Acta Pedagogia Asiana

Review
Volume 5(2), 2026, 129−154
https://doi.org/10.53623/apga.v5i2.1107

AI-Augmented Student-Centered Learning: Personalization and Agency

Kuok Ho Daniel Tang

Department of Environmental Science, The University of Arizona, Tucson, AZ 85721, USA

Correspondence: daniel.tangkh@yahoo.com

SUBMITTED: 8 March 2026; REVISED: 5 April 2026; ACCEPTED: 7 April 2026

ABSTRACT: Artificial intelligence (AI) is increasingly integrated into educational environments and is widely recognized as a transformative technology for advancing Student-Centered Learning (SCL). By enabling adaptive instruction, real-time feedback, and learning analytics, AI systems can personalize learning experiences and address diverse learners' needs. This review synthesizes current research on how AI contributes to key dimensions of SCL, including adaptive content delivery, data-driven feedback, learner agency, and human–AI collaboration. The literature indicates that AI-powered educational technologies can enhance engagement, facilitate individualized learning pathways, and support self-regulated learning by providing timely insights into performance, progress, and learning strategies. Learning analytics and intelligent tutoring systems further allow instructors to better understand learners' behavior and tailor instructional support, strengthening alignment between teaching practices and students' needs. However, integrating AI into SCL environments also presents several challenges. Concerns have emerged regarding cognitive offloading and overreliance on AI systems, which may reduce learners' active problem-solving and critical thinking if not carefully managed. Issues related to algorithmic transparency, data privacy, and equitable access also remain important considerations as educational institutions increasingly depend on data-driven technologies. Moreover, educators continue to play a critical role in guiding the effective use of AI and ensuring that technology enhances rather than replaces meaningful learning processes. By and large, AI has substantial potential to strengthen SCL when implemented as a transparent, supportive pedagogical tool. Effective integration requires balancing algorithmic guidance with learner autonomy and maintaining strong human oversight. Future research should examine long-term impacts on learner agency and self-regulation and develop pedagogical frameworks that support responsible human–AI collaboration in student-centered education.

KEYWORDS: Adaptive content delivery; cognitive; data-driven feedback; explainable AI; self-determination theory; self-regulated learning

1. Introduction

Student-Centered Learning (SCL) has long been positioned as a transformative alternative to transmission-based models of education. Rooted in constructivist traditions, SCL emphasizes learner autonomy, active knowledge construction, collaboration, and the development of metacognitive competence [1]. Rather than positioning students as passive recipients of information, student-centered approaches frame them as agents who co-create meaning, regulate their own learning, and engage in authentic problem-solving [2]. Over the past three decades, SCL has informed pedagogical reforms across higher education and K–12 systems, shaping inquiry-based learning, problem-based learning, flipped classrooms, and competency-based education [3−5]. Yet the operationalization of SCL has often faced structural constraints, including large class sizes, limited instructional time, assessment regimes focused on standardized outcomes, and uneven instructor preparedness [6, 7].

The rapid emergence of artificial intelligence (AI) in education introduces both unprecedented opportunities and profound tensions for student-centered paradigms. AI-driven systems, ranging from intelligent tutoring platforms and adaptive learning software to learning analytics dashboards and generative AI tools, are increasingly embedded in digital learning ecosystems [8,9]. Recent advances in large language models, such as those underpinning platforms like ChatGPT, have accelerated AI adoption at a pace that outstrips institutional policy development and pedagogical consensus [10, 11]. These systems can generate explanations, scaffold assignments, simulate dialogue, analyze performance data, and personalize feedback in real time [12, 13]. As a result, AI is not merely augmenting instruction; it is reshaping the epistemic, relational, and ethical architecture of learning environments.

At first glance, AI appears to align naturally with the aspirations of SCL. Adaptive learning systems promise personalized pathways tailored to individual learners' prior knowledge, pace, and preferences [14]. Intelligent tutoring systems can provide immediate formative feedback, supporting mastery learning and reducing reliance on high-stakes summative assessments [15]. Learning analytics can identify at-risk students early, enabling targeted interventions that enhance retention and equity [16]. Generative AI tools can function as brainstorming partners, writing assistants, or coding collaborators, potentially enhancing creativity and lowering barriers to entry in complex tasks [17]. These affordances suggest that AI could operationalize personalization at a scale previously unattainable in traditional classroom settings.

However, the integration of AI into SCL also raises critical questions about agency, autonomy, and authenticity [18]. Personalization driven by algorithms may inadvertently narrow exposure to diverse perspectives, creating "algorithmic tunnels" that reinforce existing strengths while limiting intellectual challenge [19]. When AI systems generate content, structure arguments, or provide ready-made solutions, learners may engage in cognitive offloading, reducing opportunities for productive struggle and deep processing [20]. The boundary between scaffolding and substitution becomes increasingly blurred. If AI systems pre-structure learning pathways too rigidly, SCL risks becoming system-centered learning, in which algorithmic optimization overrides learners' choice [21, 22].

These tensions highlight a fundamental paradox, i.e., technologies designed to empower learners may simultaneously constrain them. From a self-determination theory perspective, autonomy, competence, and relatedness are central to intrinsic motivation [23]. AI can enhance competence through timely feedback, yet it may undermine autonomy if learners perceive algorithmic control as externally imposed [24]. Similarly, while AI-mediated collaboration tools can foster interaction, excessive reliance on machine intermediaries may alter peer dynamics and instructor–student relationships [25]. Understanding how AI reshapes motivational architectures is, therefore, essential to evaluating its compatibility with student-centered principles.

Importantly, the discourse surrounding AI in education often oscillates between utopian and dystopian narratives. On the one hand, proponents envision fully personalized learning ecosystems in which each student progresses along optimized pathways guided by intelligent systems [25−27]. On the other hand, critics warn of dehumanization, deskilling of educators, and commodification of learning data [28, 29]. Neither extreme adequately captures the nuanced interplay between technology, pedagogy, and institutional context. AI does not operate in a vacuum; its educational impact depends on design choices, governance frameworks, instructor agency, and learner engagement [30, 31]. A critical synthesis of existing research is therefore necessary to move beyond polarized debates toward evidence-informed understanding.

Despite the rapidly expanding literature on AI in education and the long-standing scholarship on SCL, integrative analyses that examine their intersection remain limited. Many studies focus narrowly on learning outcomes, such as performance gains or engagement metrics, without systematically addressing questions of learner agency [32−34]. Others explore perceptions of AI use without linking findings to established theoretical frameworks of self-regulated learning or constructivism [35,36]. Furthermore, much of the empirical evidence is short-term and context-specific, with limited longitudinal or cross-cultural perspectives [37, 38]. This fragmentation underscores the need for a comprehensive review that bridges pedagogical theory, technological affordances, and ethical analysis.

This review addresses that gap by examining AI-augmented SCL through the interconnected lenses of personalization and agency. First, it synthesizes evidence on how AI systems enable or constrain personalized learning pathways, differentiating between adaptive content delivery, data-driven feedback, and generative collaboration through learning analytics. Second, it interrogates the implications of AI integration for learner autonomy and self-regulation, considering both empowerment and dependency dynamics. In doing so, this article contributes to ongoing conversations about the future of education in an AI-mediated world. Rather than asking whether AI should be used in student-centered classrooms, the more pertinent question is how it should be designed, implemented, and governed to enhance rather than erode learner agency.

2. Review Methodology

This study adopts a narrative review design to synthesize and critically interpret scholarship at the intersection of AI in education and SCL, with particular focus on personalization and learner agency. A narrative approach was chosen because the field is conceptually diverse, interdisciplinary, and rapidly evolving, especially with the emergence of generative AI [39]. Rather than statistically aggregating findings, the review aims to integrate theoretical perspectives, empirical evidence, and emerging debates to develop conceptual clarity.

A structured literature search was conducted across Scopus, Web of Science Core Collection, ERIC, and Google Scholar to capture both pedagogical and technical research. Publications from 2016 to 2026 were considered to encompass developments from intelligent tutoring systems and adaptive learning platforms to recent generative AI tools. Search terms were organized around three clusters: (1) AI-related terms (e.g., artificial intelligence in education, adaptive learning, learning analytics, generative AI, large language models); (2)

SCL constructs (e.g., learner-centered learning, active learning, self-directed learning); and (3) personalization and agency concepts (e.g., personalization, learner agency, autonomy, self-regulated learning, metacognition). Reference lists of key articles were also manually screened to identify additional relevant studies.

Studies were included if they examined AI applications within formal educational contexts and engaged substantively with personalization, autonomy, or self-regulation. Both empirical (quantitative, qualitative, mixed-methods) and theoretically grounded conceptual papers were considered. Purely technical studies without pedagogical analysis and non-analytical opinion components were excluded. Priority was given to peer-reviewed journal articles and reputable conference proceedings.

To enhance transparency, the inductive thematic analysis followed a three-stage coding process: (1) open coding, where initial labels were assigned to relevant text segments describing AI functionalities and learner interactions in line with the aim of the study to examine the role of AI in personalized learning and the implications of AI for learning agency; (2) axial coding, where related codes were grouped into higher-order categories; and (3) selective coding, where overarching themes were refined and integrated.

This process resulted in a coding scheme comprising three primary dimensions for the predefined themes of personalization and learner agency, respectively. For personalization, the sub-themes that emerged were adaptive content delivery, data-driven feedback, and learning analytics. For learner agency, the sub-themes identified were self-regulated learning, cognitive offloading and dependency, and co-creation and human-AI collaboration. In relation to these sub-themes, data extraction was conducted iteratively. For each study, information was documented regarding educational setting, type of AI system, personalization mechanisms (e.g., adaptive content, automated feedback, recommendation systems), and operationalization of learner agency (e.g., choice, metacognitive support, goal-setting).

3. Personalization in AI-Augmented SCL

Personalization lies at the core of AI-augmented SCL, representing the promise that educational experiences can be tailored to individual learners' needs, preferences, and developmental trajectories at scale [40]. In traditional student-centered classrooms, personalization is often constrained by instructor capacity, time, and class size [41−43]. AI systems, ranging from adaptive learning platforms and intelligent tutoring systems to generative tools such as ChatGPT, expand this capacity by dynamically adjusting content difficulty, pacing, feedback, and learning pathways in response to real-time data [44]. Such systems can analyze performance patterns, recommend targeted resources, and scaffold learning processes, thereby supporting differentiated instruction beyond what is typically feasible in conventional settings.

3.1. Adaptive content delivery.

Adaptive content delivery represents one of the most prominent mechanisms through which AI operationalizes SCL [45]. In traditional instructional settings, differentiation often depends on the instructor's ability to manually adjust materials for diverse learners—an effort constrained by time, scale, and available resources [41]. AI-driven adaptive systems address this limitation by dynamically modifying the sequence, complexity, format, and pacing of instructional content in response to learners' performance data, interaction patterns, and demonstrated mastery levels.

