the adoption of AI-based learning analytics, tutoring systems, and adaptive platforms that shape learner behaviour and performance (Ifenthaler & Schumacher, 2023; Zhao et al., 2023). AI tools can mediate the influence of DT on procrastination by providing reminders, progress trackers, and personalised nudges that either reduce or, in cases of overreliance, exacerbate procrastination tendencies (Broadbent & Lodge, 2021; Henderikx et al., 2019). Similarly, AIU mediates the DT–heuristic processing link, as AI technologies streamline decision-making and information processing by presenting curated content, predictive suggestions, and simplified feedback, which can promote reliance on heuristic strategies over deeper cognitive engagement (Bedenlier et al., 2020b; Bond et al., 2021b). Furthermore, AIU enhances the relationship between DT and academic performance. When higher education institutions implement DT policies, the integration of AI tools such as adaptive learning platforms, automated feedback systems, and intelligent tutoring transforms institutional capacity into measurable student learning gains (Chen et al., 2020; Sun et al., 2021b). Thus, AI usage serves as a key mechanism that operationalises DT into improved academic outcomes by addressing learning gaps, providing continuous feedback, and personalising learning trajectories.

Accordingly, this study proposes the following mediation hypotheses:

H5. AIU mediates the positive relationship between DT and procrastination.

H6. AIU mediates the positive relationship between DT and heuristic processing.

H7. AIU mediates the positive relationship between DT and academic performance.

Moderating role of AIP and AI-SRL

Pedagogical design plays a critical role in determining the success of AI integration (Voogt et al., 2018). The effective integration of AI into the learning strategies empowers students to use AI tools actively as part of the learning process (Yarlaggada, 2025). AI-SRL improves academic outcomes by helping learners set goals, manage their time, and assess their progress independently (Schunk & Greene, 2022). This is facilitated by dashboards and feedback systems, which reinforce autonomy and reduce reliance on teacher-driven support. These tools can buffer the negative effects of procrastination and shallow processing (Zimmerman & Schunk, 2021). As the UAE and other regions invest in DT, AI is progressively influencing procrastination and heuristic processing. This study addresses a balanced educational approach which aims to align AI usage with pedagogical strategies and SRL practices to enhance academic outcomes. Accordingly, this study proposes the following hypotheses:

H8. AIP moderates the positive relationship between DT and AIU so that the relationship is stronger at a higher level of AIP.

H9. AI-SRL moderates the positive relationship between AIU and procrastination so that the relationship is stronger at a lower level of AI-SRL.

H10. AI-SRL moderates the positive relationship between AIU and heuristic processing so that the relationship is stronger at a lower level of AI-SRL.

H11. AI-SRL moderates the positive relationship between AIU and academic performance so that the relationship is stronger at a higher level of AI-SRL.

H12. AIP moderates the positive indirect relationship between DT and procrastination through AIU so that the indirect relationship is stronger at a lower level of AIP.

H13. AIP moderates the positive indirect relationship between DT and heuristic processing through AIU so that the indirect relationship is stronger at a lower level of AIP.

H14. AIP moderates the positive indirect relationship between DT and academic performance through AIU so that the indirect relationship is stronger at a higher level of AIP.

Methodology

This study adopted a mixed-methods research design, beginning with a quantitative phase (Study I) followed by a qualitative phase (Study II). This approach provided a comprehensive understanding of how DT and AIU affect student outcomes while examining how AI-integrated teaching practices and AI-SRL influence these effects. The quantitative phase employed a cross-sectional survey to examine the measurement model. Building on these findings, the qualitative phase involved thematic analysis of semi-structured interviews to further explore the AIP implemented in the selected BL courses. The IRB Research Ethics Committee provided ethical approval for the study. The sample included three universities in three emirates of the UAE (coded as University A, University B, and University C), which offer BL courses. The participating universities are recognised for their strong technological infrastructure, thereby supporting AI adoption by both faculty members and students. There are numerous professional development initiatives offered to strengthen AI integration in teaching and learning, so generative AI tools, among others, are widely used by students, faculty members, and administrative staff. Beyond teaching and learning, generative AI has helped transform academic research in these institutions, making the process quicker and fostering interdisciplinary collaboration.

Study I (Quantitative)

The sample included undergraduate and postgraduate students, primarily drawn from courses in the humanities and social sciences, with a particular focus on education, social studies, and social interdisciplinary courses. At University A, participants were recruited from a postgraduate course offered by the College of Education, following a BL model consisting of approximately 70% online and 30% face-to-face instruction. At University B, the sample included students enrolled in an undergraduate general social studies course offered in multiple sections, which is an obligatory requirement for students across all disciplines, as well as a postgraduate education course, both offered within the College of Humanities and Social Sciences. These BL courses comprised approximately 80% online and 20% face-to-face learning. At University C, participants were drawn from undergraduate social interdisciplinary core courses, offered in multiple sections, and undergraduate education core courses. These BL courses included an online component (40%–60%) complemented by face-to-face instruction. A purposive sampling approach was employed to recruit a targeted population, namely students enrolled in BL courses within humanities and social sciences. Given the need to meet this predetermined criterion, purposive sampling was deemed an appropriate and feasible method for data collection (Etikan et al., 2016). Participation was entirely voluntary, and informed consent was obtained prior to data collection. The survey was developed with Google Forms and distributed via a secure online link during the Spring 2024–2025 semester. In total, there were 310 completed responses. The study variables were measured by adapting items from established and validated instruments, using a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*) (Creswell, 2009; Gay et al., 2012). AIP was assessed using four items adapted from Selwyn (2019), including “My teachers integrate AI tools into the curriculum effectively” and “The combination of AI tools and traditional teaching enhances my learning experience”. DT in higher education was measured with three items adapted from Alshammari and Alshammari (2024), including “My institution provides adequate AI resources and infrastructure” and “There are sufficient AI training programs for students and teachers”. Heuristic processing was examined through five statements adapted from the Heuristic Processing Systematic Model (HSM) scale (Yang, 2017; Bohner et al., 1995), with sample items such as “I often rely o-

