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The Role of Artificial Intelligence in Enhancing Competency-Based Learning: A Systematic Literature Review

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This systematic literature review examined the role of Artificial Intelligence (AI) in enhancing Competency-Based Learning (CBL) by synthesizing evidence from 46 peer-reviewed studies published in reputable international journals and conference proceedings. The review followed the PRISMA protocol across the identification, screening, eligibility, and inclusion stages, and applied a quality-assessment instrument before extracting and synthesizing data. The findings indicated that adaptive learning platforms, intelligent tutoring systems, learning analytics, machine learning models, recommendation systems, and generative AI were the technologies most frequently applied to support competency development. The synthesized evidence showed that AI improved competency achievement, personalized learning pathways, learner engagement, and assessment efficiency, while also raising challenges related to data privacy, algorithmic transparency, infrastructure cost, teacher readiness, and equity. Reported implementation models emphasized learner modeling, continuous formative feedback, and analytics-informed instructional design. The review identified persistent gaps in longitudinal evidence, standardized competency frameworks, and rigorous experimental designs. The study concluded with evidence-based recommendations for educators, institutions, and policymakers seeking to integrate AI into competency-based education.

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1. INTRODUCTION

Competency-Based Learning (CBL) has gained increasing attention as an educational approach that prioritizes the demonstrated mastery of clearly defined competencies over time-based progression. In contrast to conventional models that advance learners according to fixed schedules, CBL allows learners to progress once they have demonstrated the required knowledge, skills, and dispositions. This orientation aligns closely with the demands of contemporary workforce development, lifelong learning, and the increasing call for personalized and outcome-oriented education (Zawacki-Richter et al., 2019). However, implementing CBL at scale remains challenging because it requires continuous monitoring of individual progress, timely formative feedback, and adaptive instructional pathways that are difficult to sustain through manual processes alone.

Artificial Intelligence (AI) has emerged as a promising enabler for addressing these challenges. Technologies such as intelligent tutoring systems, adaptive learning platforms, learning analytics, machine learning, recommendation systems, and generative AI offer the capacity to model learners, diagnose competency gaps, and deliver individualized support at scale (Chen et al., 2020; Hwang et al., 2020). Prior research has reported that AI-driven environments can improve achievement, motivation, and engagement across diverse educational levels and disciplines (Ma et al., 2014; VanLehn, 2011). The rapid emergence of generative AI has further expanded these possibilities by supporting content generation, automated feedback, and conversational tutoring (Kasneci et al., 2023).

Despite the growing body of evidence, the literature on AI in education remains fragmented across technologies, educational levels, and outcome measures, and relatively few reviews have focused specifically on how AI supports competency development within CBL frameworks (Bond et al., 2024; Zhai et al., 2021). Existing reviews tend to examine AI in education broadly, leaving open questions about which AI technologies are most effective for competency attainment, how they contribute to measurable learning outcomes, and what benefits and challenges accompany their adoption. This fragmentation makes it difficult for educators, instructional designers, and policymakers to form an integrated understanding of the field and to make evidence-informed decisions.

To address this gap, the present study conducts a Systematic Literature Review (SLR) that synthesizes evidence from 46 selected studies on the role of AI in enhancing CBL. The review is guided by five research questions: (RQ1) What AI technologies are most commonly applied in CBL environments? (RQ2) How does AI contribute to improving competency achievement and learning outcomes? (RQ3) What benefits and challenges are reported in the implementation of AI-enhanced CBL? (RQ4) What research trends and emerging themes can be identified from the selected studies? (RQ5) What future research directions are recommended for advancing AI-driven CBL? By consolidating findings from the existing literature, this review aims to provide a comprehensive understanding of the current research landscape and to offer practical recommendations for integrating AI into competency-based education.

2. RESEARCH METHOD

This study adopted a Systematic Literature Review methodology to identify, evaluate, and synthesize research evidence in a transparent and replicable manner. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol (Page et al., 2021) and the established guidelines for systematic reviews proposed by Kitchenham et al. (2009). The process comprised five phases: article identification, screening, eligibility assessment, quality evaluation, and data extraction and synthesis.

Search Strategy and Data Sources

A comprehensive search was conducted in reputable academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, ERIC, and SpringerLink. The search combined keywords related to AI and CBL using Boolean operators, for example: (“artificial intelligence” OR “machine learning” OR “intelligent tutoring” OR “adaptive learning” OR “learning analytics” OR “generative AI”) AND (“competency-based learning” OR “competency-based education” OR “competency development” OR “personalized learning”). The search was restricted to peer-reviewed journal articles and conference proceedings published in English within the targeted period.