AI systems enable adaptive content delivery by continuously analyzing learner data and dynamically adjusting instructional content, pacing, and feedback to align with individual needs [46]. Rather than relying on fixed curricular sequences, AI-driven platforms model learners' knowledge states, participation patterns, and error trajectories to generate responsive learning pathways [47]. This capacity directly addresses long-standing structural barriers in large-class higher education, where meaningful differentiation is often constrained by instructors' workload and scale [41]. Empirical evidence demonstrates that when embedded within student-centered pedagogical frameworks, adaptive AI systems can enhance engagement, comprehension, and learning efficiency.

Across institutional contexts, AI-supported adaptive strategies have been shown to significantly improve learning outcomes [32, 33]. For example, an AI-empowered student-centered teaching model grounded in Constructivist Learning Theory demonstrated significantly higher academic performance and strong student endorsement (mean = 4.66/5), indicating that adaptive AI integration can strengthen active learning and personalized engagement in large-class settings [48]. Rather than merely automating instruction, AI tools enable dynamic feedback, alternative explanations, and interactive exploration, thereby supporting the core student-centered principles of responsiveness and learner participation [48].

At a systems level, adaptive delivery relies on real-time behavioral modeling. Machine learning architectures that track live interaction data have achieved prediction accuracies exceeding 96% and content relevance approaching 90%, alongside retention gains of over 40% compared to earlier platforms [49]. Such improvements illustrate how adaptive engines refine content sequencing based on participation intensity and demonstrated mastery. Similarly, reinforcement learning–based frameworks dynamically recalibrate instructional pathways according to learner progress and preferences, producing substantial improvements in knowledge retention and skill acquisition relative to static course designs [44]. Large-scale experimental evidence further supports these effects: AI-personalized environments have been associated with 28% higher knowledge retention, 35% greater engagement, 24% gains in cognitive skills, and 40% improvements in learning adaptability, with more than 80% of students expressing their preference for adaptive systems [50].

Data-driven clustering and recommender systems further enhance personalization by identifying learner profiles and tailoring resources accordingly [51]. Hybrid architectures integrating neural networks and optimization algorithms improve learning style identification accuracy, enabling more precise instructional targeting within learning management systems [52]. In immersive or narrative environments, classification models such as k-nearest neighbors have successfully estimated knowledge levels and delivered differentiated guidance in real time [53]. Complementing these quantitative findings, mixed-method evidence indicates that AI-driven personalization significantly enhances academic course delivery (coefficient = 0.203; $p = 0.001$), particularly through natural language processing, intelligent tutoring systems, and predictive analytics [54].

However, adaptive content delivery does not automatically guarantee enhanced learner agency. While personalization can reduce cognitive barriers and foster deeper participation, prolonged reliance on tightly structured adaptive pathways may attenuate self-regulated learning [55]. Evidence from adaptive tutoring environments shows a significant decline in self-regulated learning scores over time [56], suggesting that excessive system control or learner isolation may dampen intrinsic motivation.

Taken together, the literature indicates that AI-enabled adaptive content delivery strengthens student-centered education when it enhances responsiveness, supports metacognitive awareness, and preserves learner choice. The pedagogical challenge lies not in whether AI can adapt content (empirical evidence clearly demonstrates that it can), but in designing adaptive systems that balance algorithmic optimization with sustained learner agency. Table 1 summarizes recent studies on AI-enabled adaptive content delivery in SCL environments.

Table 1. AI-enabled adaptive content delivery in SCL environments.

Study	Context / Dataset	AI Techniques / Tools	Adaptive Content Delivery Mechanism	Key Findings / Contributions
[48]	Quasi-experimental study across three universities in China and Malaysia	Multiple AI platforms (e.g., generative AI tools) integrated into teaching; AI-assisted educational platforms	AI-supported ASIF teaching strategy combining active learning, situational discussion, inductive teaching, and feedback	Improved engagement and learning outcomes in large-class settings; students reported strong satisfaction (mean score 4.66/5), demonstrating the scalability of AI-enabled adaptive teaching approaches
[49]	Behavioral learning data from OpenEd platform	Machine learning models implemented using TensorFlow and Python	Real-time tracking of learner interactions to dynamically adjust information delivery	Achieved 96.3% prediction accuracy, 89.5% content relevance, and improved learner retention (41.7%); demonstrated improved adaptability compared with conventional rule-based systems
[44]	Adaptive educational content delivery framework	Deep reinforcement learning	Real-time adjustment of learning paths based on learner progress, preferences, and performance	Improved knowledge retention and skill acquisition compared with conventional static learning systems; scalable across multiple learning contexts
[54]	Mixed-method study in technical universities	Natural language processing (NLP), intelligent tutoring systems, and learning analytics	AI tools provide personalized explanations, adaptive content interpretation, and feedback	AI-supported personalization significantly enhanced course delivery ($\beta = 0.203$, $p = 0.001$) and improved understanding of complex technical content
[51]	EdNet dataset of student interactions	Clustering algorithms and recommender systems	Learner profiling and recommendation of personalized learning materials	AI-driven learner modeling enabled personalized learning pathways and improved responsiveness of educational systems
[50]	Experimental study with 500 students	Machine learning, NLP, reinforcement learning, predictive analytics	Dynamic personalization of educational content and feedback loops	AI-personalized learning improved knowledge retention (28%), engagement (35%), cognitive skills (24%), and adaptability (40%); 82% of students preferred AI-based learning
[57]	Large-scale digital education infrastructure	Large language models integrated with learning management systems (LMS)	Dynamic generation of tailored learning materials based on learners' performance	Enabled scalable adaptive learning through AI-generated learning pathways and intelligent tutoring systems
[56]	University course using ALEKS adaptive learning system	Knowledge-space adaptive learning algorithm	Knowledge checks and individualized learning pathways based on learner mastery	Adaptive learning improved content personalization but was associated with a decline in self-regulated learning scores over time
[52]	LMS data from 75 students	Hybrid ant colony system and artificial neural networks	Identification of learning styles to support personalized instruction	Improved accuracy of learning style identification compared with existing methods
[53]	Narrative game-based learning environment	k-nearest neighbor (kNN) classification	Real-time evaluation of learner knowledge and provision of personalized feedback	Game-based AI system successfully provided differentiated learning guidance based on student knowledge levels

3.2. Data-driven feedback and learning analytics.

AI systems enable data-driven feedback and learning analytics by transforming diverse streams of learner data, i.e., behavioral, cognitive, emotional, and performance-based, into actionable insights that inform both instruction and self-regulation [58]. At the core of this capability is the integration of machine learning models, natural language processing, and predictive analytics within continuous data-feedback loops [47]. When aligned with student-centered education, these systems shift feedback from periodic, instructor-dependent commentary to real-time, personalized guidance that supports learner agency, reflection, and adaptive progression.

Recent advances demonstrate how large language models enhance engagement analytics by analyzing student–chatbot dialogues to map emotional states, conceptual progression, and inquiry depth [59]. By incorporating Bloom's taxonomy to classify cognitive complexity and tracking indicators such as stress, curiosity, and confusion, AI tools provide multidimensional portraits of learning behavior. Faculty priorities, such as identifying frequently asked questions (80%), tracking learning progression (75%), and detecting misconceptions (73%), reflect a growing demand for analytics that illuminate not just outcomes but trajectories [59]. Such visibility strengthens student-centered instruction by enabling targeted scaffolding rather than reactive grading.

Explainable machine learning further advances this paradigm by clarifying why predictions are made and how learners can improve [60]. Instead of offering opaque performance forecasts, AI dashboards can identify specific behavioral and academic factors, such as participation in LMS, forum engagement, quiz scores, and assignment grades, and recommend concrete adjustments [61]. Satisfaction rates of 82–91% for feedback clarity and design, combined with a significant positive correlation between recommendation adherence and final performance, indicate that transparent analytics can promote self-regulated learning. This interpretability is critical in student-centered models, where learners must understand and act upon feedback rather than passively receive it.

Experimental evidence reinforces the measurable impact of AI-driven feedback. In a quasi-experimental study involving 700 STEM (Science, Technology, Engineering and Mathematics) undergraduates, students receiving AI-adaptive feedback achieved a 28% gain in conceptual mastery compared with 14% in traditional settings, along with a 35% increase in engagement and 40% higher retention linked to frequent feedback interactions [62]. Similarly, AI-supported learning factory environments integrating educational data analytics and intelligent tutoring systems increased time-on-task by 48.7%, doubled feedback interactions (+102%), and improved assessment scores from 71.4% to 84.9% ($p < 0.001$), with system adaptivity explaining 63% of performance variance [63]. These findings illustrate how continuous analytics-informed feedback loops enhance both engagement and mastery.

At scale, predictive analytics strengthens early intervention and equity. Machine learning models integrating academic and behavioral indicators achieved F1-scores exceeding 93% in identifying at-risk students, outperforming traditional statistical approaches [64]. Similarly, AI systems supporting special education interventions achieved predictive accuracy of 88.83% and significantly improved student performance through personalized recommendations [65]. Longitudinal K–12 data show that sustained AI integration predicted grade improvement with strong explanatory power ($R^2 = 0.80$), linking interaction frequency directly to academic gains [66].

Importantly, effective analytics systems also maintain a human-centered orientation. Platforms such as Student Relationship Engagement System (SRES) demonstrate how scalable querying and personalized messaging can strengthen teacher–student relationships while reducing administrative burden [27]. Multimodal learning analytics dashboards that support reflective debriefings enhance clarity and trust in collaborative learning, though transparency and privacy remain essential [67]. Acceptance studies indicate generally favorable perceptions among instructors and students, though moderate skepticism persists, particularly regarding predictive risk profiling and privacy [68,69]

Collectively, the evidence suggests that AI-driven learning analytics strengthens student-centered education when feedback is timely, interpretable, and actionable. By converting raw data into meaningful guidance, AI systems support learner reflection, informed decision-making, and adaptive progression. However, sustaining trust, transparency, and ethical safeguards remains essential to ensure that analytics empower rather than constrain learner agency. Table 2 summarizes studies on AI-enabled data-driven feedback and learning analytics in SCL environments.

Table 2. AI-enabled data-driven feedback and learning analytics in SCL environments.

