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# ARTIFICIAL INTELLIGENCE IN DIGITAL LEARNING AND EDUCATION: A SYSTEMATIC LITERATURE REVIEW

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## ABSTRACT

*Artificial intelligence (AI) is reshaping digital learning environments across higher education, medical training, and K-12 contexts, yet the field lacks a unifying conceptual account linking learner psychology, institutional readiness, and sustainability-oriented outcomes. This systematic literature review (SLR) synthesizes 29 peer-reviewed and conceptual papers spanning AI literacy, AI anxiety, self-regulated learning (SRL), human-AI delegation, algorithmic transparency, and AI-driven institutional transformation. Using a PRISMA-informed selection process, studies were screened for empirical or conceptual relevance to AI in digital learning, yielding a final corpus analyzed for research gaps, objectives, methodological design, data collection approach, and key findings. Results indicate that AI literacy and perceived opportunities consistently predict acceptance and adoption, that anxiety and trust/transparency perceptions act as critical psychological mediators, and that sustainability and organizational-culture factors increasingly shape institutional AI adoption beyond the individual learner level. The review proposes an integrated conceptual framework connecting antecedents (AI literacy, perceived opportunities/challenges, institutional readiness), mediating psychological processes (anxiety, needs satisfaction, trust), and outcomes (acceptance, SRL, work engagement, sustainable innovation). Gaps remain in cross-cultural validation, longitudinal and experimental designs, and integrated governance frameworks, pointing to a research agenda relevant to dissertation work at the intersection of AI, education, and behavioral science.*

## INTRODUCTION

Artificial intelligence has moved from a peripheral educational technology to a core infrastructural component of digital learning, spanning intelligent tutoring, automated feedback, personalized recommendation systems, and institution-wide learning analytics (Bauer et al., 2023; Ng et al., 2023). Global education-focused AI expenditure is projected to exceed USD 6 billion, with adoption accelerating unevenly across regions and institution types (Bucea-Manea-Țoniș et al., 2022). This uneven diffusion, combined with mixed learner and educator attitudes ranging from optimism about administrative and personalization uses to skepticism about high-stakes decision-making, motivates a systematic review of how AI is currently studied in digital learning contexts (Moldt et al., 2023; Rahiman & Kodikal, 2024).

Despite a growing body of empirical work, the literature remains fragmented across at least three largely separate strands: (1) individual psychological studies examining AI literacy, anxiety, and technology-acceptance constructs; (2) classroom- and tool-level studies evaluating specific AI applications such as chatbots, NLP-based feedback, and recommender systems; and (3) macro-level studies situating AI adoption within sustainability, policy, and organizational-transformation frameworks (Liu et al., 2023; Qureshi et al., 2022; Williamson, 2019). No prior review has systematically synthesized findings across all three strands to identify how individual-level readiness interacts with institutional and policy-level factors. This SLR addresses that gap by consolidating research gaps, objectives, methodologies, data collection approaches, and findings from 29 studies, and by proposing an integrated conceptual framework to guide future research.

## RESEARCH OBJECTIVES

The review is guided by four objectives: first, to map the theoretical frameworks (e.g., Technology Acceptance Model/UTAUT, Self-Determination Theory, AI-literacy competency models) used to study AI in digital learning (Ng et al., 2023; Chiu, 2024); second, to catalogue the research designs and data collection methods employed across the corpus; third, to synthesize key findings regarding AI adoption, anxiety, literacy, and institutional readiness; and fourth, to identify convergent research gaps and propose a unified conceptual model with corresponding future research directions.

