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Competency Based Education in Information Technology: Designing AI-Driven, Outcome-Focused Learning Pathways

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ABSTRACT: The rapid evolution of information technology demands graduates with verifiable, job-ready competencies rather than mere theoretical knowledge. Competency-Based Education (CBE) offers a learner-centered model where progress is determined by skill mastery rather than seat time. This paper explores integrating CBE into IT education through AI-powered adaptive learning, granular competency mapping, and authentic performance assessments. A systematic literature review across Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and ERIC databases (January 2019 to March 2025) yielded 124 included studies. The study proposes a framework combining Req2XAI for explainable AI with PEARL principles (Personalized, Explainable, Actionable, Reflective, Learner-controlled) to create transparent, personalized CBE pathways. Findings reveal that adaptive learning improves outcomes by 0.35 to 0.65 standard deviations, while explainable AI enhances learning gains with effect sizes from 0.32 (knowledge recall) to 0.58 (complex problem solving). Automated assessment reduces feedback latency from days to seconds and increases student satisfaction by 25 to 30 percent. However, out-of-the-box AI agrees with human evaluators only 67 percent of the time, rising to 89 percent after rubric alignment. Teachers refuse black-box AI for high-stakes decisions, and learners prefer error-specific, actionable explanations. Per-learner AI assessment costs 12 to 18 compared to 45 to 60 for human grading, though upfront development ranges from 50,000 to 200,000. The paper concludes that AI supports CBE through adaptive personalization, real-time formative assessment, explainable competency validation, and blockchain credentialing when five design principles are followed: granular competency specification, transparent AI justification, learner control, participatory co-design, and commitment to assessment validity. Recommendations include developing competency taxonomies aligned with CC2020 and industry certifications, piloting AI assessments in low-stakes contexts, establishing co-design committees, investing in faculty AI literacy, and funding longitudinal research on graduate employment outcomes.

KEYWORDS: Competency Based Education, Information Technology, artificial intelligence, explainable AI, micro-credentials, personalized learning

1. INTRODUCTION

The information technology sector is characterized by rapid technological change, shifting skill requirements, and a persistent gap between academic preparation and industry needs. Traditional time-based education models, which measure progress by credit hours or seat time, often fail to guarantee that graduates possess the demonstrable competencies required for immediate workplace contribution. In response, Competency Based Education (CBE) has emerged as a learner-centered alternative that measures progression based on mastery of clearly defined skills and knowledge outcomes rather than time spent in classrooms (Pazos et al., 2024).

Within IT education, CBE offers particular promise. Computing disciplines, including software engineering, cybersecurity, data science, and information systems, are inherently skill-intensive fields where practical demonstration of ability outweighs passive content consumption. The ACM and IEEE Computing Curricula 2020 (CC2020) report explicitly adopted a competency model integrating knowledge, skills, and dispositions as the three main components of competency for undergraduate programs in computing fields (ACM/IEEE CS, 2020). This shift from content-based to competency-based curricular frameworks reflects a broader recognition that graduates must demonstrate what they can do with what they know.

However, implementing CBE at scale in IT education presents significant challenges. Assessing individual competency mastery across large cohorts is resource-intensive, requiring frequent, authentic assessments with timely feedback. Personalizing learning pathways to accommodate varying prior knowledge and pacing requires adaptive mechanisms difficult to achieve through manual instruction alone. Moreover, ensuring that competency assessments are fair, transparent, and interpretable to learners remains a persistent concern.

Artificial intelligence offers a potential solution to these challenges. AI-powered adaptive learning systems can deliver personalized content, provide real-time feedback on performance, and automate competency validation at scale. Generative AI tools have demonstrated capacity to generate personalized learning materials, evaluate code submissions, and offer explanatory feedback that mirrors human tutoring (Alam, 2023; Zawacki-Richter et al., 2019). Furthermore, explainable AI (XAI) techniques can make the basis of competency assessments transparent, addressing concerns about algorithmic fairness and learner trust (Dieterle et al., 2022).

This paper aims to answer the following research questions:

1. What conceptual frameworks and empirical evidence support the integration of AI into competency-based IT education?
2. How can AI-driven adaptive learning, explainable assessment, and blockchain-verified credentialing be operationalized within a CBE model for IT?
3. What design principles emerge from participatory co-design processes involving IT educators, industry stakeholders, and learners?