-n quick impressions when making decisions" and "I don't need to think deeply if the source is trustworthy." The items were contextualised to reflect heuristic tendencies in academic and AI-mediated learning contexts academic learning environments. Academic performance was measured through three items adapted from Pintrich and De Groot (1990), with items like "My academic performance has improved since I started using AI-based learning tools, in my blended courses", "AI tools enhance my ability to retain and apply knowledge, in my blended courses". AIU was assessed with five items adopted from the unified theory of acceptance and use of technology (UTAUT) model, including "I frequently use AI for academic/work purposes" and "I rely on AI-based tools for research and problem-solving" (Rahim et al., 2022; Venkatesh et al., 2012). Procrastination was measured using five items adapted from Steel (2007),such as "I delay my studies because AI tools provide quick answers" and "AI-based auto-completion tools make me less likely to think critically." Finally, AI-SRL was measured using four items adapted from Azevedo et al. (2020) and Zimmerman and Schunk (2021), with items including "I use AI-based tools (e.g., chatbots, recommendation systems) to organize my study schedule" and "I rely on AI-generated feedback to improve my learning". As shown in Table 1, the sample is largely composed of students aged 17–24 years (87.4%) and is predominantly female (82.3%). Most participants are undergraduate students (90.3%) and single (89.7%). The majority report an intermediate level of AI proficiency (71.9%), just over a quarter identify as beginners (26.1%), and only a small proportion consider themselves advanced users (1.9%).

Table 1. The Demographic Characteristics of the Participants

Demographic	Frequency (F)	Per cent
Gender		
Male	55	17.7
Female	255	82.3
Age		
17–24 years	271	87.4
25–35 years	27	8.7
35+ years	12	3.9
Study level		
Undergraduate student (Bachelor's)	280	90.3
Master's degree/post-graduate diploma programme	30	9.7
Marital status		
Single	278	89.7
Married	32	10.3
Artificial intelligence competency		
Beginner	81	26.1
Intermediate	223	71.9
Advanced	6	1.9

Note. *N = 310.*

Study II (Qualitative)

Study II aimed to explore the nature of AI pedagogy adopted and implement by faculty members in the selected BL courses. This phase involved conducting qualitative interviews with a mix of faculty and academic staff members holding either junior or senior administrative roles in the courses and/or programmes addressed in Study I. The faculty members were either directly involved in the planning, delivery, and student assessments within the BL courses, or had a substantial role in the course design, delivery, assessment, and coordination of the teaching process within courses offered across several sections. The interviews were conducted using a combination of face-to-face and videoconferencing modes, with each interview lasting approximately 20–30 minutes. Formal consent for participation was obtained via e-mail. A total of 11 interviewees participated in the study, of whom three hold the role of head of department, director and program coordinator, three serve as course coordinators, and five are teaching faculty members. The ranks include instructors with master's degrees (n = 3), assistant professors (n = 6), and associate professors (n = 2). Their teaching experience varies: two interviewees have 2–6 years of experience, two have 10-11 years of experience, and the remainder have more than 20 years of experience in teaching. The majority of the interviewees (n = 9) have a degree in education, while the others have a degree in psychology (n = 1) or social studies (n = 1). The interview questions were of the semi-structured type, focusing on the modality of blended learning courses under study, the nature of AI-pedagogies adopted, and the AI apps and tools assigned for students to use.

Quantitative findings

SPSS version 26 was used to calculate correlation coefficients between the study variables and to develop the descriptive analysis of the participants' demographic characteristics. SMART-PLS4 was used to conduct the two-step structural equation modelling (Henseler et al., 2009). Confirmatory factor analysis (CFA) was used to check the hypothesised model fit indices. Given the satisfactory results, the structural model was assessed by using SMART-PLS4. Bootstrapping with 5000 replications was used to test the hypotheses (Wetzels et al., 2009). A hypothesis can be considered supported under three conditions: (1) when the t-value is ≥ 1.96; (2) when the p-value is ≤ .05; and (3) when the 95% confidence interval does not include zero within its lower and upper bounds (Hair et al., 2019). In addition, a variance inflation factor (VIF) of < 3.3 indicates that the results are not biased due to bias in the single source data (Hair et al., 2011). $Q2$ and $R2$ were used to assess the predictive accuracy of the model (Geisser, 1975; Stone, 1974; Zhang, 2009). $R2$ values are interpreted as follows: 0.02–0.12, weak; 0.13–0.25, moderate; and ≥ 0.26, substantial (Cohen, 1988). The effect size ($F2$) was used to check the effect of endogenous variable while omitting a specified exogenous variable from the structural model (Hair et al., 2019). $F2$ values are interpreted as follows: < 0.02, no effect; 0.02–0.15, small effect; 0.15–0.35, medium effect; and > 0.35, large effect (Carte & Ressell, 2003).