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## REVIEW OF LITERATURE

### Individual Psychological Antecedents

A substantial cluster of studies grounds AI adoption in individual psychological constructs. Ronaghi and Ronaghi's (2024) extended Technology Acceptance Model (TAM) study found that AI literacy improves AI acceptance both directly and indirectly by reducing AI anxiety, with anxiety's "Learning" and "Sociotechnical Blindness" dimensions independently suppressing acceptance. Ng et al.'s (2023) validated AI Literacy Questionnaire (AILQ) established a four-factor Affective-Behavioural-Cognitive-Ethical (ABCE) structure among secondary students, confirming that affective and behavioural dimensions matter as much as technical knowledge. Complementing this, Xia et al. (2023) demonstrated that Self-Determination Theory (SDT) needs satisfaction—specifically autonomy and competence rather than relatedness—mediates the relationship between prior knowledge and self-regulated learning (SRL) in AI-chatbot-supported English learning. Chiu's (2024) Delphi study with Hong Kong teachers similarly found that ChatGPT-based learning activities best support competence needs while relatedness remains least supported, echoing the same asymmetry.

### Institutional and Faculty-Level Adoption

A second cluster examines faculty and institutional adoption dynamics. Rahiman and Kodikal's (2024) PLS-SEM survey of 250 faculty across QS-ranked Asian institutions found that performance expectancy, perceived risk, and awareness shape attitudes, which in turn mediate work engagement and AI adoption under a combined TAM/UTAUT framework. Bucea-Manea-Țoniș et al.'s (2022) exploratory CFA/PLS survey of Romanian and Serbian teachers reinforced this pattern in a different geographic context: perceived opportunities (creating materials, personalizing learning plans) exerted a stronger and more consistent influence on teachers' willingness to adopt AI than perceived challenges such as privacy risk or digital illiteracy. A near-identical replication of this dataset confirmed the robustness of these loading factors, particularly the strong link between AI utility and professional success perceptions (Bucea-Manea-Țoniș et al., 2022).

### Trust, Transparency, and Human-AI Collaboration

A distinct strand addresses the cognitive and trust-related dimensions of human-AI interaction. Fügener et al.'s (2022) behavioral experiments (902 subjects) found that while AI-to-human delegation improved combined performance, human-to-AI delegation barely improved outcomes because humans lack "metaknowledge"—the ability to accurately assess their own capabilities—a finding with direct implications for how learners might over- or under-rely on AI tutoring systems. Complementing this, research on algorithmic transparency in educational technology shows that explainable dashboards and open learner models increase trust and perceived accuracy, though excessive complexity can overwhelm non-expert users, and teacher trust is further shaped by professional-development support (Nazaretsky et al., 2022).

### Domain-Specific and Sector Applications

Medical education studies consistently reveal cautious optimism: students and faculty support AI for administrative and research tasks but resist its expansion into diagnosis or therapy, citing privacy and dehumanization concerns (Moldt et al., 2023). Reviews of digital recommendation systems and NLP-supported peer feedback report measurable engagement and feedback-quality gains, tempered by cold-start, data-sparsity, and scaffolding challenges (Bauer et al., 2023). Systematic reviews of "Education 4.0" technologies and generative AI adoption among Chinese scholars converge on cautious, framework-guided integration, with concerns over academic integrity and critical-thinking erosion (Liu et al., 2023; Qureshi et al., 2022).

### Sustainability and Macro-Level Framing

A final cluster situates AI within sustainability and industrial-transformation narratives. Hoosain et al. (2020) connect 4IR technologies and circular-economy principles to the UN Sustainable Development Goals, including SDG 4 (Quality Education). Cross-industry evidence on AI-powered predictive analytics and innovation demonstrates that organizational culture and leadership moderate successful AI integration, with the Analytic Hierarchy Process (AHP) proposed as a structured tool for future evaluation of adoption barriers (Al-Kubaisi et al., 2024). Williamson's (2019) critical policy analysis cautions that the same learning-analytics infrastructures celebrated for personalization can simultaneously function as performance-metric technologies that intensify marketization and inequality.