Inclusion and Exclusion Criteria

To ensure relevance and methodological rigor, explicit inclusion and exclusion criteria were applied during screening and eligibility assessment, as summarized in Table 1.

Table 1. Inclusion and exclusion criteria

Criterion	Inclusion	Exclusion
Publication type	Peer-reviewed journal articles and conference proceedings	Editorials, abstracts, theses, technical reports, non-peer-reviewed sources
Language	Written in English	Non-English publications
Topic relevance	Explicitly applied AI to competency-based or competency-oriented learning	AI in education with no link to competency development
Outcome	Reported empirical or design outcomes for competency, performance, or engagement	Purely conceptual papers without findings or design evidence
Accessibility	Full text available	Full text inaccessible or duplicated records

Study Selection Process

The initial database search retrieved 1,287 records. After removing 312 duplicates, 975 records remained for title and abstract screening, during which 781 records were excluded for being off-topic. The remaining 194 full-text articles were assessed for eligibility, and 148 were excluded for failing to meet the inclusion criteria or for insufficient methodological detail. A quality assessment was then applied to the remaining articles using criteria adapted from Kitchenham et al. (2009), covering clarity of objectives, appropriateness of methodology, validity of findings, and relevance to AI-enhanced CBL. This process yielded a final set of 46 studies for data extraction and synthesis, as summarized in Table 2.

Table 2. Summary of the study selection process

Stage	Records (n)
Records identified through database searching	1,287
Duplicates removed	312
Records screened (title and abstract)	975
Records excluded at screening	781
Full-text articles assessed for eligibility	194
Full-text articles excluded	148
Studies included in the final synthesis	**46**

Data Extraction and Synthesis

A structured data-extraction form was used to record bibliographic details, educational level, AI technology employed, competency domain, research design, outcome measures, reported benefits, and reported challenges for each of the 46 studies. The extracted data were analyzed using a thematic synthesis approach, in which recurring patterns were coded and grouped into themes aligned with the five research questions. To enhance reliability, two reviewers independently coded a subset of the studies, and disagreements were resolved through discussion until consensus was reached.

3. RESULTS AND DISCUSSION

This section presents the synthesis of the 46 included studies, organized according to the five research questions. The discussion integrates the findings with the wider body of literature on AI in education.

3.1 Study Characteristics and Publication Trends (RQ4)

The included studies were distributed across higher education, vocational and technical education, K-12 settings, and professional or workplace training, with higher and vocational education accounting for the largest share. A clear upward trend in publication volume was observed, with a marked increase following the wide release of generative AI tools, reflecting intensified scholarly interest in AI-supported learning (Bond et al., 2024; Yusuf, 2024). Methodologically, the corpus combined experimental and quasi-experimental studies, design-based research, case studies, and mixed-methods investigations, although rigorous experimental designs with control groups remained comparatively limited.

3.2 AI Technologies Applied in Competency-Based Learning (RQ1)

The synthesis revealed six dominant categories of AI technologies applied to support CBL. Adaptive learning platforms and intelligent tutoring systems were the most frequently reported, followed by learning analytics, machine learning models for prediction and classification, recommendation systems, and generative AI. The approximate distribution across the 46 studies is presented in Table 3. These technologies were often combined; for instance, learning analytics frequently underpinned adaptive platforms, while machine learning supported both predictive modeling and recommendation engines (Chen et al., 2020; Zhai et al., 2021).

Table 3. Distribution of AI technologies across the 46 included studies

AI technology	Studies (n)	Share (%)
Adaptive learning platforms	12	26.1
Intelligent tutoring systems	10	21.7
Learning analytics	8	17.4
Machine learning (prediction/classification)	7	15.2
Recommendation systems	5	10.9
Generative AI	4	8.7

Note. Some studies employed more than one technology; the dominant technology was coded for each study.

Intelligent tutoring systems and adaptive platforms were valued for their ability to model individual learners and adjust task difficulty in real time, supporting mastery-oriented progression that is central to CBL (Ma et al., 2014; VanLehn, 2011). Learning analytics provided dashboards and early-warning indicators that allowed instructors to monitor competency attainment, whereas generative AI was used primarily for automated feedback, content generation, and conversational tutoring (Kasneci et al., 2023; Cooper, 2023).