Bootstrapping with 5000 replications was used to run the mediation analysis (Hayes, 2013). First, using the bootstrapping technique, the path model was run without including the mediator. The effects of direct and indirect paths are derived from the sampling distribution (Awang, 2015). The variance accounted for (VAF) score is highly recommended to identify the strength of mediation (Hair et al., 2006). It was only considered when the indirect effect was statistically significant. The VAF score is interpreted as follows: >80%, full mediation; 20%–80%, partial mediation; and < 20%, absence of mediation.

Moderation analysis was performed using a two-way interaction with bootstrapping on 5000 replications. This was achieved by incorporating the interaction effect into the study model and assessing its significance on the dependent variable. During the moderation analysis, the predictor variables should be mean centred to minimise multicollinearity and facilitate clearer interpretation of the results (Aiken & West, 1991). If the effect of the interaction term on the dependent variable is significant, then this establishes a significant moderation effect. To further explain the moderation effect, Aiken and West's (1991) technique of generating plots was used to observe the effect of predictors on outcome variables. Finally, the moderated mediation models were tested using PROCESS Macro Model 8, in accordance with the methodological guidelines proposed by Hayes (2018) and Preacher and Hayes (2008).

CFA Findings

Two key criteria – discriminant validity and convergent validity – were employed to evaluate the CFA results. The details of the convergent validity assessment are presented in Table 2. All standardised factor loadings exceed the recommended threshold of .70 (Hair et al., 2006). Similarly, the average variance extracted (AVE) values for all constructs are above the minimum acceptable level of .50 (Hair et al., 2006). In addition, the composite reliability (C-

-R) for all study variables exceeds the recommended cut-off of .60, indicating satisfactory internal consistency (Peterson & Kim, 2013). Lastly, Cronbach's alpha for all constructs exceeds the recommended minimum threshold of .70, confirming acceptable internal reliability (Nunnally & Bernstein, 1994).

Table 2. Assessment of Internal Reliability and Convergent Validity

Construct	Item	FL	AVE	CR	α	Construct	Item	FL	AVE	CR	A
Digital transformation (DT)	DT1	.952	.885	.943	.935	Heuristic processing (HP)	HP1	.950	.837	.954	.95
	DT2	.933					HP2	.790			
	DT3	.938					HP3	.954			
AI usage (AIU)	AIU1	.887	.741	.923	.911		HP4	.929			
	AIU2	.918					HP5	.940			
	AIU3	.925				Academic performance (AP)	AP1	.886	.81	.884	.883
	AIU4	.840					AP2	.928			
	AIU5	.716					AP3	.886			
Procrastination (PR)	PR1	.815	.748	.933	.916	Artificial intelligence–supported self-regulated	AISRL1	.895	.829	.95	.931
	PR2	.909					AISRL2	.889			
	PR3	.864					AISRL3	.917			
	PR4	.912					AISRL4	.940			
	PR5	.819				Artificial intelligence–integrated pedagogy (AIP)	AIP1	.929	.784	.908	.907
							AIP2	.926			
							AIP3	.880			
							AIP4	.801			

Note. *α, internal reliability based on Cronbach's alpha; AVE, average variance extracted; CR, composite reliability; FL, factor loading.*

Table 3 presents the descriptive analysis (see the next page). To assess discriminant validity, the Fornell and Larcker (1981) criterion was applied by comparing the square roots of the AVE values with the inter-construct correlations. Additionally, the heterotrait-monotrait ratio of correlations (HTMT) was analysed using the approach proposed by Henseler et al. (2015). The square root of the AVE for each construct exceeds its correlations with other constructs, thereby confirming discriminant validity (Hair et al., 2010). In addition, the correlations between the variables are lower than the threshold of .85, showing discriminant validity among the study variables (Kline, 2010). Similarly, the HTMT values for all latent constructs are below the recommended threshold of .90, confirming that each construct is distinct and demonstrates adequate discriminant validity (Henseler et al., 2015). Overall, the results indicate a good model fit, with a standardised root mean square residual (SRMR) of .062, below the acceptable cut-off of .08 (Hu & Bentler, 1999).

Findings related to the hypotheses

Causal effects

Table 4 presents the results of the four causal effect hypotheses (H1, H2, H3, and H4) (see the next page). The $R2$ values for AIU, procrastination, heuristic processing, and academic performance are .247, .442, .506, and .639, respectively, all of which are substantial according to Cohen (1988). The $Q2$ values are much larger than the threshold of zero. The bo-

-otstrapping results with 5,000 replications indicate that DT has a significant positive effect on AIU, providing support for H1. The results also indicate that AIU has significant positive effects on procrastination, heuristic processing and academic performance, thus supporting H2, H3, and H4, respectively.