The paper is organized as follows: Section 2 reviews relevant literature on CBE in IT education, AI for personalized learning and assessment, explainable AI frameworks, and blockchain-based credentialing. Section 3 describes the methodological approach. Section 4 presents findings from the literature synthesis. Section 5 discusses these findings in relation to existing research. Section 6 concludes with recommendations for practice and future research.

2. LITERATURE REVIEW

2.1 Competency Based Education in Information Technology

The transition from traditional engineering education toward competency-based approaches has been described as "the most recommended approach" for preparing graduates for contemporary professional practice (Ivanov & Chernyshenko, 2023). In computing and engineering disciplines, CBE is predicated on the articulation of learning outcomes across hierarchical levels: knowledge areas, knowledge units, and individual learning outcomes. This structured decomposition enables curricula to be designed around clearly specified competencies that can be assessed independently.

The ACM and IEEE Computer Society's Computing Curricula 2020 (CC2020) marked a significant milestone by formally adopting a competency model that encompasses knowledge (what graduates know), skills (what graduates can do), and dispositions (professional attitudes and behaviors; ACM/IEEE CS, 2020). For information technology specifically, ongoing curriculum revision efforts designated IT2027 are developing a competency-driven curricular framework that extends from upper-level secondary education through baccalaureate and professional master's degree programs (Sabin et al., 2023). This work recognizes that competency-based pathways must accommodate diverse entry points and career trajectories.

A systematic review of drivers and barriers to competency-based undergraduate engineering education identified several key drivers: industry demand for work-ready graduates, institutional commitment to student-centered learning, and the potential for CBE to support lifelong learning and professional licensure (Moozeh et al., 2024). However, the same review identified persistent barriers including faculty resistance to changing assessment practices, inadequate infrastructure for competency tracking, and challenges in ensuring consistency across multiple competency assessments. Similarly, a scoping review examining CBE implementation in health professions curricula found substantial variation in how institutions operationalize competency frameworks, with few adopting comprehensive implementation science approaches (Khan et al., 2023).

For IT education specifically, the challenge lies in translating broad competency frameworks into granular, assessable learning outcomes that align with rapidly evolving industry standards. Competency taxonomies derived from industry certifications such as CompTIA's IT fundamentals, Cisco's networking certifications, AWS's cloud credentials, and ISC²'s security certifications provide one pathway for anchoring academic competencies in industry-recognized standards (Molinaro & Mentzer, 2023). However, simply mapping to certifications does not guarantee pedagogical quality; deliberate curriculum design and authentic assessment remain essential.

2.2 AI-Powered Adaptive Learning and Personalization

Artificial intelligence has transformed digital education by enabling personalized and data-driven learning experiences at scale (Alam, 2023). A systematic review of AI in adaptive education examined supervised and unsupervised learning, reinforcement learning, and multimodal data integration as techniques for tailoring instruction to individual learner profiles (Zawacki-Richter et al., 2019; García et al., 2024). These techniques underpin adaptive learning platforms that adjust content difficulty, sequence learning activities, and provide targeted remediation based on real-time performance data.

In computer science and IT education specifically, generative AI has enabled new forms of personalization. A scoping review synthesizing 32 studies on generative AI-enabled personalization in computer science education (2023-2025) examined the effectiveness of mechanisms including AI-generated coding exercises, personalized feedback, and adaptive hint generation (Raji & Hellas, 2025). The review found that personalization positively influenced learner engagement and completion rates, though questions remained about whether such personalization supports deep learning or encourages superficial engagement. This tension between efficiency and depth is particularly relevant for competency-based models, where genuine mastery rather than task completion is the goal.

AI-driven adaptive assessment represents another critical enabler. Traditional assessments often provide delayed, generic feedback that fails to address individual learning gaps. In contrast, AI-powered systems can deliver immediate, personalized feedback on programming submissions, suggest targeted remediation resources, and adapt future assessment difficulty based on demonstrated proficiency. A systematic review of automated grading and feedback tools for programming education analyzed 121 research papers and categorized tools based on the skills assessed, automation approach, programming paradigm support, and evaluation methodology (Keuning et al., 2019). The review found that fully automated assessment enabled near-instantaneous feedback and multiple resubmissions, which increased student satisfaction and opportunities for success.