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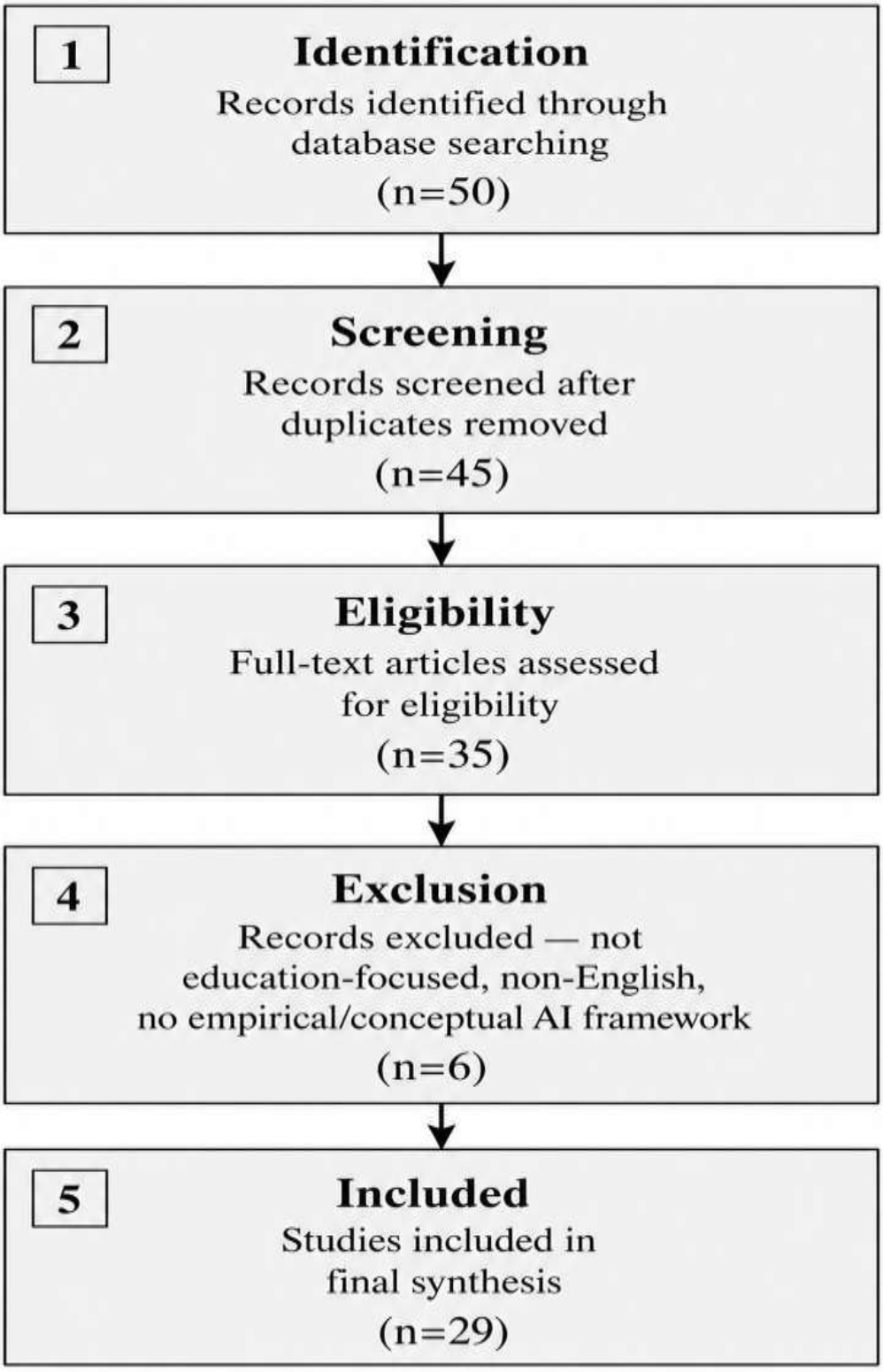
## RESEARCH METHODOLOGY