Table 3. Descriptive Statistics and Assessment of Discriminant Validity

	M	SD	AIP	AI-SRL	AIU	AP	HP	DT	PR
AIP	3.386	.905	**.886**	.521	.353	.476	.041	.425	.450
AI-SRL	3.504	1.039	.483	**.910**	.443	.382	.067	.381	.322
AIU	3.192	1.007	.330	.420	**.861**	.887	.376	.747	.679
AP	3.345	1.010	.426	.353	.798	**.900**	.392	.798	.574
HP	3.335	.968	.007	.061	.347	.357	**.941**	.371	.317
DT	3.291	1.155	.394	.363	.697	.734	.349	**.915**	.698
PR	2.835	.991	.403	.300	.641	.530	.298	.652	**.865**

Note. *Assessed based on the Fornell and Larcker approach and the heterotrait-monotrait ratio of correlations. AIP, artificial intelligence–integrated pedagogy; AP, academic performance; AI-SRL, artificial intelligence–supported self-regulated learning; AIU, artificial intelligence usage; DT, digital transformation; HP, heuristic processing; PR, procrastination.*

Mediation effects

Table 5 presents the results of examining the three mediation effect hypotheses (H5, H6, and H7). In the absence of AIU as a mediating variable, DT has significant positive indirect effects on procrastination, heuristic processing, and academic performance, providing support for H5, H6, and H7, respectively. The VAF values for all indirect effects are 1.000, demonstrating full mediation.

Table 4. Results for the Causal Effect Hypotheses

Path: IV→DV	β	SE	t	P	95% CI LL	95% CI UL	VIF	F^2	R^2	Q^2
H1⁺: DT → AIU	.319***	.056	5.745	0	.206	.424	1.033	0.131	.247	.612
H2⁺: AIU → PR	.647***	.038	17.159	0	.571	.719	1.23	0.61	.442	.617
H3⁺: AIU → HP	.676***	.046	14.611	0	.578	.761	1.23	0.753	.506	.745
H4⁺: AIU → AP	.784***	.032	24.122	0	.717	.845	1.23	1.382	.639	.584

Note. *The "+" at the end of each hypothesis indicates the proposed direction. The p values are two-tailed. ∗∗∗p < .001.*

Table 5. Results for the Mediation Effect Hypotheses

	β	SD	t	p	95% CI LL	95% CI UL	VAF
H5⁺: DT → AIU → PR	.207***	.04	5.123	0	.128	.287	1.000
• Total effect	.207***	.04	5.123	0	.128	.287	
H6⁺: DT → AIU → HP	.216***	.045	4.794	0	.129	.305	1.000
• Total effect	.216***	.045	4.794	0	.129	.305	
H7⁺: DT → AIU → AP	.250***	.047	5.29	0	.157	.342	1.000
• Total effect	.250***	.047	5.29	0	.157	.342	

Note. *Total effect refers to the effect of the independent variable on the dependent variable in absence of a mediating variable. The p values are two-tailed. ∗∗∗p < .001.*

Table 6. Results for the Moderation Effect Hypotheses

Path: IV→DV	β	*SD*	*t*	*p*	95% CI LL	95% CI UL	VIF	F^2	R^2	Q^2
H8^{+}: AIP × DT → AIU	$.123^{*}$	.049	2.503	.012	.028	.223	1.033	.026	.247	.612
H9^{-}: AI-SRL × AIU → PR	$-.173^{***}$	.045	3.869	0	-.263	-.085	1.257	.054	.442	.617
H10^{-}: AI-SRL × AIU → HP	$-.120^{**}$	.045	2.638	.008	-.212	-.035	1.257	.029	.506	.745
H11^{+}: AI-SRL × AIU → AP	.039	.041	0.957	.339	-.039	.123	1.257	.004	.639	.584

Note. *$*p < .05$. $**p < .01$. $***p < .001$.*

Moderation effects

Table 6 presents the results for the four moderation effect hypotheses (H8, H9, H10, and H11) (see above). The two way-interaction term of AIP × DT has a significant positive effect on AIU, providing support for H8. The two way-interaction term of AI-SRL × AIU has a significant negative effect on procrastination (supporting H9), a significant negative effect on heuristic processing (supporting H10), and a nonsignificant positive effect on academic performance (not supporting H11).

The plotted interactions in Figure 1 (see below) show that DT increases AIU to a higher degree when AIP is high rather than low, which confirms H8. In addition, AI-SRL negatively moderates (dampens) the positive effects of AIU on procrastination and heuristic processing: the positive relationship is stronger at a lower level of AI-SRL than at a higher level. The findings support H9 and H10. Finally, the relationship between AIU and academic performance is nearly identical at low, medium, and high levels of AI-SRL (denoted by the three parallel lines), indicating no moderation effect or support for H11.