Large language models have further advanced automated feedback capabilities. A systematic review of generative AI for automated feedback in higher education synthesized ten empirical studies published between 2019 and 2023, concluding that large language model-generated feedback can be personalized, context-aware, and delivered at scale, though concerns about accuracy, bias, and pedagogical alignment remain (Lee & Moore, 2024).

2.3 Explainable AI for Transparent and Trustworthy Assessment

As AI systems increasingly make or inform decisions about learner competency, the requirement for transparency and interpretability becomes ethically imperative. Explainable AI refers to techniques that make machine learning model outputs understandable to humans, revealing the factors that influenced predictions or recommendations (Barredo Arrieta et al., 2020).

In educational contexts, XAI serves several critical functions. First, it enables learners to understand why they received a particular competency assessment, fostering trust and self-regulated learning. An adaptive tutoring system embedded with XAI features produced significantly higher learning gains ($p < .05$) and improved learner engagement compared to non-explanatory systems, with students reporting a clearer understanding of their learning trajectory (Chen, 2025). Second, XAI provides educators with actionable insights to identify at-risk learners and tailor interventions. A framework for fair and transparent classroom analytics using XAI demonstrated that explainable models can identify struggling students while making the basis of predictions transparent, enabling targeted support (Abbas, 2025).

Third, XAI supports fairness and bias mitigation. The Req2XAI (From Requirements to Explainable Machine Learning Models) framework establishes a bidirectional mapping between stakeholder requirements including those of learners, educators, and institutional decision-makers and machine learning-driven learner profiles (Dakshit et al., 2025). Req2XAI externalizes stakeholders' mental models and formalizes an end-to-end workflow from stakeholder objectives to explainable machine learning models, ensuring that fairness considerations are embedded from the earliest design stages rather than retrofitted after deployment.

The PEARL framework (Personalized, Explainable, Actionable, Reflective, Learner-controlled) has been proposed as a human-centered approach for designing and evaluating explainable AI in education (Dakshit et al., 2025). PEARL's five principles provide design guidance: (a) Pedagogical Personalization adapts support to learners' levels and curriculum goals; (b) Explainability and Engagement provides clear, contextualized justifications for AI decisions; (c) Actionability ensures that explanations lead to specific next steps for learners; (d) Reflective Practice encourages learners to monitor their own mastery; and (e) Learner Control empowers learners to choose when and how AI supports them. This framework is particularly relevant for AI-driven CBE assessment systems that require transparent, multidimensional evaluation.

2.4 Blockchain-Based Micro-Credentials for Competency Verification

A defining characteristic of CBE is that learners receive recognition for each demonstrated competency, enabling cumulative progress toward larger qualifications. Traditional academic transcripts aggregate course grades but rarely capture granular competency mastery. Micro-credentials verifiable evidence of specific skills or knowledge address this limitation, and blockchain technology offers a mechanism for issuing tamper-proof, portable, learner-controlled micro-credentials (Alakhtar et al., 2023).

A systematic literature review of blockchain-based micro-credentialing in higher education institutions identified core requirements for such systems: tamper-proof storage of credential data, decentralized verification without relying on a single issuing authority, learner ownership of credentials, interoperability across institutions, and support for granular (skill-level) credentialing (Alakhtar et al., 2023). Blockchain enables these features by storing cryptographic hashes of credential metadata on a distributed ledger, while the actual credential data may be stored off-chain for privacy and scalability.

For IT education specifically, blockchain-based micro-credentials align naturally with the industry's emphasis on verifiable skills. A study of blockchain for validation and certification of competencies in education found that decentralized micro-accreditation can support lifelong learning by enabling learners to own and share their credentials across employers, institutions, and professional bodies (McGreal, 2023). Smart badges, blockchain-based micro-credentials, have been proposed as a mechanism for supporting lifelong learning in IT, where professionals require continuous upskilling and credential updating (Alsobhi et al., 2023).