**Figure 1. PRISMA Flow Diagram for Study Selection**



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This review followed a PRISMA-informed systematic literature review protocol. Records were identified from an aggregated corpus of academic publications spanning the *British Journal of Educational Technology*, *Sustainability*, *Information Systems Research*, *Educational Technology Research and Development*, and related peer-reviewed outlets. After removing duplicates and screening titles/abstracts for relevance to AI in digital learning and education, records were assessed for full-text eligibility against inclusion criteria requiring an empirical, conceptual, or review-based focus on AI adoption, literacy, anxiety, or institutional integration in educational contexts. Studies not focused on education, non-English texts, or those lacking an identifiable AI framework were excluded, yielding a final synthesis corpus of 29 studies. Across the corpus, three broad methodological families were identified: quantitative cross-sectional surveys analyzed via Structural Equation Modeling (SEM) or Partial Least Squares SEM (PLS-SEM), used in studies of AI literacy, anxiety, and faculty adoption (Ronaghi & Ronaghi, 2024; Rahiman & Kodikal, 2024; Bucea-Manea-Țoniș et al., 2022); qualitative or mixed-methods designs including Delphi studies, classroom interventions, and content analysis, used to explore ChatGPT activity classification and medical-student attitudes (Chiu, 2024; Moldt et al., 2023); and systematic/narrative literature reviews and conceptual/model-building papers, used to synthesize AI-literacy frameworks, recommendation-system architectures, and sustainability-oriented AI applications (Ng et al., 2023; Kaddoura et al., 2022; Hoosain et al., 2020; Al-Kubaisi et al., 2024). Behavioral experiments, exemplified by Fügener et al.'s (2022) image-classification delegation study, represent a smaller but methodologically distinct cognitive-science approach.

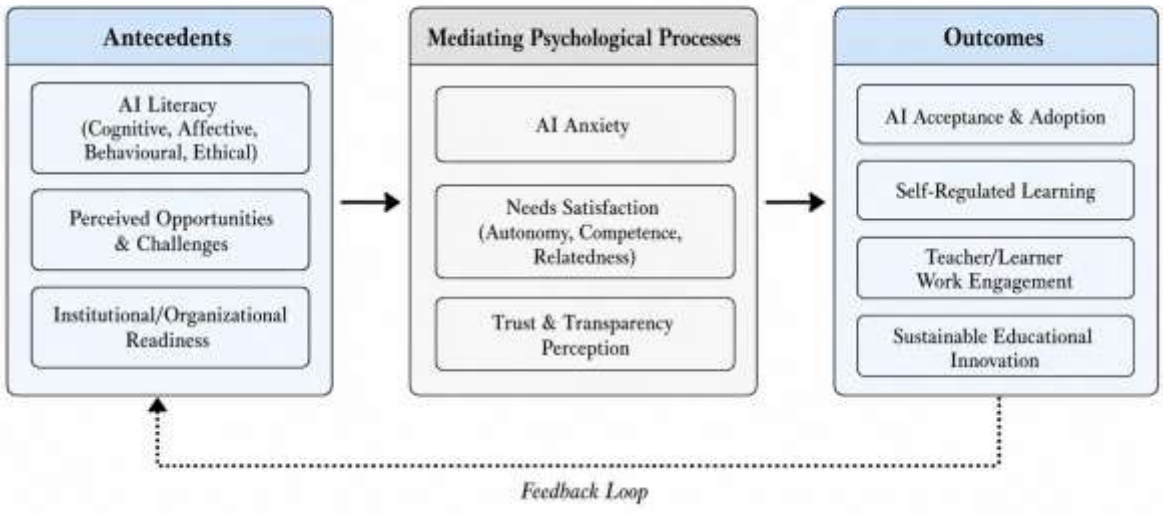
## DATA ANALYSIS AND FINDINGS

Data collection instruments varied by methodological family. Survey-based studies relied on validated Likert-scale questionnaires (e.g., the 32-item AILQ, 47-item UTAUT/TAM instruments) administered to samples ranging from 103 to 363 respondents (Ng et al., 2023; Rahiman & Kodikal, 2024; Bucea-Manea-Țoniș et al., 2022). Qualitative studies used semi-structured interviews, Delphi panel rounds, and Mayring-style content analysis of group discussions (Chiu, 2024; Moldt et al., 2023). Review-based papers synthesized secondary literature through database searches, such as a Scopus-based PRISMA screening of 3,378 records narrowed to 47 final studies in one Education 4.0 review (Qureshi et al., 2022).