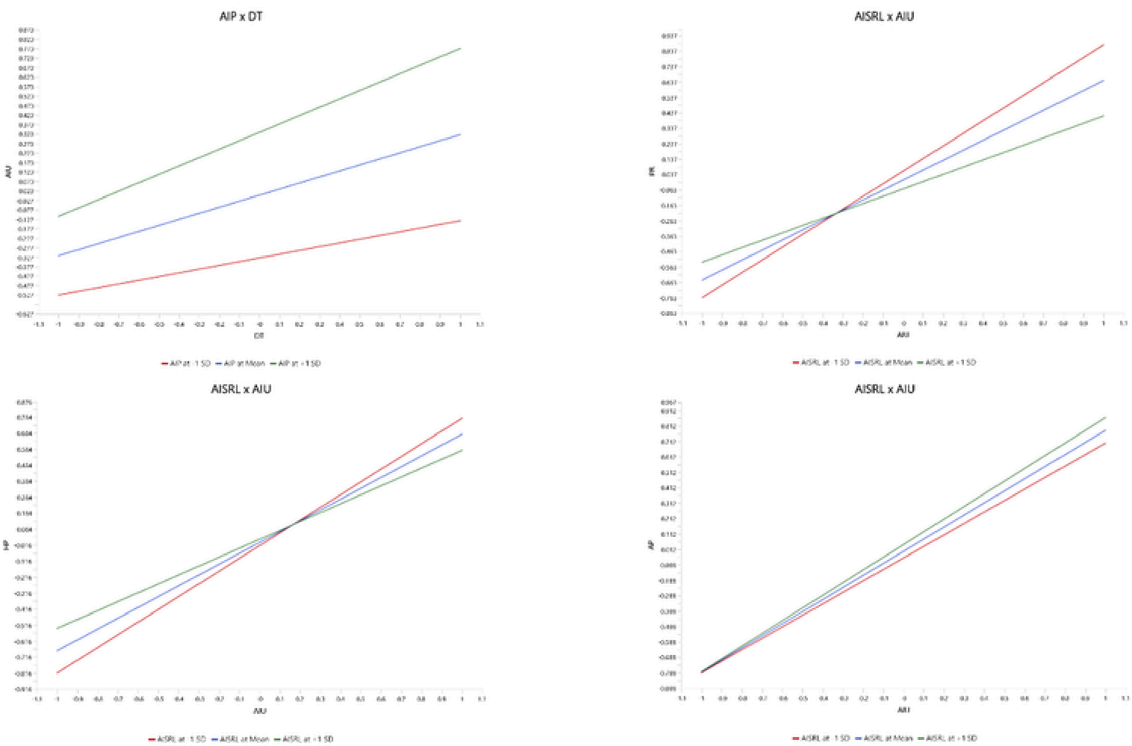

Figure 1. Moderation Effect Graphs

Moderated-mediation effects

Table 7 presents the results of examining the three moderated-mediation effect hypotheses (H12, H13, and H14). The conditional indirect effect of DT on procrastination through AIU is significantly positive and stronger for a high level of AIP than for a low level of AIP, supporting H12, but in opposite direction as hypothesised. The conditional indirect effect of DT on heuristic processing through AIU is significantly positive and stronger for a high level of AIP than for a low level of AIP. These results support H13, although in the opposite direction of what was originally proposed. Finally, the conditional indirect effect of DT on academic performance through AIU is significantly positive and stronger for a high level of AIP than for a low level of AIP, supporting H14. In other words, the positive indirect relationship between DT and academic performance through AIU is stronger at a higher level of AIP.

Table 7. Results for the Moderated-Mediation Effect Hypotheses

	β	*SD*	*t*	*p*	95% CI LL	95% CI UL
H12^{-}: AIP × DT → AIU → PR	**.077***	**.032**	**2.382**	**.017**	**.018**	**.145**
• -1SD (-.905); low AIP	.152*	.061	2.500	.012	.023	.262
• 0SD (.000); medium	.248***	.047	5.261	.000	.153	.339
• +1SD (.905); high AIP	.345***	.063	5.517	.000	.217	.463
H13^{-}: AIP × DT → AIU → HP	**.084***	**.036**	**2.331**	**.020**	**.018**	**.158**
• -1SD (-.905); low AIP	.131*	.053	2.472	.013	.021	.231
• 0SD (.000); medium	.215***	.045	4.775	.000	.127	.303
• +1SD (.905); high AIP	.298***	.062	4.844	.000	.176	.418
H14^{+}: AIP × DT → AIU → AP	**.097***	**.040**	**2.437**	**.015**	**.022**	**.177**
• -1SD (-.905); low AIP	.121*	.049	2.492	.013	.019	.210
• 0SD (.000); medium	.198***	.039	5.016	.000	.120	.276
• +1SD (.905); high AIP	.275***	.053	5.154	.000	.169	.376

Note. *The "+" or "-"at the end of each hypothesis indicates the proposed direction. The p values are two-tailed.* $*p < .05$. $***p < .001$

Figure 2 presents the model with the results for each hypothesis (see below).