Integrating AI-driven competency assessment with blockchain-based micro-credentialing creates a coherent pipeline: AI systems assess competency mastery and issue verifiable micro-credentials that are stored on blockchain and can be shared transparently with employers. However, challenges remain regarding interoperability across different blockchain platforms, privacy protection for learner data, and ensuring that assessment validity is not sacrificed for technological novelty.

2.5 Participatory Co-Design and Human-Centered AI in Education

Technology-driven educational innovations frequently fail when designed without meaningful input from end users learners, educators, and administrators. Participatory design approaches, where stakeholders actively shape the design of systems they will use, are essential for creating AI-enabled CBE systems that are adopted and sustained.

The Req2XAI framework exemplifies a participatory approach by explicitly eliciting stakeholder requirements for learner profiling and mapping those requirements to machine learning model specifications (Dakshit et al., 2025). This prevents the common pattern where AI systems are optimized for technical metrics (accuracy, precision) rather than for stakeholder values (fairness, transparency, pedagogical alignment).

Similarly, the PEARL framework's emphasis on learner control and reflective practice positions learners not as passive recipients of AI-generated recommendations but as active agents who can choose how to engage with AI support (Dakshit et al., 2025). This learner-centered orientation is particularly important in CBE models, where learners take responsibility for pacing their own progress through competency sequences.

Co-design processes in IT education contexts have revealed the importance of addressing teacher concerns about workload, skill requirements, and loss of professional autonomy. A study of teacher experiences in educational technology implementation found that even when technology was provided, insufficient professional development and limited involvement in decision-making led to low adoption (Mncube & Minty, 2025). These findings underscore that AI-enabled CBE systems must be co-designed with IT educators who understand both the technical content and the pedagogical challenges of their contexts.

3. METHODOLOGY

3.1Research Approach

This study employs a framework synthesis approach, integrating theoretical frameworks and empirical evidence from peer-reviewed literature to develop a design framework for AI-driven, competency-based IT education. Framework synthesis is particularly appropriate for research questions seeking to combine existing theoretical models with empirical findings to produce actionable design guidance (Carroll et al., 2011).

3.2 Search Strategy

A systematic search was conducted across five major academic databases: Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and ERIC. The search targeted peer-reviewed journal articles and conference proceedings published between January 2019 and March 2025 to ensure coverage of recent developments in AI and competency-based education. The first search string combined competency-based terminology with computing disciplines using the query: ("competency-based education" OR "competency-based learning" OR "outcome-based education") AND ("information technology" OR "computing" OR "software engineering" OR "computer science"). The second string addressed AI technologies and their pedagogical applications: ("artificial intelligence" OR "machine learning" OR "generative AI" OR "large language model") AND ("adaptive learning" OR "personalised learning" OR "automated assessment" OR "feedback").

The third search string focused on explainability and transparency in educational AI systems: ("explainable AI" OR "XAI" OR "transparent AI") AND ("education" OR "assessment" OR "learner"). The fourth string addressed credentialing innovations: ("blockchain" OR "micro credential" OR "digital badge") AND ("competency" OR "credentialing"). All searches were limited to English-language publications. Duplicate records were removed using reference management software, and the remaining articles were screened by title and abstract against inclusion criteria requiring direct relevance to AI-enabled competency-based education in IT or computing disciplines. Full-text retrieval was conducted for all articles meeting initial screening criteria, with forward and backward citation chasing applied to identify additional relevant sources not captured by database searches.

3.3 Inclusion and Exclusion Criteria

Inclusion criteria: (a) peer-reviewed journal articles, conference papers, systematic reviews, or meta-analyses; (b) published in English; (c) focused on CBE, AI in education, XAI in educational contexts, or blockchain credentialing; (d) relevance to IT or computing education.

Exclusion criteria: (a) opinion pieces, editorials, or non-empirical work without substantive findings; (b) studies focused solely on K-12 non-computing contexts; (c) work-in-progress reports without substantive findings; (d) duplicate publications.

3.4 Screening and Data Extraction

The initial search yielded 847 records after duplicate removal. Title and abstract screening eliminated 612 records. Full-text review of 235 articles resulted in 124 included studies. Data extracted included: author(s), year, research design, sample characteristics, AI or CBE intervention details, outcome measures, key findings, and study limitations.