Findings converge on four points. First, AI literacy and perceived opportunities are consistently stronger predictors of acceptance and adoption than perceived challenges or risks, replicated across faculty samples in Asia and Eastern Europe (Rahiman & Kodikal, 2024; Bucea-Manea-Țoniș et al., 2022). Second, psychological mediators—AI anxiety, needs satisfaction, and trust/transparency perceptions—shape whether literacy or opportunity translates into actual acceptance or self-regulated learning behavior (Ronaghi & Ronaghi, 2024; Xia et al., 2023; Nazaretsky et al., 2022). Third, human-AI collaboration is asymmetric: AI systems delegate to humans effectively, but humans struggle to delegate well to AI due to limited metaknowledge, a finding with direct implications for AI-assisted learning design (Fügener et al., 2022). Fourth, sustainability and organizational-culture factors are emerging as institutional-level moderators of AI adoption success, extending the analysis beyond individual psychology to governance and infrastructure (Hoosain et al., 2020; Al-Kubaisi et al., 2024; Williamson, 2019).

### Proposed Conceptual Framework

**Figure 2. Integrated Conceptual Framework of AI Adoption in Digital Learning**



Synthesizing these findings, this review proposes an integrated conceptual framework organized into three stages: antecedents (AI literacy, perceived opportunities/challenges, institutional readiness), mediating psychological processes (AI anxiety, needs satisfaction, trust and transparency perception), and outcomes (AI acceptance/adoption, self-regulated learning, work engagement, and sustainable educational innovation), with a feedback loop from outcomes back to antecedents reflecting how adoption experience reshapes future literacy and institutional readiness.

This framework is justified by the corpus: the antecedents box synthesizes findings from AI-literacy and faculty-adoption studies (Ng et al., 2023; Rahiman & Kodikal, 2024; Bucea-Manea-Țoniș et al., 2022); the mediating-processes box integrates AI-anxiety, SDT-needs-satisfaction, and transparency/trust research (Ronaghi & Ronaghi, 2024; Xia et al., 2023; Nazaretsky et al., 2022); and the outcomes box reflects acceptance, SRL, engagement, and sustainability outcomes documented across the reviewed studies (Ronaghi & Ronaghi, 2024; Rahiman & Kodikal, 2024; Hoosain et al., 2020; Al-Kubaisi et al., 2024).

## CONCLUSION

This systematic review demonstrates that AI adoption in digital learning cannot be explained by literacy or technology-acceptance constructs alone; anxiety, trust, institutional culture, and sustainability considerations jointly shape outcomes across learner, faculty, and institutional levels. The proposed integrated framework offers a structure for positioning future empirical work at the intersection of individual psychology and institutional readiness, addressing a gap left by prior siloed reviews of AI-in-education research.

## FUTURE RESEARCH DIRECTIONS

Future research should prioritize cross-cultural validation of AI-literacy and adoption instruments beyond the Asian and Eastern European contexts currently dominating the evidence base (Ng et al., 2023; Bucea-Manea-Țoniș et al., 2022). Longitudinal and experimental designs are needed to move beyond the cross-sectional surveys that dominate the corpus, particularly to test causal pathways between anxiety reduction and sustained AI acceptance (Ronaghi & Ronaghi, 2024). Deeper investigation into the relatedness/social-emotional dimension of AI-mediated learning is warranted, given its consistent underperformance relative to autonomy and competence across SDT-based studies (Xia et al., 2023; Chiu, 2024). Finally, future work should apply structured multi-criteria decision-making tools such as the Analytic Hierarchy Process to evaluate institutional AI-adoption barriers and integrate ethical governance frameworks addressing the marketization risks flagged in critical policy scholarship (Al-Kubaisi et al., 2024; Williamson, 2019).

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