Study	Context / Participants	AI Techniques / Tools	Feedback/ Analytics Mechanism	Key Findings / Contributions
[68]	Survey of 98 teachers and policymakers in Europe	Learning analytics systems	Real-time feedback, prediction of at-risk students, learning activity recommendations	Learning analytics widely perceived as useful, especially for recommending learning activities; attitudes toward implementation were moderately cautious
[63]	180 higher education students in AI-supported learning factory model	Educational data analytics and intelligent tutoring systems	Continuous data-feedback loop enabling adaptive interventions and real-time feedback	Engagement increased by 48.7%, task completion by 28%, and feedback interactions by 102%; assessment scores improved significantly (71.4% to 84.9%)
[66]	Longitudinal study of AI integration in K−12 STEM education	AI-driven analytics and classroom AI tools	Monitoring engagement, interaction frequency, and assignment completion	STEM scores increased substantially (Math 58% to 80%); AI usage strongly predicted grade improvement and assignment completion
[27]	Deployment of SRES across 19 departments	Learning analytics platform with data querying and messaging engine	Personalized instructor messaging based on performance, attendance, and LMS activity	Enabled scalable personalized interventions, improved attendance, reduced attrition, and enhanced academic performance
[67]	Multimodal learning analytics study with 399 students and 17 teachers	Multimodal learning analytics (audio, positioning, physiological data)	Dashboards visualizing team communication patterns, spatial activity, and task prioritization	Supported reflective learning and structured feedback; users valued insights but highlighted complexity and data transparency concerns
[64]	Higher education datasets for retention prediction	Machine learning and deep learning predictive models (Random Forest, Support Vector Machine, neural networks)	Early-warning analytics identifying at-risk students based on academic and behavioral data	Deep learning models achieved highest predictive accuracy (F1-score 93.05%); behavioral engagement indicators were strong predictors
[65]	33 students with special education needs and 26 therapists/teachers	AI-based learning analytics integrating physiological, behavioral, and environmental data	Predictive analytics generating personalized intervention recommendations	Achieved predictive accuracy of 88.83%; improved student learning outcomes and supported individualized intervention planning

3.3. Benefits and limitations.

The integration of AI into SCL, particularly through adaptive content delivery and data-driven feedback systems, offers substantial pedagogical advantages while also introducing important conceptual and ethical challenges. At its best, AI enhances the core principles of student-centered education, namely personalization, responsiveness, and learner agency, by making instruction more flexible, data-informed, and scalable [3, 41, 70]. However, the same mechanisms that enable precision and efficiency may also constrain autonomy, amplify inequities, or narrow educational aims if not thoughtfully designed and implemented.

One of the most significant benefits of AI in SCL is scalable personalization. Adaptive systems dynamically adjust content difficulty, sequencing, pacing, and representation based on real-time learners' performance and interaction data [44, 45]. This capacity addresses a persistent structural limitation in traditional student-centered classrooms: the difficulty of meaningfully differentiating instruction in large or diverse cohorts [41]. Reinforcement learning models and predictive analytics engines can model evolving knowledge states and deliver tailored learning pathways that support mastery while reducing cognitive overload [71]. As a result, learners receive instruction aligned with their readiness levels and needs, fostering deeper engagement and improving retention.

AI also transforms feedback from a periodic, instructor-dependent process into a continuous and formative learning loop [67]. Through learning analytics dashboards and explainable machine learning systems, students can receive immediate, actionable insights into their progress, misconceptions, and behavioral patterns [61, 63]. When designed transparently, such systems enhance metacognitive awareness by helping learners understand not only what they achieved but why certain recommendations are made [59, 67]. This real-time feedback strengthens self-regulated learning, a foundational dimension of student-centered education, by encouraging reflection, goal setting, and strategic adjustment.

In addition, AI systems can enhance engagement and persistence. Conversational tools such as ChatGPT enable iterative questioning, personalized explanations, and exploratory dialogue, thereby stimulating inquiry-based learning [72]. Multimodal analytics, capable of detecting patterns of confusion or disengagement, further enable adaptive scaffolding in moments of difficulty [73]. Predictive analytics models also support early identification of at-risk learners, enabling timely interventions that improve retention and promote equity when implemented responsibly [64].

Despite these advantages, AI integration in SCL raises significant limitations. A central concern is the potential erosion of learner agency. While adaptive systems personalize learning pathways, excessive algorithmic control may reduce opportunities for learners to make meaningful choices about their learning trajectories [74, 75]. If instructional sequences are automatically determined without transparency or options for override, students may become passive recipients of optimized instruction rather than active constructors of knowledge [76]. In such cases, personalization may paradoxically undermine autonomy.

Overreliance on AI tools also poses cognitive risks. Generative systems that provide instant explanations or solutions may discourage productive struggle, critical analysis, and independent problem-solving if learners substitute AI outputs for their own reasoning [13, 77]. SCL depends on active knowledge construction and reflective thinking; therefore, AI must be positioned as a scaffold rather than a substitute for cognitive effort.

Ethical considerations further complicate AI deployment. Data-driven systems rely on an extensive collection of learner data, raising concerns about privacy, consent, and surveillance [8]. Algorithmic bias embedded in training datasets can result in inequitable recommendations or misclassification of learners, potentially reinforcing existing disparities [78]. Moreover, predictive risk profiling may inadvertently stigmatize students if safeguards and transparency measures are insufficient [79]. Trust in AI-supported environments depends on explainability, fairness, and responsible governance [80].

Finally, AI systems are often optimized for measurable performance indicators such as accuracy, completion rates, or retention [47, 64]. While these metrics are important, student-centered education encompasses broader goals, including critical thinking, creativity, collaboration, and identity development [17, 26, 77]. Overemphasis on quantifiable outcomes may narrow educational experiences and diminish the relational and socio-emotional dimensions of learning that require human facilitation [81]. In this context, an important distinction emerges between adaptive and adaptable systems. Adaptive systems are primarily system-driven, automatically adjusting content, pacing, and feedback based on learner data and algorithmic predictions. While efficient, such systems may inadvertently reduce learner agency by constraining choices within predefined pathways. In contrast, adaptable systems are user-driven, enabling learners (and educators) to actively modify learning trajectories, select resources, and influence the degree and direction of personalization [82]. This distinction is critical, as adaptable systems are more closely aligned with student-centered learning principles that emphasize autonomy, self-regulation, and co-construction of knowledge.

In sum, AI holds transformative potential for SCL when it enhances personalization, strengthens feedback loops, and supports informed decision-making. Yet its benefits are inseparable from its design choices. AI must augment rather than replace human judgment, preserve learner choice, and align with holistic educational values. The challenge is not simply to make learning more adaptive, but to ensure that adaptation deepens agency, equity, and meaningful engagement rather than constraining them. Figure 1 summarizes the benefits and limitations discussed.

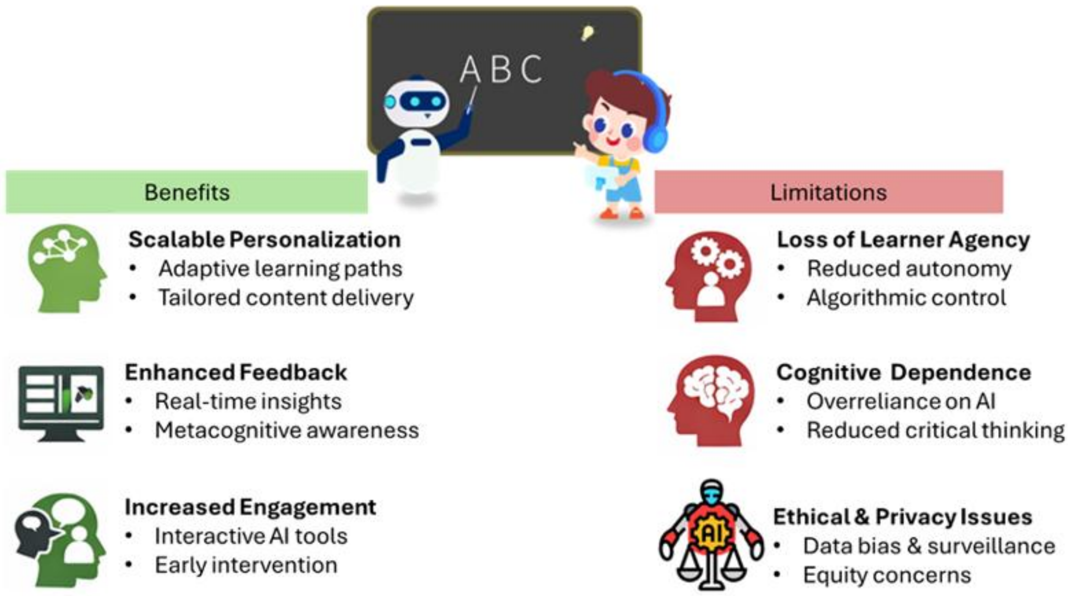

Figure 1. Benefits and limitations of AI in SCL.

3.4. *Implications from long-term studies.*

A critical observation emerging from the reviewed literature is the relative scarcity of long-term empirical studies on AI-driven personalization compared to the predominance of short-term or cross-sectional evaluations. Most studies on adaptive content delivery and data-driven feedback are conducted over short intervention periods, typically ranging from a few weeks to a single academic term. For instance, quasi-experimental and experimental studies consistently report substantial improvements in learning outcomes, engagement, and retention within relatively brief timeframes (e.g., a 20-week intervention in [62]; single-semester implementations in [48]; controlled experiments in [50]). These short-term findings demonstrate strong effect sizes, including gains in conceptual mastery, engagement, and cognitive skills, suggesting that AI-enabled personalization is highly effective in initial adoption phases. However, such studies often capture novelty effects, where increased motivation and engagement may be driven by the introduction of new technologies rather than sustained pedagogical transformation.

In contrast, the relatively few longitudinal studies provide a more nuanced and, at times, cautionary perspective. Evidence from semester-long and multi-year implementations indicates that the benefits of personalization may evolve or attenuate over time. For example, the study using the ALEKS adaptive learning system [56] found a significant decline in self-regulated learning scores over a four-month period, suggesting that prolonged exposure to highly structured adaptive pathways may reduce learner autonomy, motivation, or engagement. Similarly, longer-term system use has been associated with emerging issues of boredom, system fatigue, and perceived isolation, highlighting the limits of purely algorithm-driven personalization. At a broader temporal scale, the five-year study of AI integration in K–12 STEM education [66] shows a more positive trajectory, with sustained improvements in academic performance and engagement over time. However, these gains were strongly mediated by external enabling factors, including teacher training, infrastructure development, and increasing familiarity with AI systems, indicating that long-term effectiveness depends on broader ecosystem support rather than personalization alone.

Taken together, the comparison suggests a temporal divergence in outcomes: short-term studies tend to emphasize performance gains and engagement improvements, whereas long-term studies reveal complex dynamics involving motivation, self-regulation, system dependency, and contextual constraints. This highlights a critical gap in the literature, namely, the lack of sustained, multi-contextual longitudinal research that tracks how personalization impacts learner agency, cognitive development, and educational equity over time.

3.5. *Cross-cultural perspectives.*

A cross-cultural synthesis of AI-enabled personalized learning reveals important contrasts between developing and developed contexts, while also highlighting shared pedagogical opportunities. Evidence from China and Malaysia demonstrates that AI-integrated strategies such as ASIF (Active learning, Situational discussion, Inductive teaching and Feedback) can effectively enhance student-centered learning and engagement in large-class environments [48], while studies in Ghana, Pakistan, and Hong Kong similarly confirm that AI-driven personalization, through intelligent tutoring systems, reinforcement learning, and learning analytics, improves comprehension, retention, and academic performance across diverse educational systems [54, 65, 66]. These findings indicate that AI technologies possess strong cross-cultural transferability, particularly in addressing linguistic diversity, varying learner needs, and discipline-specific challenges.