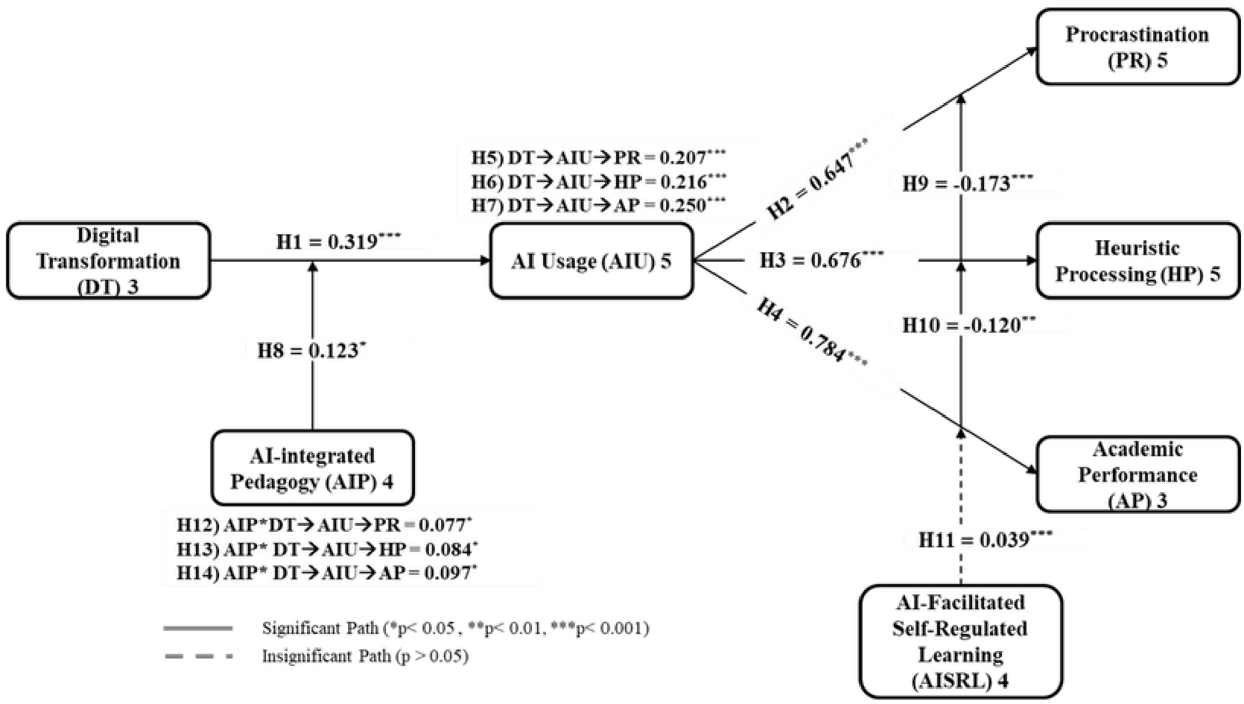

Figure 2. Model Findings and Estimation Results

Qualitative findings

Study II employed thematic analysis to better understand the interviewees' responses. The six-stage model of familiarisation with data was used as a basis of the analysis process (Braun & Clarke, 2006). The researchers read the responses on several occasions to immerse themselves in the data. Then, inductive coding was conducted to extract meaningful textual segments in reference to the experiences of the participants. These codes were combined into more general themes of language, including fluency and coherence, response precision, cultural and contextual fit, and educational applicability.

This section reports the two main resulting themes, along with their associated subthemes and emerging patterns, namely, AI-powered pedagogies at the advanced core courses in blended learning context, along with AI-powered pedagogies at the early undergraduate level. AI appeared to be fundamentally integrated into the online component (i.e. synchronous), hence, harnessing the powers of AI in delivering engaging learning experience, while reinforcing critical thinking and innovativeness.

Theme 1: AI-integrated pedagogies at the core course level

AI adoption in the core postgraduate courses is aligned more strategically with the nature of the discipline and the professional context of students. Results showed that faculty members teaching blended learning courses actively implement AI-powered pedagogies, using several AI tools, that are either supported via the institution's digital learning systems, or are considered to be effective open-access tools. As such, faculty endorse "collaborative human-AI" pedagogies, where learning experiences are designed to engage AI as partners to the learning process.

Enhancing students' critical thinking skills

Some faculty members frame AI as a so-called teammate, or cognitive partner, for the students. In this sense, it helps prompt students to think and brainstorm, and supports iterative thinking and reflection.

> During the Zoom sessions, I introduce breakout rooms, where I ask students to add ChatGPT as a teammate. (CF3)
>
> I engage students in comparative activities using different generative AI applications. Students are divided into groups, each assigned a specific AI tool to research the same question (such DeepSeeq group, ChatGPT group, etc.), analyze the responses, and present their findings. This activity helps students recognize variations in reasoning, interpretation, and emotional framing across AI tools, as well as the limited ability of some applications to account for cultural and contextual differences. (BF2)
>
> My students are distributed into breakout rooms, where they collaborate and brainstorm well using AI, to better create persona, mind maps with multiple branches and journey maps, then assess biasness effectively, before they develop creative solutions to problems understudy. (CC1)

Integration of AI research tools

Given that postgraduate assignments often involve extensive research, students are introduced to the ways they can use AI to facilitate their research, including a way to explore the literature, support for synthesis, and thematic analysis. CoPilot and other tools are used extensively. In this sense, AI is not merely used for engagement; rather, it is positioned as a strategic support mechanism for high-level academic tasks, including research design, analysis, and professional documentation.

> In classroom activities, we ask students to use AI applications to search for research materials, identify relevant academic sources, and support preliminary literature exploration. However, they are guided to critically evaluate and verify all AI-generated suggestions before inclusion in academic work. (D1)

Professional advantage

Faculty members aim to equip postgraduate students with AI competencies to enhance their academic performance as well as their effectiveness in the workplace once they graduate. Nearpod with AI features and GAI, among other apps, are used extensively for this purpose.

> We ensure that the apps we choose are highly career-aligned and professionally embedded within our delivery so that it gives students a competitive professional advantage. For instance, our education students who are in-service and pre-service teachers will implement these apps in their own classes as well. (PC1)

Theme 2: AI-powered pedagogies in the early undergraduate BL context

AI integration at the undergraduate level primarily serves foundational and engagement-oriented purposes, allowing instructors and students to harness the power of data analytics.