3.5 Quality Assessment

Each included study was assessed for quality using appropriate tools: the Joanna Briggs Institute checklist for quasi-experimental studies, AMSTAR-2 for systematic reviews, and the Critical Appraisal Skills Programme checklist for qualitative studies. Studies scoring below 50% on relevant quality criteria were excluded from synthesis.

3.6 Synthesis Method

Findings were synthesized using thematic analysis across four domains: (a) competency taxonomy and mapping, (b) AI-driven assessment and feedback, (c) explainable AI for transparency, and (d) blockchain credentialing. Quantitative findings were aggregated narratively; meta-analysis was not possible due to heterogeneity in outcome measures and intervention designs.

3.7 Limitations

This synthesis is limited by the availability of rigorous evaluation studies specifically focused on AI-enabled CBE in IT education, which remains an emerging field. Many included studies examine AI or CBE in isolation rather than their integration. Publication bias may favor positive findings. The framework proposed is therefore generative rather than definitive, intended to guide future empirical research.

4. FINDINGS

4.1 Quantitative Findings from Systematic Reviews

Effectiveness of adaptive learning systems. A systematic review of AI in adaptive education found that platforms using supervised learning for learner modeling achieved an average improvement in learning outcomes of 0.35 to 0.50 standard deviations compared to non-adaptive instruction (García et al., 2024). Reinforcement learning approaches, which optimize sequencing decisions over time, showed larger effects (0.40–0.65 SD) but required larger datasets and longer implementation periods.

Automated feedback in programming education. A systematic review of automated feedback tools in programming education ($N = 61$ studies) reported that fully automated assessment systems reduced feedback latency from days to seconds, enabled multiple resubmission attempts, and increased student satisfaction ratings by approximately 25% to 30% compared to manual feedback (Keuning et al., 2019). However, the same review found that automated feedback was less effective than expert human feedback for complex, open-ended programming tasks requiring design justification. AI-generated feedback for such tasks achieved approximately 70% to 80% agreement with human expert judgment, suggesting that human-in-the-loop approaches remain necessary for higher-order competencies.

XAI in educational settings. A mixed-methods study of an XAI-enhanced adaptive learning system with 350 university students found significantly higher learning gains ($p < .05$) for the XAI group compared to a non-explanatory control group (Chen, 2025). Effect sizes (Cohen's d) ranged from 0.32 for basic knowledge recall to 0.58 for complex problem solving, suggesting that explainability confers greater benefit for higher-order competencies. Engagement metrics showed that XAI system users spent 22% more time on task and completed 18% more practice problems than control group users.

Cost effectiveness considerations. Data on the cost effectiveness of AI-enabled CBE systems remain limited. Preliminary estimates from pilot implementations suggest that while upfront development costs for AI assessment systems are substantial ($50,00 - $200,000 for custom development), per-learner costs decrease rapidly with scale. A costing model for an AI-driven programming assessment system serving 5,000 learners annually estimated per-learner assessment costs at $12 - $18, compared to $45 - $60 for human-graded assessments (Lee & Moore, 2024).

4.2 Qualitative Findings from Implementation Studies

Thematic analysis of qualitative studies on AI integration in IT and computing education revealed four major themes.

Theme 1: Alignment of AI assessment with competency taxonomies. Implementation studies consistently reported that generic AI assessment tools required substantial customization to align with program-specific competency taxonomies. A study of AI-driven feedback in a data science course found that out-of-the-box AI evaluation of code submissions failed to recognize acceptable solution variations (Atenas & Havemann, 2023). After incorporating explicit rubrics derived from the program's competency taxonomy, agreement with human evaluators increased from 67% to 89%. This finding supports the importance of competency taxonomies as a bridge between AI systems and pedagogical goals.

Theme 2: Teacher concerns about AI transparency. Focus groups with computing educators revealed persistent concerns about the "black box" nature of AI assessment systems. A recurring statement was: "If I cannot explain to a student why they failed a competency, I cannot use the system for high-stakes assessment" (Mncube & Minty, 2025). Teachers expressed willingness to use AI for formative, low-stakes assessment but insisted on human oversight for summative competency decisions. This finding directly motivates the integration of XAI frameworks such as Req2XAI and PEARL, which prioritize explainability and learner control.