In developed contexts, however, the focus shifts from access and adoption to optimization and pedagogical refinement. For instance, research in Switzerland shows that technology-supported personalized learning contributes to cognitive activation and a supportive learning climate, albeit with moderate effect sizes, suggesting that personalization enhances specific dimensions of instructional quality rather than transforming all aspects of learning [83]. Similarly, large-scale institutional initiatives in the United States, such as the University of Florida's AI Across the Curriculum program, emphasize interdisciplinary AI literacy, workforce readiness, and systemic integration across disciplines, reflecting a mature stage of AI adoption where personalization is embedded within broader educational transformation [84]. These examples highlight that developed systems prioritize scalability, curriculum integration, and long-term skill development over basic access.

Despite these advances, the digital divide remains a defining challenge in developing regions. While AI-driven systems significantly improve learning outcomes when infrastructure and training are adequate, as evidenced by sustained gains in Pakistan's STEM education [66], limited access to devices, unreliable internet connectivity, and insufficient teacher preparedness continue to constrain equitable implementation. In contrast, developed countries benefit from robust digital ecosystems that enable widespread adoption and experimentation with AI at scale. Consequently, while AI demonstrates global applicability in personalized learning, its impact is unevenly distributed, necessitating policy interventions that address infrastructural inequities, enhance digital literacy, and promote inclusive, context-sensitive AI integration to prevent the widening of educational disparities [68, 85].

4. Learner Agency and Autonomy

Learner agency refers to students' capacity to intentionally direct their learning through choice, reflection, and self-regulation, while autonomy emphasizes independent decision-making and ownership of learning goals [86]. AI has the potential to strengthen these dimensions by expanding access to tailored pathways and actionable insights; however, because AI systems also structure options, prioritize content, and influence decision processes, they simultaneously shape the boundaries within which agency is exercised.

4.1. AI and self-regulated learning.

Self-regulated learning refers to learners' ability to plan, monitor, control, and reflect on their cognitive, motivational, and behavioral processes in pursuit of learning goals [87]. In SCL, self-regulated learning is not peripheral but foundational. Learners are expected to assume responsibility for goal setting, strategy selection, and self-evaluation. AI systems, through adaptive content delivery, predictive analytics, and real-time feedback, can both strengthen and complicate these regulatory processes [88].

From the perspective of Zimmerman's cyclical model of self-regulated learning, which comprises forethought (goal setting and planning), performance (self-monitoring and strategy use), and self-reflection (self-evaluation and adaptation), AI has the potential to scaffold each phase [89,90]. In the forethought phase, adaptive systems can help learners set realistic goals by analyzing prior performance data and suggesting achievable targets [91]. During performance, AI-driven dashboards and real-time analytics support self-monitoring by visualizing progress, identifying misconceptions, and prompting strategy adjustments [57, 58]. In the reflection phase, automated feedback and predictive modeling enable learners to evaluate outcomes and recalibrate efforts [67]. When feedback is transparent and actionable, AI effectively operationalizes formative assessment principles central to SCL, strengthening metacognitive awareness and strategic adaptation.

AI also aligns with Constructivist Learning Theory, which positions learners as active constructors of knowledge [92]. Adaptive platforms that adjust task complexity based on demonstrated understanding can maintain learners within their optimal challenge range, preventing both cognitive overload and disengagement [93]. In doing so, AI can approximate Vygotsky's concept of the Zone of Proximal Development by providing scaffolding calibrated to learners' evolving competence levels [94]. Rather than delivering uniform instruction, AI-mediated scaffolds can fade as mastery increases, encouraging a gradual transfer of regulatory control from the system to the learner [95]. This is an essential condition for the authentic development of self-regulated learning.

In addition, AI intersects with Self-Determination Theory, which emphasizes autonomy, competence, and relatedness as core psychological needs [96]. Well-designed AI systems can enhance perceived competence through timely feedback and mastery tracking, and they can support autonomy by offering meaningful choices among learning pathways or resources [61, 62]. However, Self-Determination Theory also highlights a critical tension: if AI systems over-direct decisions, restrict options, or obscure the logic behind recommendations, they may undermine autonomy despite offering personalization [97]. Thus, AI's impact on self-regulated learning depends heavily on whether learners retain decision-making authority or simply follow algorithmic prompts. The former steers the adaptive AI system toward an adaptable one, in which learners play an active role in shaping their learning trajectory, thus assuming genuine autonomy.

Empirically, AI-supported learning analytics and adaptive tutoring systems have been associated with improved time-on-task, higher engagement, and increased conceptual mastery [44, 50, 63]. These outcomes are often associated with improved self-monitoring and strategic regulation. Predictive analytics can further support self-regulated learning by alerting students to risk patterns early, encouraging proactive behavioral adjustments [64, 79, 91]. Conversational AI tools may also foster self-regulated learning by enabling iterative questioning, clarification, and reflective dialogue, thereby supporting metacognitive processes when used as cognitive scaffolds rather than answer providers [98, 99] .

Nevertheless, AI introduces important limitations for self-regulated learning. Overreliance on automated feedback may weaken learners' intrinsic monitoring skills if systems externalize regulatory processes that students would otherwise develop independently [56]. Highly prescriptive adaptive pathways can reduce opportunities for productive struggle, experimentation, and error-based learning, which are essential for deep metacognitive growth [12,58]. From a constructivist standpoint, excessive algorithmic optimization risks shifting learning from active knowledge construction to guided consumption [100]. Furthermore, predictive risk labeling may inadvertently influence learners' self-efficacy beliefs, thereby affecting motivational components of self-regulated learning [79].

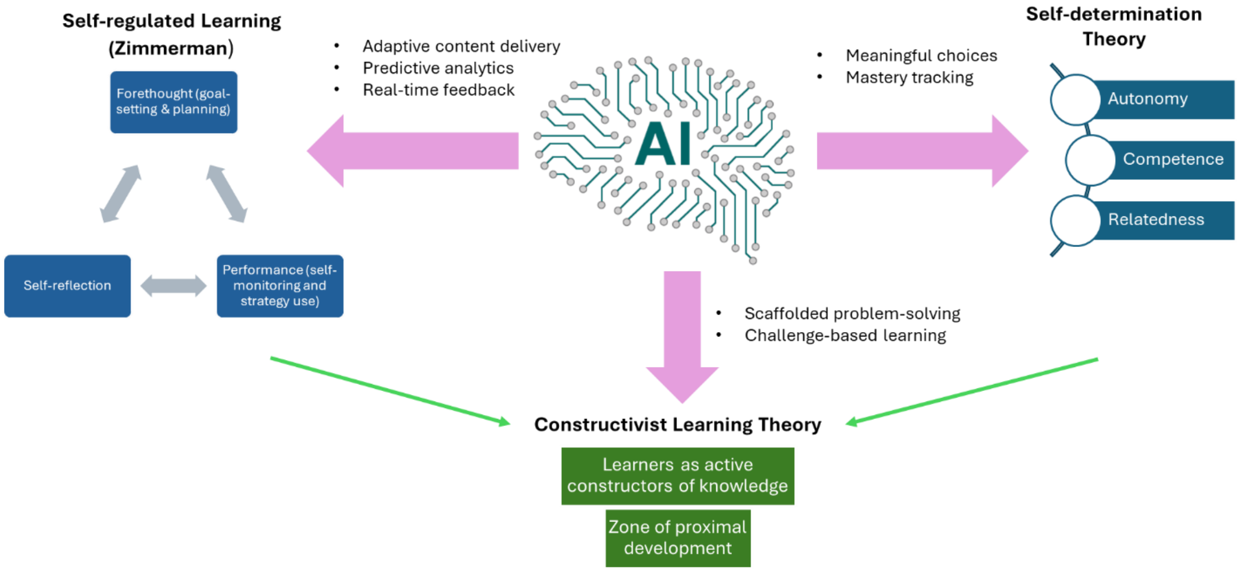

Figure 2. Connection between AI and student-centered theories.

4.2. Cognitive offloading and dependency.

AI introduces new dynamics in how learners distribute cognitive effort, particularly through the processes of cognitive offloading and technological dependency. Cognitive offloading refers to the use of external tools or resources to reduce internal memory, processing, or problem-solving demands [101]. In educational settings, tools such as calculators, note-taking systems, and search engines have long served this function [102]. AI systems, however, extend offloading from simple storage or retrieval to higher-order tasks such as summarizing texts, generating explanations, organizing arguments, or even proposing solutions [103]. This shift raises important questions about how AI-mediated offloading influences learning depth, knowledge retention, and intellectual autonomy.

From a cognitive perspective, offloading is not inherently detrimental. According to Cognitive Load Theory, working memory has a limited capacity. Strategically reducing extraneous load can free cognitive resources for deeper processing [104]. AI tools can support this by automating routine tasks, such as formatting, transcription, or basic information retrieval, thereby allowing learners to focus on conceptual reasoning or creative application [105]. In this sense, AI can function as a cognitive amplifier, extending intellectual reach and enabling engagement with more complex problems than would otherwise be manageable [106].

However, the benefits of offloading depend on how and when it occurs. Research in metacognition suggests that durable learning requires effortful retrieval, elaboration, and self-explanation [107]. When AI performs core cognitive operations, such as constructing arguments or synthesizing readings, learners may bypass the generative processes that strengthen long-term memory and transferable understanding [108]. The issue is not the presence of assistance, but whether the learner remains cognitively engaged in evaluating, modifying, and integrating AI outputs. Passive acceptance of AI-generated responses may reduce desirable difficulties that foster deep learning [105].

The concept of distributed cognition provides a useful theoretical lens. This framework posits that cognition is not confined to the individual mind but is distributed across tools, environments, and social interactions [109]. From this perspective, AI becomes part of the learner's cognitive ecosystem. Dependency, therefore, is not simply reliance but integration [110]. The critical question is whether AI integration expands cognitive capability while preserving evaluative control, or whether it shifts epistemic authority away from the learner. When students rely on AI without understanding the underlying principles, they risk developing procedural fluency without conceptual grounding [111].

Dependency concerns also intersect with motivational and identity dimensions of learning. If learners perceive AI as the primary source of knowledge construction, their sense of intellectual ownership may weaken [112]. Over time, habitual reliance on AI-generated reasoning may diminish confidence in independent problem-solving [105]. Conversely, when AI is framed as a collaborative tool, one that requires critique, refinement, and iterative questioning, it can enhance epistemic agency rather than erode it [113]. For example, conversational systems can either function as answer engines or as dialogic partners that stimulate reflection, depending on how learners are guided to use them [72].