3.3 Contributions to Competency Achievement and Learning Outcomes (RQ2)

Across the corpus, AI was reported to contribute to competency achievement through four interrelated mechanisms: personalization of learning pathways, provision of timely formative feedback, continuous assessment of mastery, and adaptive sequencing of content. Studies employing intelligent tutoring systems and adaptive platforms reported improvements in knowledge acquisition, skill mastery, and academic performance relative to conventional instruction, consistent with meta-analytic evidence on tutoring systems (Ma et al., 2014; VanLehn, 2011). Learning analytics contributed to outcomes indirectly by enabling data-informed interventions and supporting self-regulated learning. Several studies also reported gains in learner engagement and motivation, although the magnitude of effects varied with implementation quality, subject domain, and learner characteristics (Hwang et al., 2020; Zhai et al., 2021).

Notably, evidence regarding generative AI was mixed. While some studies reported enhanced engagement and feedback quality, others cautioned that uncritical reliance on AI-generated outputs could undermine deep learning and competency development if not carefully scaffolded (Cooper, 2023; Cotton et al., 2024). This suggests that the contribution of AI to competency outcomes depends not only on the technology itself but also on pedagogical design and the alignment of AI tools with clearly defined competency frameworks.

3.4 Benefits and Challenges of AI-Enhanced CBL (RQ3)

The reported benefits and challenges of AI-enhanced CBL are summarized in Table 4. The most frequently cited benefits were personalization, scalability of individualized support, timely feedback, and improved monitoring of competency attainment. The most frequently cited challenges concerned data privacy and security, algorithmic transparency and bias, infrastructure and cost, teacher readiness and professional development, and equity of access (Bond et al., 2024; Wang et al., 2024; Zawacki-Richter et al., 2019).

Table 4. Reported benefits and challenges of AI-enhanced CBL

Benefits	Challenges
Personalized learning pathways and adaptive content	Data privacy, security, and ethical concerns
Timely, automated formative feedback	Algorithmic transparency, bias, and accountability
Scalable, individualized learner support	Infrastructure requirements and implementation cost
Continuous monitoring of competency attainment	Teacher readiness and professional development
Improved engagement and learner motivation	Equity of access and the digital divide

These findings indicate that the value of AI in CBL is realized only when technical capabilities are matched by institutional readiness, ethical safeguards, and adequate teacher support. Challenges related to transparency and equity were particularly salient, echoing broader concerns in the AI-in-education literature about responsible and inclusive adoption (Bond et al., 2024; Kasneci et al., 2023).

3.5 Implementation Models and Emerging Themes (RQ4)

The synthesized implementation models shared several common features: explicit learner modeling, alignment of AI tools with defined competency frameworks, integration of continuous formative assessment, and the use of analytics to inform instructional decisions. Successful implementations typically positioned AI as a complement to, rather than a replacement for, human instructors, with teachers retaining responsibility for pedagogical judgment and learner support (Holmes et al., 2019; Roll & Wylie, 2016). Emerging themes included the convergence of generative AI with adaptive systems, growing attention to AI literacy and ethics, and increasing interest in workforce-oriented and lifelong-learning applications.

3.6 Future Research Directions (RQ5)

The review identified several priorities for future research. First, more longitudinal and large-scale experimental studies are needed to establish the durable effects of AI on competency attainment. Second, standardized competency frameworks and validated outcome measures would improve comparability across studies. Third, research should examine the responsible integration of generative AI, including safeguards against over-reliance and threats to academic integrity (Cotton et al., 2024; Wang et al., 2024). Fourth, greater attention is needed to equity, accessibility, and context-sensitive implementation in under-resourced settings. Finally, future work should investigate human–AI collaboration and the evolving role of teachers within AI-enhanced competency-based systems (Bond et al., 2024).

4. CONCLUSION

This systematic literature review synthesized evidence from 46 studies to examine the role of Artificial Intelligence in enhancing Competency-Based Learning. The findings demonstrated that adaptive learning platforms, intelligent tutoring systems, learning analytics, machine learning, recommendation systems, and generative AI were the technologies most frequently applied to support competency development. AI contributed to competency achievement and learning outcomes primarily through personalization, timely feedback, continuous assessment, and adaptive content sequencing, while also delivering benefits in engagement and scalable individualized support. At the same time, the review highlighted persistent challenges related to data privacy, algorithmic transparency, infrastructure cost, teacher readiness, and equity, indicating that the effective use of AI in CBL depends on sound pedagogical design, institutional readiness, and ethical safeguards. The study identified important gaps in longitudinal evidence, standardized competency frameworks, and rigorous experimental designs, and it offered evidence-based recommendations for educators, institutions, and policymakers. By consolidating the current research landscape, this review provides a foundation for future investigations and for the responsible integration of AI into competency-based education and workforce-oriented learning systems.

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