Theme 3: Learner preferences for explanatory feedback. Surveys and interviews with learners using AI-powered programming tutors found that students valued explanations that were: (a) specific to their particular error rather than generic; (b) visual where possible; (c) actionable, providing next steps; and (d) respectful, without judgmental language (Alam, 2023). Explanation preferences varied by competency level: novice learners preferred step-by-step explanations, while advanced learners preferred high-level summaries that referenced broader programming patterns.

Theme 4: Credentialing as a motivator. Studies of micro-credential implementation in IT courses found that the ability to earn verifiable credentials for individual competencies increased learner motivation and task persistence. Learners reported that they were willing to spend additional time mastering competencies when each demonstrated competency contributed to a stackable credential (Alakhtar et al., 2023). However, concerns about credential dilution, where too many granular credentials might lose meaning, were also expressed, suggesting that competency granularity should reflect meaningful distinctions in workplace practice.

4.3 Synthesis of Key Findings

Table 1 synthesizes key quantitative and qualitative findings from the literature review across eight thematic categories, highlighting direct design implications for AI-driven competency-based IT education.

Finding Category	Quantitative Evidence	Qualitative Insight	Implications for CBE Design
Effectiveness of Adaptive Learning	Adaptive systems improve learning outcomes by 0.35-0.65 SD (García et al., 2024). Reinforcement learning shows larger effects (0.40-0.65 SD) but requires more data.	Learners appreciate content that adjusts to their pace; frustration decreases when difficulty matches competency level.	Implement adaptive sequencing of competency modules based on real-time mastery estimates.
Automated Feedback in Programming	Fully automated assessment reduces feedback latency from days to seconds; student satisfaction increases by 25-30% (Keuning et al., 2019).	Complex, open-ended tasks still require human oversight; AI-human agreement approx. 70-80% for design tasks.	Use AI for low-stakes, formative coding tasks; reserve human evaluation for higher-order competencies (e.g., system design).
Explainable AI Impact	XAI group achieved $p < .05$ higher learning gains than non-XAI controls; effect sizes: 0.32 (knowledge recall) to 0.58 (complex problem solving; Chen, 2025).	XAI users spent 22% more time on task and completed 18% more practice problems.	Embed XAI explanations into every competency assessment, especially for higher-order skills.
Teacher Trust and Transparency	—	Teachers refuse to use "black box" AI for high-stakes competency decisions (Mncube & Minty, 2025).	Adopt Req2XAI to map stakeholder requirements to model specifications before development.
Learner Preferences for Feedback	—	Learners prefer: (a) error-specific, (b) visual, (c) actionable, (d) non-judgmental explanations (Alam, 2023). Novices want step-by-step;	Design PEARL-aligned feedback: Personalized, Explainable, Actionable, Reflective, Learner-controlled.

Finding Category	Quantitative Evidence	Qualitative Insight	Implications for CBE Design
		advanced learners want high-level summaries.	
Micro-Credentials and Motivation	—	Granular, verifiable credentials increase task persistence; risk of “credential dilution” if granularity too fine (Alakhtar et al., 2023).	Issue blockchain-based micro-credentials for each demonstrated competency; validate granularity with industry partners.
Cost Effectiveness	Per-learner AI assessment costs: 12–18 vs. human grading 45–60 (Lee & Moore, 2024).	Upfront development costs high (50,000–200,000), but scale reduces marginal cost.	Pilot at moderate scale first; model total cost of ownership including maintenance and teacher training.
Competency Taxonomy Alignment	Out-of-the-box AI agrees with human evaluators only 67%; after rubric alignment, agreement rises to 89% (Atenas & Havemann, 2023).	Generic AI fails to recognize acceptable solution variations without explicit competency rubrics.	Develop granular, observable competency taxonomies aligned with CC2020 and industry certifications.

5. DISCUSSION

5.1 Interpretation of Findings

The findings confirm that AI can address several key challenges in implementing CBE for IT education while also highlighting critical design considerations. The quantitative evidence for adaptive learning effectiveness (0.35-0.65 SD improvements) is comparable to effect sizes reported for one-to-one human tutoring (Bloom, 1984), suggesting that AI-driven adaptation can approximate aspects of personalized instruction at scale. However, these effects depend crucially on the quality of the underlying competency model and the AI system's alignment with that model.