Importantly, cognitive offloading is context-dependent. In the early stages of skill acquisition, excessive reliance can impede the development of foundational schemas [111]. In advanced stages, strategic delegation of routine tasks may enable higher-level synthesis and innovation [114]. This aligns with research on expertise, suggesting that novices require structured practice to build mental models, whereas experts benefit from tools that extend their capabilities [115]. Thus, AI dependency becomes problematic primarily when it replaces, rather than supplements, internal cognitive development.

Educational design plays a central role in mediating these effects. Tasks that require learners to explain, critique, or improve AI outputs can transform offloading into metacognitive engagement [20]. Similarly, assessment structures that prioritize reasoning processes over final answers reduce incentives for uncritical dependence [116]. Transparent discussion of AI's limitations, including potential inaccuracies or bias, also encourages evaluative judgment and epistemic vigilance [117].

Overall, AI-mediated cognitive offloading presents both opportunities and risks. It can reduce unnecessary cognitive strain, extend problem-solving capacity, and support complex inquiry. Yet unchecked dependency may undermine deep processing, conceptual mastery, and intellectual confidence. The pedagogical challenge is not to eliminate offloading, which is an inevitable feature of human cognition, but to cultivate strategic, reflective use of AI that preserves learner agency and strengthens, rather than supplants, internal cognitive growth.

4.3. Co-creation and Human–AI collaboration.

Co-creation and human–AI collaboration in SCL extend beyond personalization to involve learners and educators actively working with AI systems to shape knowledge, feedback, and instructional pathways [118]. Across the studies presented, AI does not merely deliver content; rather, it becomes a participatory partner in inquiry, reflection, assessment, and adaptive intervention. When grounded in constructivist principles, this collaboration can enhance learner agency, creativity, and shared meaning-making.

A clear example emerges in the AI-empowered ASIF strategy implemented across universities in China and Malaysia [48]. Students were granted access to multiple generative

AI platforms, including ChatGPT, ERNIE Bot, and others, to explore concepts, generate alternative explanations, and refine their understanding during active learning and situational discussions. Rather than passively consuming AI outputs, students independently selected tools, experimented with prompts, and integrated AI-generated insights into classroom dialogue. Instructors simultaneously co-designed learning environments using AI-powered platforms such as Quizlet and DingTalk to develop adaptive materials and evaluate student performance. This reciprocal dynamic, where students co-construct knowledge with AI while instructors co-create adaptive structures, illustrates a multilayered human–AI collaboration model [48].

Human–AI co-creation also appears in adaptive content systems driven by reinforcement learning. In the work of Reddy et al. [44], the framework continuously adjusted learning pathways based on learner progress and choices. Here, collaboration was iterative: the learner's actions informed the AI model, which in turn reshaped subsequent content delivery. The system's predictive analytics and modular feedback loops created a dialogic cycle between human behavior and algorithmic response, embodying a co-adaptive process rather than unilateral automation. Similarly, Kumaresan et al. [50] reported that their natural language processing- and reinforcement learning-integrated adaptive system analyzed error patterns and engagement metrics to generate personalized recommendations, resulting in significant improvements in knowledge retention and cognitive skills. These gains suggest that collaborative feedback loops, where AI responds dynamically to learner input, can strengthen the learning process when students actively engage with recommendations.

Co-creation is particularly evident in AI-driven feedback systems. In the study of Afzaal et al. [61], an explainable machine learning dashboard did not merely predict performance but provided actionable recommendations tied to specific behavioral indicators (e.g., LMS participation, quiz scores). Students who followed more recommendations achieved higher final performance, indicating meaningful interaction between human judgment and AI insight. Likewise, the AI-driven adaptive feedback platform evaluated by Naseer and Khawaja [62] integrated live tutoring, personalized learning paths, and engagement analytics; students who frequently interacted with AI feedback experienced higher mastery and retention rates. In these cases, learning outcomes were shaped not only by AI output but also by students' decisions to engage, interpret, and act on AI suggestions.

Teacher-AI collaboration is equally significant. The GPT-4-based learning analytics tool developed by Sajja et al. [59] analyzed student–chatbot dialogues, emotional states, and cognitive levels to inform instructional decisions. Faculty valued features such as identifying frequently asked questions and tracking learning progression, demonstrating how AI-supported analytics can enhance pedagogical responsiveness. Similarly, the AI-assisted feedback platform examined by Xavier et al. [69] enabled instructors to deliver high-quality personalized feedback more efficiently, with 76% of AI-suggested feedback messages adopted without modification. These examples reflect co-creation at the instructional level: AI augments teachers' analytical capacity, while educators retain evaluative authority and contextual judgment.

In collaborative and simulation-based contexts, co-creation becomes multimodal. Yan et al. [67] described a multimodal learning analytics system that integrated positioning data, audio recordings, and visual dashboards to support reflective debriefings in healthcare education. Teachers and students jointly interpreted visual analytics, such as communication heatmaps and task distribution charts, to guide reflection and behavioral adaptation. Here, AI-generated insights served as catalysts for human discussion, reinforcing collective sense-making rather than replacing it.

At the systemic level, AI-driven early warning systems further illustrate collaborative intervention. Predictive models developed by Bhat and Jayaram [64] and Wong et al. [65] generated risk forecasts and personalized intervention recommendations, but final decisions remained with educators and therapists. In special education contexts, teachers reported that AI enhanced individualized profile development and intervention planning without displacing professional expertise [65]. This hybrid decision-making structure reflects responsible human–AI collaboration in high-stakes educational settings.

Overall, the examples demonstrate that co-creation in SCL occurs when AI systems respond dynamically to learner input, provide interpretable insights, and invite human critique and adaptation. Human–AI collaboration is most productive when it operates as a reciprocal partnership: learners and educators shape AI processes through their actions, while AI augments their capacity for analysis, personalization, and reflection. When designed with transparency and pedagogical intentionality, such collaboration advances constructivist ideals by transforming AI from a content-delivery mechanism into an active and adaptable participant in the construction of shared knowledge.

4. Conclusions and Recommendations

AI has become an influential component of SCL, particularly through adaptive content delivery, learning analytics, intelligent feedback systems, and generative tools. The evidence reviewed suggests that AI can meaningfully enhance engagement, personalization, formative assessment, and retention when it is thoughtfully aligned with constructivist and self-regulated learning principles. Adaptive systems that respond dynamically to learners' performance can support differentiated pathways at scale, while analytics dashboards and AI-driven feedback mechanisms can enhance learners' awareness of their progress and areas for improvement. However, the findings also make clear that AI does not automatically foster student-centered outcomes. Its impact on learner agency and autonomy depends largely on design, transparency, and pedagogical integration. A key conclusion is that AI is most effective when positioned as an augmentative, adaptable partner rather than an autonomous instructor. Systems that provide interpretable recommendations and invite learners to reflect on and act upon feedback are more likely to strengthen agency than systems that make opaque decisions or overly structure learning pathways. While automation can increase efficiency, excessive algorithmic control may narrow choice, encourage cognitive offloading, or weaken self-regulated learning. Thus, the central challenge is not simply implementing AI, but designing it in ways that preserve and extend learner ownership. To enhance agency in AI-supported SCL, several recommendations emerge. First, transparency and explainability should be foundational. Learners should understand why particular resources, difficulty levels, or feedback messages are generated. Clear visualizations and explanatory prompts can help students interpret AI outputs and make informed decisions, reinforcing metacognitive development rather than passive compliance. Second, adaptive systems should embed meaningful choice. Rather than silently adjusting instruction, AI platforms can offer alternative resources, varied representations, or optional challenge levels that students can select based on their goals. Structured choice within adaptive environments maintains personalization while reinforcing autonomy. Third, AI should be deliberately integrated to support self-regulated learning. This includes embedding prompts for goal-setting, reflection, and strategy evaluation into AI interactions. Generative systems such as ChatGPT can be used to scaffold questioning, debate perspectives, or refine drafts, provided students are guided to critically evaluate outputs rather than rely on them uncritically. Educators play a crucial role in modeling reflective AI use and framing it as a cognitive partner rather than a shortcut. Fourth, sustained professional development is essential. Teachers must be equipped to interpret learning analytics, integrate AI insights into instructional design, and maintain pedagogical and ethical oversight. AI should enhance, not replace, educators' judgment. Institutional policies should similarly emphasize ethical governance, including data privacy, fairness audits, and equitable access to prevent algorithmic bias from undermining student-centered values. Future research should prioritize longitudinal studies examining the sustained effects of AI on autonomy, motivation, and self-regulation. Comparative investigations into levels of AI transparency, degrees of learner control, and cultural variations in human–AI collaboration are also needed. Additionally, more empirical work should explore how to balance efficiency gains with the preservation of deep cognitive engagement. Ultimately, AI's contribution to SCL lies not in automation itself but in its capacity to expand learners' opportunities to think, choose, reflect, and act intentionally. When designed and implemented responsibly, AI can strengthen, not diminish, learner agency within evolving educational ecosystems.

Acknowledgments

The author wishes to thank the University of Arizona for the administrative support provided.

Author Contribution

Conceptualization and writing: K.H.D.T.

Competing Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

References

[1] Kharroubi, S.; ElMediouni, A. (2024). Conceptual Review: Cultivating Learner Autonomy Through Self-Directed Learning & Self-Regulated Learning: A Socio-Constructivist Exploration. *International Journal of Language and Literary Studies*, *6*(2), 276–296. https://doi.org/10.36892/ijlls.v6i2.1649.

[2] Tang, K. H. D. (2022). A model of behavioral climate change education for higher educational institutions. *Environmental Advances*, *9*, 100305. https://doi.org/10.1016/j.envadv.2022.100305.

[3] Jiang, H.; Zhu, D.; Chugh, R.; Turnbull, D.; Jin, W. (2025). Virtual reality and augmented reality-supported K-12 STEM learning: trends, advantages and challenges. *Education and Information Technologies*, *30*(9), 12827–12863. https://doi.org/10.1007/s10639-024-13210-z.

[4] Tang, D. K. H. (2021). A Case Study of Outcome-based Education: Reflecting on Specific Practices between a Malaysian Engineering Program and a Chinese Science Program. *Innovative Teaching and Learning*, *3*(1). https://doi.org/10.4208/itl.20210005.

[5] Maia, D.; Andrade, R.; Afonso, J.; Costa, P.; Valente, C.; Espregueira-Mendes, J. (2023). Academic Performance and Perceptions of Undergraduate Medical Students in Case-Based

Learning Compared to Other Teaching Strategies: A Systematic Review with Meta-Analysis. *Education Sciences*, *13*(3), 238. https://doi.org/10.3390/educsci13030238.

[6] Tang, K. H. D. (2023). Climate change education in China: a pioneering case of its implementation in tertiary education and its effects on students' beliefs and attitudes. *International Journal of Sustainability in Higher Education*, *24*(5), 1058–1081. https://doi.org/10.1108/IJSHE-05-2022-0151.