AI Literacy development

Students are introduced to the fundamentals of AI use, including understanding capabilities, limitations, responsible application, and how to prompt effectively while taking bias and cultural variation into consideration. Generative AI tools, such as ChatGPT, are mainly used, alongside apps that improve students' academic writing skills (e.g., Studiosity) and apps that support students' understanding, thereby generating reports (e.g., NotebookLM), Gamma AI, Gemini Think Aloud, DeepSeeq and Perplexity.

> I adopt AI activities and pedagogies in my classes, where I train students on effective AI prompting. Since ChatGPT is the main platform we use, we guide students on how to construct high-quality prompts, critically evaluate AI-generated responses, verify accuracy, and determine whether outputs are appropriate and academically sound. We are not bounded by certain tools. Some of my pedagogies include: Design Thinking, Think-aloud and Mind mapping with AI**.** (CC2)

> I use AI companions, ChatGPT, DeepSeq, and other tools to enhance student participation, provide summaries, and demonstrate AI biases and limitations, especially in cultural contexts. The tools are employed to foster critical thinking, test AI responses, and address emotional intelligence (BF2).

Ethical AI use in academic submissions

Emphasis is placed on transparency, proper acknowledgement, and responsible integration of AI-generated content; hence, antiplagiarism safe-guards are in place.

> Previously, I used to require students to include a disclaimer indicating whether AI tools were used. Currently, we require students to formally reference their use of AI within the reference list. (CC2)
> Students have to include an appendix detailing the specific prompts they used; the type of ideas or outputs generated by AI and used in their submissions; Specifying how the AI-generated content was modified, refined, or critically evaluated. This approach promotes transparency, discourages copying, and ensures that students demonstrate meaningful engagement with AI rather than passive reliance. (CC3)

Interactive teaching strategy alongside monitoring engagement and participation

AI tools are used to enhance classroom interactivity, making lessons more engaging and participatory while supporting instructional efficiency. Instructors use platforms with AI-powered features, such as Nearpod and Padlet with AI features, to track student interaction, responses, and participation levels, particularly in large classes.

> I currently teach large classes, where often maintaining meaningful interaction and ensuring active participation can be extremely challenging. To address this, I integrate interactive platforms such as Nearpod, which includes AI-supported features. These tools allow me to monitor student engagement in real time, prompt students to reflect accurately on their understanding, and verify that participation extends across the entire class rather than being limited to a small group of vocal students. Students highly like the activities and games generated by AI in Nearpod. (BF1)

Discussion

This study explored the complex relationships between DT, AIU, AIP, AI-SRL, and student outcomes within BL environments. Grounded in student regulated learning and cognitive load theories, it employed structural equation modelling (Henseler et al., 2009), mediation and moderation analysis (Hayes, 2018), and CFA (Hair et al., 2019). The results indicate that AIU has positive outcomes on academic performance, but it can have unintended negative consequences, leading to increased heuristic processing and procrastination. These findings are consistent with studies on adaptive and personalised AI tools (e.g., intelligent tutoring systems and adaptive quizzes), which enhance performance by providing real-time feedback and structured learning pathways (Chen et al., 2020; Ifenthaler & Schumacher, 2023). As a matter of fact, this study focuses on university students, a sector where earlier research has shown significantly stronger effect of AI on BL, compared to secondary school, thus, aligning with Wu et al.'s (2025) findings. However, given the nature of blended learning, it is not surprising that such systems can cause surface-level engagement with the material (Broadbent & Lodge, 2021; Tomasik et al., 2022), exacerbating the potential negative impact of AI integration in the case of overreliance, leading to procrastination (Rasanty & Qudsyi, 2023). This emphasises the importance of students applying effective student regulation mechanisms (Broadbent & Lodge, 2021; Rasanty & Qudsyi, 2023). The moderation results further underscore the importance of AI-SRL: when students actively monitor and adjust their own learning strategies with AI support, negative tendencies such as procrastination and heuristic shortcuts are significantly reduced. This suggests that future implementations should not only provide access to AI tools but also embed self-regulatory scaffolds that guide students in using them productively. The positive association between AIU and academic performance provided by this study aligns well with the findings of previous studies conducted in BL and hybrid learning environments (Chen et al., 2020; Ifenthaler & Schumacher, 2023), poising that AI feedback strengthens knowledge retention and task completion. A major criticism of AI is that it may potentially strengthen procrastination, especially when learners rely on quick responses generated by AI tools, which may contain incorrect or misleading information. Some critics suggest that AI may allow learners to fall into an “illusion of productivity.” However, the present study and others (Yarlaggada, 2025; Zimmerman & Schunk, 2021) have reported that AI-SRL significantly reduces this impact. This particular finding signals the importance of self-regulatory scaffolding within the digitally augmented educational ecosystems, aligning with Broadbent and Poon (2015). The observed positive impact of such systems on heuristic processing supports the findings of previous research employing the dual-process model. AI prompts and responses may potentially lead learners to think less (Kahneman, 2011). AI-SRL reduces this suggestive tendency while providing pedagogical support encourages learners to process more deeply. The present study was conducted in the UAE, where AI usage is deeply rooted within the institutional initiatives which are taken in the context of DT. Therefore, the improved performance reported in this study is also related to institutional support. While studies conducted in the United States, the United Kingdom, and East Asia describe univocal, decentralised AI adoption in higher education, the UAE context illustrates a more state-led, centralised DT model in higher education. This may explain the strong reinforcing effect of AI usage observed in this study. Of all contexts featuring fragmented digital governance, the UAE National AI strategy (UAE Ministry of Education, 2022) appears to positively and significantly strengthen the effect within the digitally transformed educational ecosystems. The nature of AI-pedagogies adopted by the faculty teaching blended courses, further explains the role of AI-pedagogies as a moderator in the AIU-student outcomes nexus. AI-powered pedagogies presented as a critical component of the learning experience, fostering the “collaborative human-AI pedagogy” (Gupta et al., 2023), and harnessing the power of data analytics in delivering highly engaging and effective lessons (Ifenthaler & Schumacher, 2023). Unlike findings reported by Park and Doo (2024), AI-powered pedagogies complement and support synchronous learning, hence, AI is not projected towards maintaining control by faculty over the learning experience but rather towards accepting and embracing AI as a collaborative partner, leveraging its capabilities in the learning process. Furthermore, such pedagogies reinforce meeting industry-specific requirements and provide advantages for students’ future careers.