The finding that XAI enhances both learning outcomes and engagement, particularly for complex, higher-order competencies, supports the inclusion of explainability as a core design principle rather than an optional add-on. As Dieterle et al. (2022) argued, the ethical deployment of AI in education requires addressing not only access divides but also interpretation divides: whether learners and educators can understand and appropriately act on AI outputs. The Req2XAI framework operationalizes this requirement by mandating bidirectional mapping between stakeholder requirements and machine learning model specifications (Dakshit et al., 2025). Any AI-enabled CBE system for IT education should incorporate Req2XAI or a similar requirements elicitation process before development begins.

The PEARL framework's five principles provide concrete design guidance that aligns with CBE's emphasis on learner agency (Dakshit et al., 2025). The learner control principle is particularly transformative for CBE: learners in a CBE model already choose when to attempt competency assessments; extending this control to how they receive AI support such as choosing between detailed versus summary explanations further empowers self-regulated learning.

The qualitative theme of teacher transparency concerns points to a significant implementation barrier. If teachers do not trust AI assessment systems, they will not adopt them for high-stakes competency decisions, limiting AI's impact to formative contexts. This barrier is not merely technical (providing better explanations) but social (building trust through participatory design). Including IT educators in the co-design process from the earliest stages, as Req2XAI advocates, is more likely to produce systems that teachers perceive as legitimate and useful than top-down technology mandates.

Blockchain-based micro-credentialing offers a promising mechanism for making competency mastery verifiable and portable. However, issuing a blockchain credential for a poorly assessed competency does not improve the validity of the assessment. The primary focus must remain on assessment validity—whether AI systems actually measure the competencies they claim to measure. Blockchain addresses credential integrity and portability, not credential validity.

5.2 Comparison with Existing Frameworks

The proposed framework extends existing CBE models in three significant ways. First, unlike traditional CBE implementations that rely on manual assessment or simple automated grading, this framework integrates XAI to make competency decisions transparent and interpretable. Second, while previous work has recognized the potential of micro-credentials, this framework explicitly connects AI-driven assessment with blockchain verification to create a coherent pipeline from demonstrated competency to verifiable credential. Third, the explicit incorporation of co-design processes (Req2XAI, PEARL) addresses the implementation failures that have plagued many technology-driven educational innovations.

5.3 Theoretical Contributions

This paper makes three theoretical contributions. First, it synthesizes disparate literatures CBE, AI adaptive learning, XAI, and blockchain credentialing into a coherent framework specifically for IT education. Second, it demonstrates how the PEARL principles operationalize learner-centered values within AI-driven assessment systems. Third, it provides design guidance that bridges the gap between technical AI capabilities and pedagogical requirements.

5.4 Practical Implications

For IT educators, the findings suggest that AI-driven CBE is feasible but requires deliberate attention to competency taxonomy development, rubric alignment, and teacher training. For curriculum designers, the framework provides a blueprint for sequencing competency modules and integrating AI assessment tools. For institutional leaders, the cost-effectiveness estimates inform resource allocation decisions. For industry partners, blockchain-verified micro-credentials offer verifiable evidence of graduate competencies.

5.5 Limitations

This study has several limitations. First, the synthesis is limited by the availability of rigorous evaluation studies specifically focused on AI-enabled CBE in IT education, which remains an emerging field. Second, many included studies examine AI or CBE in isolation rather than their integration. Third, publication bias may favor studies reporting positive findings. Fourth, the long-term outcomes of AI-driven CBE particularly graduate employment and workplace performance have not yet been studied longitudinally. Fifth, the framework proposed is generative rather than definitive, intended to guide future empirical research rather than serve as a prescriptive implementation guide.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

This paper concludes that artificial intelligence can meaningfully support competency-based information technology education through four primary mechanisms: adaptive personalization, real-time formative assessment, explainable competency validation, and verifiable blockchain credentialing. However, effectiveness depends critically on five interrelated design principles. First, competencies must be specified as granular, observable outcomes aligned with industry standards and CC2020 guidelines. Second, AI systems must provide transparent justifications for competency decisions using established explainable artificial intelligence techniques.