[7] Ortega-Alvarez, J.D.; Mohd-Addi, M.; Guerra, A.; Krishnan, S.; Mohd-Yusof, K. (2025). Creating Student-Centric Learning Environments Through Evidence-Based Pedagogies and Assessments. In Academic Leadership in Engineering Education: Learnings and Case Studies from Educational Leaders Around the Globe; Kandakatla, R., Kulkarni, S., Auer, M.E., Eds.; Springer Nature: Cham, Switzerland. pp. 123–142

[8] Tang, K. H. D. (2024). Implications of Artificial Intelligence for Teaching and Learning. *Acta Pedagogia Asiana*, *3*(2), 65–79. https://doi.org/10.53623/apga.v3i2.404.

[9] Holmes, W.; Tuomi, I. (2022). State of the art and practice in AI in education. *European Journal of Education*, *57*(4), 542–570. https://doi.org/10.1111/ejed.12533.

[10] Kshetri, N. (2024). The academic industry's response to generative artificial intelligence: An institutional analysis of large language models. *Telecommunications Policy*, *48*(5), 102760. https://doi.org/10.1016/j.telpol.2024.102760.

[11] Shahzad, T.; Mazhar, T.; Tariq, M. U.; Ahmad, W.; Ouahada, K.; Hamam, H. (2025). A comprehensive review of large language models: issues and solutions in learning environments. *Discover Sustainability*, *6*(1), 27. https://doi.org/10.1007/s43621-025-00815-8.

[12] Chen, J.; Liu, Z.; Huang, X.; Wu, C.; Liu, Q.; Jiang, G.; Pu, Y.; Lei, Y.; Chen, X.; Wang, X.; Zheng, K.; Lian, D.; Chen, E. (2024). When large language models meet personalization: perspectives of challenges and opportunities. *World Wide Web*, *27*(4), 42. https://doi.org/10.1007/s11280-024-01276-1.

[13] Kasneci, E.; Sessler, K.; Küchemann, S.; Bannert, M.; Dementieva, D.; Fischer, F.; Gasser, U.; Groh, G.; Günnemann, S.; Hüllermeier, E.; Krusche, S.; Kutyniok, G.; Michaeli, T.; Nerdel, C.; Pfeffer, J.; Poquet, O.; Sailer, M.; Schmidt, A.; Seidel, T.; Stadler, M.; Weller, J.; Kuhn, J.; Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274.

[14] Zhang, Q. (2024). Harnessing artificial intelligence for personalized learning pathways: A framework for adaptive education management systems. *Applied and Computational Engineering*, *82*(1), 167–172.

[15] Trajkovski, G.; Hayes, H. (2025). AI-Assisted Formative Assessment and Feedback. In AI-Assisted Assessment in Education: Transforming Assessment and Measuring Learning; Trajkovski, G., Hayes, H., Eds.; Springer Nature: Cham, Switzerland. pp. 283–312.

[16] Foster, E.; Siddle, R. (2020). The effectiveness of learning analytics for identifying at-risk students in higher education. *Assessment & Evaluation in Higher Education*, *45*(6), 842–854. https://doi.org/10.1080/02602938.2019.1682118.

[17] Wei, X.; Wang, L.; Lee, L.-K.; Liu, R. (2025). The effects of generative AI on collaborative problem-solving and team creativity performance in digital story creation: an experimental study. *International Journal of Educational Technology in Higher Education*, *22*(1), 23. https://doi.org/10.1186/s41239-025-00526-0.

[18] Mouta, A.; Pinto-Llorente, A. M.; Torrecilla-Sánchez, E. M. (2025). "Where is Agency Moving to?": Exploring the Interplay between AI Technologies in Education and Human Agency. *Digital Society*, *4*(2), 49. https://doi.org/10.1007/s44206-025-00203-9.

[19] Nopas, D.-s. (2025). Algorithmic learning or learner autonomy? Rethinking AI's role in digital education. *Qualitative Research Journal*. https://doi.org/10.1108/QRJ-11-2024-0282.

[20] Gerlich, M. (2025). AI Tools in Society: Impacts on Cognitive Offloading and the Future of Critical Thinking. *Societies*, *15*(1), 6. https://doi.org/10.3390/soc15010006.

[21] Chandrasekera, T.; Hosseini, Z.; Perera, U. (2025). Can artificial intelligence support creativity in early design processes? *International Journal of Architectural Computing*, *23*(1), 122–136. https://doi.org/10.1177/14780771241254637.

[22] Manousou, E. (2025). Critical Thinking in Distance Education: The Challenges in a Decade (2016–2025) and the Role of Artificial Intelligence. *Education Sciences*, *15*(6), 757. https://doi.org/10.3390/educsci15060757.

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

[24] Mohebbi, A. (2025). Enabling learner independence and self-regulation in language education using AI tools: a systematic review. *Cogent Education*, *12*(1), 2433814. https://doi.org/10.1080/2331186X.2024.2433814.

[25] Yan, L.; Alwabel, S. A.; Mohamad, U. H. (2025). AI-Powered Education: Transforming Teacher-Student Interactions and Advancing Sustainable Learning Practices. *European Journal of Education*, *60*(4), e70351. https://doi.org/10.1111/ejed.70351.

[26] Ramkissoon, L. (2024). AI: Powering Sustainable Innovation in Higher EdThe Evolution of Artificial Intelligence in Higher Education: Challenges, Risks, and Ethical Considerations. Emerald Publishing Limited. https://doi.org/10.1108/978-1-83549-486-820241013.

[27] Liu, D.Y.-T.; Bartimote-Aufflick, K.; Pardo, A.; Bridgeman, A.J. (2017). Data-Driven Personalization of Student Learning Support in Higher Education. In Learning Analytics: Fundaments, Applications, and Trends; Peña-Ayala, A. Ed.; Springer Nature: Cham, Switzerland. pp. 283–312.

[28] Hughes, J. (2021). The Deskilling of Teaching and the Case for Intelligent Tutoring Systems. *Journal of Ethics and Emerging Technologies*, *31*(2), 1–16. https://doi.org/10.55613/jeet.v31i2.90.

[29] Reeves, J. (2016). Automatic for the people: the automation of communicative labor. *Communication and Critical/Cultural Studies*, *13*(2), 150–165. https://doi.org/10.1080/14791420.2015.1108450.

[30] Meng, N.; Mat Deli, M.; Abdul Rauf, U. A. (2025). Educational Technology and AI: Bridging Cognitive Load and Learner Engagement for Effective Learning. *Sage Open*, *15*(4), 21582440251395930. https://doi.org/10.1177/21582440251395930.

[31] Matar, S. (2025). The development of educational technology and artificial intelligence and their impact on the future of education: Opportunities and risks. *Journal of Posthumanism*, *5*(7), 1271–1292.

[32] Wu, R.; Yu, Z. (2024). Do AI chatbots improve students learning outcomes? Evidence from a meta-analysis. *British Journal of Educational Technology*, *55*(1), 10–33. https://doi.org/10.1111/bjet.13334.

[33] Boubker, O. (2024). From chatting to self-educating: Can AI tools boost student learning outcomes? *Expert Systems with Applications*, *238*, 121820. https://doi.org/10.1016/j.eswa.2023.121820.

[34] Weng, X.; Ye, H.; Dai, Y.; Ng, O.-l. (2024). Integrating Artificial Intelligence and Computational Thinking in Educational Contexts: A Systematic Review of Instructional Design and Student Learning Outcomes. *Journal of Educational Computing Research*, *62*(6), 1420–1450. https://doi.org/10.1177/07356331241248686.

[35] Bergdahl, N.; Sjöberg, J. (2025). Attitudes, perceptions and AI self-efficacy in K-12 education. *Computers and Education: Artificial Intelligence*, *8*, 100358. https://doi.org/10.1016/j.caeai.2024.100358.

[36] Chounta, I.-A.; Bardone, E.; Raudsep, A.; Pedaste, M. (2022). Exploring Teachers' Perceptions of Artificial Intelligence as a Tool to Support their Practice in Estonian K-12 Education. *International Journal of Artificial Intelligence in Education*, *32*(3), 725–755. https://doi.org/10.1007/s40593-021-00243-5.

[37] Slimi, Z.; Benayoune, A.; Alemu, A. E. (2025). Students' perceptions of artificial intelligence integration in higher education. *European Journal of Educational Research*, *14*(2), 471–484.

[38] Alwaqdani, M. (2025). Investigating teachers' perceptions of artificial intelligence tools in education: potential and difficulties. *Education and Information Technologies*, *30*(3), 2737–2755. https://doi.org/10.1007/s10639-024-12903-9.

[39] Tang, K. H. D. (2021). Education for sustainable development from the perspective of Christianity: Pedagogies and prospects. *European Journal of Education Studies*, *8*(4). http://dx.doi.org/10.46827/ejes.v8i4.3678.

[40] Garg, N.; Kaur, A.; Ahmad, F.; Dutta, R. (2025). Augmenting Education: The Transformative Power of AR, AI, and Emerging Technologies. *Human Behavior and Emerging Technologies*, *2025*(1), 5681184. https://doi.org/10.1155/hbe2/5681184.

[41] Bhardwaj, V.; Zhang, S.; Tan, Y. Q.; Pandey, V. (2025). Redefining learning: student-centered strategies for academic and personal growth. *Frontiers in Education*, *10*. https://doi.org/10.3389/feduc.2025.xxxxxx.

[42] Tang, K. H. D. (2021). Engaging Students in the Development of an Atmospheric Science Course: A Discourse Analysis. *Asian Journal of Education and Social Studies*, *19*(3), 1–9. https://doi.org/10.9734/AJESS/2021/v19i330463.

[43] Tang, K. H. D. (2025). A Narrative Review of How Students Perceive a Good Teacher. *Acta Pedagogia Asiana*, *4*(2), 66–85. https://doi.org/10.53623/apga.v4i2.593.

[44] Reddy, B. L.; Nirmala; Lathika, V.; Vidhyasree, M.; Manimegalai, V.; Kavya, K. (2025). Personalized Learning Systems Using AI for Adaptive Educational Content Delivery Based on Reinforcement Learning Algorithms. 2025 3rd International Conference on Communication, Security, and Artificial Intelligence (ICCSAI).

[45] Kabudi, T.; Pappas, I.; Olsen, D. H. (2021). AI-enabled adaptive learning systems: A systematic mapping of the literature. *Computers and Education: Artificial Intelligence*, *2*, 100017. https://doi.org/10.1016/j.caeai.2021.100017.

[46] Er-Rafyg, A.; Zankadi, H.; Idrissi, A. (2024). AI in Adaptive Learning: Challenges and Opportunities. In Modern Artificial Intelligence and Data Science 2024: Tools, Techniques and Systems; Idrissi, A. Ed.; Springer Nature: Cham, Switzerland. pp. 329–342.