Limitations

There are a few limitations to this study. First, the cross-sectional design did not allow for the examination of changes over time. Longitudinal studies may be able to capture how AIU changes in the future, especially as regulations continue to shift and develop. Second, the results of this study are not necessarily generalisable to other contexts. Indeed, the use of purposive sampling means that only undergraduate and postgraduate students enrolled in BL programmes were considered. This approach ensured that the participants were engaged with meaningful AI-supported learning. However, it is unclear whether the findings would be the same for students who are engaged strictly in online or face-to-face learning. Moreover, it is unclear whether the findings hold for other cultures and countries that do not focus as extensively on DT as the UAE. Finally, the participants were only from humanities and social sciences programmes. Future research should explore disciplinary variations in AIU.

Conclusion

Grounded in SRL theory and cognitive load theory, this study examined how DT and AIU influence student outcomes in higher education that employs BL, with a particular focus on procrastination, heuristic processing, and academic performance. Based on the findings, AIU is a critical mediator in the pathway from DT to learning outcomes, with both positive and negative effects. Specifically, AIU enhances academic performance and supports cognitive engagement, but it also contributes to increased procrastination and reliance on heuristic strategies. Importantly, AI-SRL and AIP are essential moderators in these relationships: AI-SRL mitigates the negative behavioural effects of AI, while AIP augments the academic benefits of DT-driven AI adoption.

From a practical perspective, the results underscore that the value of AI depends on the specific pedagogical framework and learner self-regulation. Adaptive tools, including intelligent tutoring systems and AI-powered academic support, offer personalised pathways and continuous feedback to enhance performance. However, they require safeguards so that learners do not come to rely on them extensively and thus do not engage deeply with the material. Institutions should prioritise embedding self-regulatory scaffolds, such as goal-setting prompts, reflec-

-tive dashboards, and adaptive feedback loops, into AI-enhanced systems to help students engage productively. Ultimately, DT alone does not guarantee improved educational outcomes; its success depends on deliberate alignment between infrastructure, pedagogy, and learner agency. When AIP is formalised in institutional policies that promote AI-SRL, AI can transform education and mitigate unintended consequences, thereby advancing equitable and sustainable BL environments.

Instructors play a pivotal role in fostering students' SRL strategies by designing AI-supported tasks that strengthen cognition, metacognition, time and resource management, and behavioural regulation. Instructors can introduce in-class activities that prompt students to use online resources critically, to evaluate the credibility of information generated by AI tools, and to engage in structured self-reflection. As part of this process, students can participate actively by setting their specific academic goals monitoring their progress and performance using AI-powered analytics. This allows for personalised and dynamic feedback that can be used to refine learning strategies. AI-SRL can also be fostered through the integration of AI into contemporary pedagogical approaches such as inquiry-based learning, team-based learning, flipped classrooms, simulation labs, personalised learning experiences (e.g., through systems like Alexa or differentiated lesson plans), and the design of AI-resistant assessments. As part of this process, faculty members must have the necessary knowledge and skills to use AI tools effectively. This is particularly important considering the rapid evolution of teaching and learning standards in the face of AI. Faculty development programmes could be offered to help faculty members integrate AI into their courses so that students' SRL is strengthened but not replaced, allowing them to develop the skills necessary to compete in a competitive job market. At the same time, institutional hiring practices must prioritise the recruitment of candidates who possess both technological fluency and a strong pedagogical vision, ensuring they can guide students not only toward academic success but also toward becoming reflective, ethical, and adaptive individuals in AI-enhanced learning environments. Extensive faculty professional development is needed to support faculty member sin effective use of AI in pedagogy and assessment.

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Data availability: The datasets used and analysed during the current study are available from the first author on reasonable request.

Ethical approval: This research was performed in line with the principles of the Declaration of Helsinki. Approval was granted by the IRB Research Ethics Committee at Ajman University (Approvals No. H-F-H-20-Mar; H-F-H-19-Feb).

Participant consent: All participants provided informed consent to participate in this research.

Conflict of interest: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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