Third, learners must retain meaningful control over when and how they receive AI support, consistent with the PEARL framework's emphasis on learner control. Fourth, IT educators, industry partners, and learners must co-design systems from the outset using participatory approaches such as Req2XAI. Fifth, assessment validity must never be sacrificed for credentialing convenience or technological novelty. These five principles collectively provide a practical framework for distinguishing responsible AI integration from superficial adoption that prioritizes technological spectacle over pedagogical substance.

6.2 Recommendations for Practice

For higher education institutions, priorities include developing IT competency taxonomies aligned with CC2020 and major industry certifications such as CompTIA, AWS, Cisco, and ISC². Institutions should pilot AI-driven formative assessments in low-stakes contexts before scaling to summative competency decisions. Establishing co-design committees with IT educators, industry partners, and learner representatives ensures systems address authentic needs. Institutions must also invest in faculty professional development for AI literacy and explainable AI interpretation.

For AI developers, implementing stakeholder requirement elicitation processes such as Req2XAI before development ensures pedagogical and ethical requirements shape technical design. Developers must integrate PEARL principles as core specifications, design for interoperability with existing platforms, and provide transparency documentation including model cards and fairness audits. For industry partners, active participation in co-design processes ensures competency taxonomies reflect workplace needs, while recognition of blockchain-verified micro-credentials in hiring decisions provides market incentives for adoption. Industry partners should also contribute longitudinal data on graduate performance to validate AI assessments.

For policymakers and accreditation bodies, priorities include establishing rigorous standards for evaluating AI-based assessment validity and fairness, formally recognizing blockchain-verifiable micro-credentials as legitimate evidence of professional competency, and funding research on long-term outcomes of AI-enabled CBE programs. These stakeholders must work collaboratively to create regulatory environments that encourage innovation while protecting learners from unvalidated or biased assessment systems. Without coordinated action, the potential of AI-enabled competency-based education will remain unrealized.

6.3 Recommendations for Future Research

Future research must prioritize longitudinal studies comparing AI-enabled CBE with traditional IT programs on graduate employment outcomes, workplace performance, and lifelong learning trajectories measured over extended timeframes. Validation studies investigating large language model-based assessment reliability across IT subdisciplines including networking, cybersecurity, data science, and software engineering are urgently needed. Cost-effectiveness analyses of AI-enabled CBE at institutional, regional, and national scales, including total cost of ownership modeling, will be essential for institutional decision-makers.

Design-based research implementing and refining the proposed framework in authentic IT education contexts will generate practical implementation knowledge that controlled studies cannot provide. Equity studies examining whether AI-driven CBE reduces or exacerbates achievement gaps across demographic groups are critically important. Teacher professional development research identifying effective models for building IT educator capacity to work alongside AI assessment systems must examine initial training and sustained support structures. Interoperability research developing technical standards for blockchain credentials across platforms and institutions will be essential for realizing portable, lifelong learning records.

6.4 Concluding Remarks

The integration of AI into competency-based IT education represents not merely a technological upgrade but a fundamental reorientation toward learner-centered, outcome-driven education. When designed with transparency, fairness, and stakeholder participation, AI-driven CBE has the potential to produce graduates who possess not just knowledge but verified, demonstrable competencies aligned with industry needs. The framework proposed in this paper provides a starting point for institutions, developers, and policymakers seeking to realize this potential. The path forward requires continued collaboration across educational, technical, and industry stakeholders, with sustained commitment to the principles of explainability, learner agency, and assessment validity that lie at the heart of authentic competency-based education.

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Appendix A: Proposed Framework Components Summary

Component	Description	Key References
Competency Taxonomy	Granular, observable outcomes aligned with CC2020 and industry certifications	ACM/IEEE CS (2020); Sabin et al. (2023)
AI Adaptive Learning	Reinforcement learning and supervised learning for personalized content sequencing	García et al. (2024); Zawacki-Richter et al. (2019)
XAI Assessment	Req2XAI requirements elicitation; PEARL-aligned explanatory feedback	Dakshit et al. (2025); Chen (2025)
Blockchain Credentials	Tamper-proof, learner-owned micro-credentials for each demonstrated competency	Alakhtar et al. (2023); McGreal (2023)
Co-Design Process	Participatory design with IT educators, industry partners, and learners	Mncube & Minty (2025); Dakshit et al. (2025)