[47] Chu, T. S.; Ashraf, M. (2025). Artificial Intelligence in Curriculum Design: A Data-Driven Approach to Higher Education Innovation. *Knowledge*, *5*(3), 14. https://doi.org/10.3390/knowledge5030014.

[48] Meng, X.; Yang, B.; Yang, L.; Zhang, J.; Liu, Y. (2025). A Novel AI-Empowered, Student-Centered Teaching Strategy for Large Classes in Higher Education. *International Journal of Science and Mathematics Education*, *23*(7), 3093–3121. https://doi.org/10.1007/s10763-025-10573-8.

[49] Sampath, K.; Kandaswamy, M.; Ramu, V.; Devi, K.; Venkatesan, S. (2025). AI-Driven Learning Behavior Analysis for Adaptive Content Delivery and Enhanced Productivity. 2025 IEEE International Conference on Blockchain and Distributed Systems Security (ICBDS).

[50] Kumaresan, V.; Jeyakarthic, M.; Manjula Devi, P.; Jona Innisai Rani, P.; Mohan, E.; Surendra, K. R. (2025). Personalized AI-Driven Online Education Technologies for Adaptive Learning and Cognitive Skill Enhancement. Conference paper.

[51] Kolluru, V.; Mungara, S.; Chintakunta, A. N. (2018). Adaptive learning systems: Harnessing AI for customized educational experiences. International Journal of Computational Science and Information Technology, 6(3).

[52] Bernard, J.; Popescu, E.; Graf, S. (2022). Improving online education through automatic learning style identification using a multi-step architecture with ant colony system and artificial neural networks. *Applied Soft Computing*, *131*, 109779. https://doi.org/10.1016/j.asoc.2022.109779.

[53] Tang, Y.; Liang, J.; Hare, R.; Wang, F. Y. (2020). A Personalized Learning System for Parallel Intelligent Education. *IEEE Transactions on Computational Social Systems*, *7*(2), 352–361. https://doi.org/10.1109/TCSS.2020.2965198.

[54] Adabor, E. S.; Addy, E.; Assyne, N.; Antwi-Boasiako, E. (2025). Enhancing sustainable academic course delivery using AI in technical universities: An empirical analysis using adaptive learning theory. *Sustainable Futures*, *10*, 100828. https://doi.org/10.1016/j.sftr.2025.100828.

[55] Teich, K.; Loock, V. S.; Rummel, N. (2024). Meeting the challenges of continuing education online courses: Can we promote self-regulated learning strategies with adaptive support? *British Journal of Educational Technology*, *55*(4), 1437–1455. https://doi.org/10.1111/bjet.13453.

[56] Harati, H.; Sujo-Montes, L.; Tu, C.-H.; Armfield, S. J. W.; Yen, C.-J. (2021). Assessment and Learning in Knowledge Spaces (ALEKS) Adaptive System Impact on Students' Perception and Self-Regulated Learning Skills. *Education Sciences*, *11*(10), 603. https://doi.org/10.3390/educsci11100603.

[57] Filipović, A.M.; Fastić-Pajk, I.; Puljiz, H.; Šabić, I. (2026). AI-Driven Customization of Adaptive Learning Content: Lessons from Applying LLMs in Personalized Education. In Digital Transformation in Education and Artificial Intelligence Application; Vasić, D., Brajković, E., Eds.; MoStart 2025. Communications in Computer and Information Science, vol 2609. Springer, Cham. https://doi.org/10.1007/978-3-032-02801-3_5.

[58] Rodríguez-Ortiz, M. Á.; Santana-Mancilla, P. C.; Anido-Rifón, L. E. (2025). Machine Learning and Generative AI in Learning Analytics for Higher Education: A Systematic Review of Models, Trends, and Challenges. *Applied Sciences*, *15*(15), 8679. https://doi.org/10.3390/app15158679.

[59] Sajja, R.; Sermet, Y.; Cwiertny, D.; Demir, I. (2025). Integrating AI and Learning Analytics for Data-Driven Pedagogical Decisions and Personalized Interventions in Education. *Technology, Knowledge and Learning*. https://doi.org/10.1007/s10758-025-09897-9.

[60] Jang, Y.; Choi, S.; Jung, H.; Kim, H. (2022). Practical early prediction of students' performance using machine learning and eXplainable AI. *Education and Information Technologies*, *27*(9), 12855–12889. https://doi.org/10.1007/s10639-022-11120-6.

[61] Afzaal, M.; Nouri, J.; Zia, A.; Papapetrou, P.; Fors, U.; Wu, Y.; Li, X.; Weegar, R. (2021). Explainable AI for Data-Driven Feedback and Intelligent Action Recommendations to Support Students Self-Regulation. *Frontiers in Artificial Intelligence*, *4,* 72344. https://doi.org/10.3389/frai.2021.723447.

[62] Naseer, F.; Khawaja, S. (2025). Mitigating Conceptual Learning Gaps in Mixed-Ability Classrooms: A Learning Analytics-Based Evaluation of AI-Driven Adaptive Feedback for Struggling Learners. *Applied Sciences*, *15*(8), 4473. https://doi.org/10.3390/app15084473.

[63] Abas, S.; Sunarjo, R. A.; Abbas, M.; Al-Kamari, O. A.; Sabda, M. (2025). AI-Driven Educational Data Analytics and Intelligent Tutoring in Learning Factory Environments. *International Transactions on Education Technology*, *4*(1), 14–30. https://doi.org/10.33050/itee.v4i1.950.

[64] Bhat, J.; Jayaram, Y. (2023). Predictive Analytics for Student Retention and Success Using AI/ML. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, *4*(4), 121–131. https://doi.org/10.63282/3050-9262.IJAIDSML-V4I4P114.

[65] Wong, C. M. V.; Yum, Y. N.; Chan, R. Y. Y. (2025). AI-Driven Learning Analytics for Applied Behavior Analysis Therapy. *IEEE Transactions on Learning Technologies*, *18*, 1097–1111. https://doi.org/10.1109/TLT.2025.3637864.

[66] Haider, A.; Yasin, A.; Muneer, A. (2025). AI-Driven Learning Analytics for Evidence-Based Decision-Making in K–12 STEM Classrooms. *Social Sciences Spectrum*, *4*(4), 260–280. https://doi.org/10.71085/sss.04.04.411.

[67] Yan, L.; Echeverria, V.; Jin, Y.; Fernandez-Nieto, G.; Zhao, L.; Li, X.; Alfredo, R.; Swiecki, Z.; Gašević, D.; Martinez-Maldonado, R. (2024). Evidence-based multimodal learning analytics for feedback and reflection in collaborative learning. *British Journal of Educational Technology*, *55*(5), 1900–1925. https://doi.org/10.1111/bjet.13498.
[68] Mavroudi, A.; Papadakis, S.; Ioannou, I. (2021). Teachers' Views Regarding Learning Analytics Usage Based on the Technology Acceptance Model. *TechTrends*, *65*(3), 278–287. https://doi.org/10.1007/s11528-020-00580-7.
[69] Xavier, C.; Rodrigues, L.; Costa, N.; Neto, R.; Alves, G.; Falcão, T. P.; Gašević, D.; Mello, R. F. (2025). Empowering Instructors With AI: Evaluating the Impact of an AI-Driven Feedback Tool in Learning Analytics. *IEEE Transactions on Learning Technologies*, *18*, 498–512. https://doi.org/10.1109/TLT.2025.3562379.
[70] Dervić, D.; Glamočić, D. S.; Gazibegović-Busuladžić, A.; Mešić, V. (2018). Teaching physics with simulations: Teacher-centered versus student-centered approaches. *Journal of Baltic Science Education*, *17*(2), 288. https://doi.org/10.33225/jbse/18.17.288.
[71] Amin, S.; Uddin, M. I.; Alarood, A. A.; Mashwani, W. K.; Alzahrani, A.; Alzahrani, A. O. (2023). Smart E-Learning Framework for Personalized Adaptive Learning and Sequential Path Recommendations Using Reinforcement Learning. *IEEE Access*, *11*, 89769–89790. https://doi.org/10.1109/ACCESS.2023.3305584.
[72] Li, P.-H.; Wu, T.-T.; Wang, S.-C.; Lin, C.-J.; Huang, Y.-M. (2025). Leveraging ChatGPT in inquiry-based learning: effects of generated personalized prompts on self-reflection. *Journal of Research on Technology in Education*, 1–19. https://doi.org/10.1080/15391523.2025.2586518.
[73] Sharma, K.; Giannakos, M. (2020). Multimodal data capabilities for learning: What can multimodal data tell us about learning? *British Journal of Educational Technology*, *51*(5), 1450–1484. https://doi.org/10.1111/bjet.12993.
[74] Li, F.; He, Y.; Xue, Q. (2021). Progress, challenges and countermeasures of adaptive learning. *Educational Technology & Society*, *24*(3), 238–255.
[75] Tetzlaff, L.; Schmiedek, F.; Brod, G. (2021). Developing Personalized Education: A Dynamic Framework. *Educational Psychology Review*, *33*(3), 863–882. https://doi.org/10.1007/s10648-020-09570-w.
[76] Zagkotas, V. (2025). Artificial Intelligence and the Didactic Transposition of Knowledge: Implications for Curriculum Development and Knowledge Gatekeeping. *Futurity Education*, *5*(2), 44–66. https://doi.org/10.57125/FED.2025.06.25.03.
[77] Hou, C.; Zhu, G.; Liu, Y.; Sudarshan, V.; Chong, J. L. L.; Zhang, F. Y.; Tan, M. Y. H.; Ong, Y. S. (2026). The effects of critical thinking intervention on reliance behaviors, problem-solving quality, and creativity during human-Generative AI collaborative learning. *Computers & Education*, *247*, 105576. https://doi.org/10.1016/j.compedu.2026.105576.
[78] Nazer, L. H.; Zatarah, R.; Waldrip, S.; Ke, J. X. C.; Moukheiber, M.; Khanna, A. K.; Hicklen, R. S.; Moukheiber, L.; Moukheiber, D.; Ma, H.; Mathur, P. (2023). Bias in artificial intelligence algorithms and recommendations for mitigation. *PLOS Digital Health*, *2*(6), e0000278. https://doi.org/10.1371/journal.pdig.0000278.
[79] Sacher, S. (2022). Risking Children: The Implications of Predictive Risk Analytics Across Child Protection and Policing for Vulnerable and Marginalized Children. *Human Rights Law Review*, *22*(1), ngab028. https://doi.org/10.1093/hrlr/ngab028.
[80] Sai Srinivas, M.; Manish, B. (2023). Trustworthy AI: Explainability & Fairness in Large-scale Decision Systems. *Review of Applied Science and Technology*, *2*(04), 54–93. https://doi.org/10.63125/3w9v5e52.
[81] Leighton, J. P.; Guo, Q.; Chu, M.-W.; Tang, W. (2018). A pedagogical alliance for academic achievement: Socio-Emotional effects on assessment outcomes. *Educational Assessment*, *23*(1), 1–23. http://doi.org/10.1080/10627197.2017.1411188.

[82] Fischer, G. (2021). End-User Development: Empowering Stakeholders with Artificial Intelligence, Meta-Design, and Cultures of Participation. End-User Development. End-User Development: 8th International Symposium, IS-EUD 2021, Virtual Event, July 6–8, 2021, Proceedings, Pages 3 – 16. https://doi.org/10.1007/978-3-030-79840-6_1.
[83] Schmid, R.; Pauli, C.; Stebler, R.; Reusser, K.; Petko, D. (2022). Implementation of technology-supported personalized learning—its impact on instructional quality. *The Journal of Educational Research*, *115*(3), 187–198. http://doi.org/10.1080/00220671.2022.2089086.
[84] Southworth, J.; Migliaccio, K.; Glover, J.; Glover, J. N.; Reed, D.; McCarty, C.; Brendemuhl, J.; Thomas, A. (2023). Developing a model for AI Across the curriculum: Transforming the higher education landscape via innovation in AI literacy. *Computers and Education: Artificial Intelligence*, *4*, 100127. http://doi.org/10.1016/j.caeai.2023.100127.
[85] Otto, D.; Assenmacher, V.; Bente, A.; Gellner, C.; Waage, M.; Deckert, R.; Siepermann, M.; Kammer, F.; Kuche, J. (2024). Student acceptance of AI-based feedback systems: An analysis based on the technology acceptance model (TAM). 18th International Technology, Education and Development Conference, Valencia, Spain. https://doi.org/10.21125/inted.2024.0973.
[86] Gupta, N.; Ali, K.; Jiang, D.; Fink, T.; Du, X. (2024). Beyond autonomy: unpacking self-regulated and self-directed learning through the lens of learner agency—A scoping review. *BMC Medical Education*, *24*(1), 1519. http://doi.org/10.1186/s12909-024-06476-x.
[87] Zeidner, M.; Stoeger, H. (2019). Self-Regulated Learning (SRL): A guide for the perplexed. *High Ability Studies*, *30*(1–2), 9–51. http://doi.org/10.1080/13598139.2019.1589369.
[88] Khalil, M.; Wong, J.; Wasson, B.; Paas, F. (2024). Adaptive support for self-regulated learning in digital learning environments. *British Journal of Educational Technology*, *55*(4), 1281–1289. http://doi.org/10.1111/bjet.13479.
[89] Adam, N.L., Alzahri, F.B., Cik Soh, S., Abu Bakar, N., Mohamad Kamal, N.A. (2017). Self-Regulated Learning and Online Learning: A Systematic Review. In Advances in Visual Informatics; Badioze Zaman, H., *et al.* IVIC 2017. Lecture Notes in Computer Science(), vol 10645. Springer: Cham, Switzerland. https://doi.org/10.1007/978-3-319-70010-6_14.
[90] Brünner, B.; Burgsteiner, H.; Schön, S.; Ebner, M. (2025). The Synergy of Educational Technologies and Self-regulated Learning: A Systematic Scoping Literature Review. In Futureproofing Engineering Education for Global Responsibility; Auer, M.E., Rüütmann, T., Eds.; ICL 2024. Lecture Notes in Networks and Systems, vol 1261. Springer, Cham. https://doi.org/10.1007/978-3-031-85649-5_30.
[91] Kizilcec, R. F.; Pérez-Sanagustín, M.; Maldonado, J. J. (2017). Self-regulated learning strategies predict learner behavior and goal attainment in Massive Open Online Courses. *Computers & Education*, *104*, 18–33. http://doi.org/10.1016/j.compedu.2016.10.001.
[92] Grubaugh, S.; Levitt, G.; Deever, D. (2023). Harnessing AI to power constructivist learning: An evolution in educational methodologies. *EIKI Journal of Effective Teaching Methods*, *1*(3). https://doi.org/10.59652/jetm.v1i3.43.
[93] Gupta, P.; Prashar, A. (2025). Learners' psychological needs in online learning environment for executive education: role of cognitive overload and learning self-efficacy. *Behaviour & Information Technology*, *44*(9), 1942–1963. http://doi.org/10.1080/0144929X.2024.2383777.
[94] Eun, B. (2019). The zone of proximal development as an overarching concept: A framework for synthesizing Vygotsky's theories. *Educational Philosophy and Theory*, *51*(1), 18–30. http://doi.org/10.1080/00131857.2017.1421941.
[95] Hutson, J. (2025). Scaffolded Integration: Aligning AI Literacy with Authentic Assessment through a Revised Taxonomy in Education. *FAR Journal of Education and Sociology*, *2*(1).
[96] Tsai, C.Y.; Huang, T.C.; Shu, Y.; Chiang, Y.H. (2026). Investigating the Influence of Autonomy, Competence, Relatedness, and Excitement on User Satisfaction with ChatGPT: A Self-Determination Theory Perspective. In Innovative Technologies and Learning; Wang, W.S.,

Sandnes, F.E., Lai, C.F., Sandtrø, T.A., Huang, Y.M., Eds.; ICITL 2025. Lecture Notes in Computer Science, vol 15914. Springer: Cham, Switzerland. https://doi.org/10.1007/978-3-031-98197-5_41.

[97] Druga, S.; Otero, N.; Ko, A. J. (2022). The Landscape of Teaching Resources for AI Education. Proceedings of the 27th ACM Conference on Innovation and Technology in Computer Science Education, Vol. 1, Dublin, Ireland. http://doi.org/10.1145/3502718.3524782.

[98] Du, Q. (2025). How artificially intelligent conversational agents influence EFL learners' self-regulated learning and retention. *Education and Information Technologies*, *30*(15), 21635–21701. http://doi.org/10.1007/s10639-025-13602-9.

[99] Lai, J. W. (2024). Adapting Self-Regulated Learning in an Age of Generative Artificial Intelligence Chatbots. *Future Internet*, *16*(6), 218. http://doi.org/10.3390/fi16060218.

[100] Sun, Y.; Xu, C. (2025). Hybrid cognitive authority and algorithmic subjectivity: rethinking knowledge management in AI-driven communication. *Journal of Knowledge Management*, 1–26. http://doi.org/10.1108/JKM-02-2025-0252.

[101] Risko, E. F.; Gilbert, S. J. (2016). Cognitive Offloading. *Trends in Cognitive Sciences*, *20*(9), 676–688. http://doi.org/10.1016/j.tics.2016.07.002.

[102] Carter, J. A. (2018). Autonomy, Cognitive Offloading, and Education. *Educational Theory*, *68*(6), 657–673. http://doi.org/10.1111/edth.12338.

[103] Chirayath, G.; Premamalini, K.; Joseph, J. (2025). Cognitive offloading or cognitive overload? How AI alters the mental architecture of coping. *Frontiers in Psychology*, *16*, 2025.

[104] Meguerdichian, M.; Walker, K.; Bajaj, K. (2016). Working memory is limited: improving knowledge transfer by optimising simulation through cognitive load theory. *BMJ Simulation & Technology Enhanced Learning*, *2*(4), 131.

[105] Shukla, P.; Bui, P.; Levy, S. S.; Kowalski, M.; Baigelenov, A.; Parsons, P. (2025). De-skilling, Cognitive Offloading, and Misplaced Responsibilities: Potential Ironies of AI-Assisted Design. Paper presented at Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems. http://doi.org/10.1145/3706599.3719931.

[106] Chiriatti, M.; Bergamaschi Ganapini, M.; Panai, E.; Wiederhold, B. K.; Riva, G. (2025). System 0: Transforming Artificial Intelligence into a Cognitive Extension. *Cyberpsychology, Behavior, and Social Networking*, *28*(7), 534–542. http://doi.org/10.1089/cyber.2025.0201.

[107] Braad, E.; Degens, N.; Barendregt, W.; Ijsselsteijn, W. (2022). Improving metacognition through self-explication in a digital self-regulated learning tool. *Educational Technology Research and Development*, *70*(6), 2063–2090. http://doi.org/10.1007/s11423-022-10156-2.

[108] Bai, L.; Liu, X.; Su, J. (2023). ChatGPT: The cognitive effects on learning and memory. *Brain-X*, *1*(3), e30. http://doi.org/10.1002/brx2.30.

[109] Heersmink, R.; Knight, S. (2018). Distributed learning: Educating and assessing extended cognitive systems. *Philosophical Psychology*, *31*(6), 969–990. http://doi.org/10.1080/09515089.2018.1469122.

[110] Pratiwi, H.; Riwanda, A.; Hasruddin, H.; Sujarwo, S.; Syamsudin, A. (2025). Transforming Learning or Creating Dependency? Teachers' Perspectives and Barriers to AI Integration in Education. *Journal of Pedagogical Research*, *9*(2), 127–142.

[111] Klein, C. R.; Klein, R. (2025). The extended hollowed mind: why foundational knowledge is indispensable in the age of AI. *Frontiers in Artificial Intelligence*, *8*, 2025.

[112] Frenkenberg, A.; Hochman, G. (2025). It's Scary to Use It, It's Scary to Refuse It: The Psychological Dimensions of AI Adoption—Anxiety, Motives, and Dependency. *Systems*, *13*(2), 82. http://doi.org/10.3390/systems13020082.

[113] Wu, J.-Y.; Lee, Y.-H.; Chai, C. S.; Tsai, C.-C. (2025). Strengthening Human Epistemic Agency in the Symbiotic Learning Partnership With Generative Artificial Intelligence. *Educational Researcher*, *54*(6), 358–368. http://doi.org/10.3102/0013189X251333628.

[114] Truong, Y.; Papagiannidis, S. (2022). Artificial intelligence as an enabler for innovation: A review and future research agenda. *Technological Forecasting and Social Change*, *183*, 121852. http://doi.org/10.1016/j.techfore.2022.121852.

[115] Thomas, C. M.; Kellgren, M. (2017). Benner's Novice to Expert Model: An Application for Simulation Facilitators. *Nursing Science Quarterly*, *30*(3), 227–234. http://doi.org/10.1177/0894318417708410.

[116] Zlatkin-Troitschanskaia, O.; Beck, K.; Fischer, J.; Braunheim, D.; Schmidt, S.; Shavelson, R. J. (2020). The Role of Students' Beliefs When Critically Reasoning From Multiple Contradictory Sources of Information in Performance Assessments. *Frontiers in Psychology*, *11*, 2020.

[117] Chavanayarn, S. (2023). Navigating Ethical Complexities Through Epistemological Analysis of ChatGPT. *Bulletin of Science, Technology & Society*, *43*(3–4), 105–114. http://doi.org/10.1177/02704676231216355.

[118] Zhan, Z.; Zhong, C.; Zheng, J.; Zhong, W. (2024). Human-AI Co-Innovation: Navigating the Innovative Problem-Solving Landscape with the Process Model and Technology Empowerment. Paper presented at Technology in Education: Digital and Intelligent Education, Singapore.