

Artificial intelligence for experience-based credit bank evaluation in electrical technology programs at vocational education institutes



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ABSTRACT

This study examines the Scopus-indexed research landscape of artificial intelligence (AI) in experience-based credit bank evaluation within vocational electrical technology education using an integrated PRISMA-based systematic review and bibliometric analysis. Peer-reviewed articles published between 2022 and 2025 were systematically screened to identify studies related to AI-supported assessment and recognition of prior learning. The PRISMA process refined the initial dataset into a focused body of literature representing recent developments in AI-enabled evaluation systems. Bibliometric mapping was used to analyze citation relationships and keyword co-occurrence patterns, revealing the intellectual structure of the research field. The findings indicate that artificial intelligence serves as a central enabling mechanism associated with machine learning, decision-making, learning systems, cybersecurity, and sustainability considerations. These relationships suggest that AI-supported credit bank evaluation can be understood as an integrated evaluation approach that connects technological analytics with competency evidence and quality assurance considerations. Two dominant thematic clusters were identified, distinguishing security- and risk-related evaluation concerns from technology-driven analytical and decision-support processes. The study provides a structured synthesis of current research trends and highlights the role of AI in supporting transparent, scalable, and competency-oriented credit recognition practices in vocational electrical technology education. Future research should focus on empirical validation and real-world implementation to improve the practical applicability of AI-supported evaluation systems.

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1. Introduction

Artificial intelligence (AI) has rapidly transformed contemporary educational environments, particularly in vocational education where competency-based assessment and practical skill validation are fundamental components of modern learning systems (Ahmad et al., 2025;

Angolkar et al., 2025). In vocational engineering disciplines, AI has progressed beyond instructional support toward intelligent evaluation systems capable of analyzing learner performance, technical experience, and professional competencies (Celik, 2023a; 2023b). This transformation is especially relevant in electrical engineering and electrical technology education, where learners must demonstrate applied technical knowledge, operational safety awareness, and practical problem-solving skills within industrial environments. Electrical Technology Programs at vocational education institutes are strongly experience-based and closely linked to industrial training and workplace practice. Electrical technicians are

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expected to develop competencies related to system installation, equipment maintenance, operational reliability, and safety compliance.

Consequently, vocational institutions require evaluation mechanisms capable of recognizing workplace experience and industrial training outcomes alongside formal academic learning. Experience-Based Credit Bank Evaluation has therefore emerged as an important mechanism for translating experiential learning outcomes into academic credit that reflects learners' professional capabilities and occupational competencies (Angolkar et al., 2025; Celik, 2023a; Ramirez-Montoya et al., 2024).

Credit bank systems and Recognition of Prior Learning (RPL) frameworks support flexible learning pathways by recognizing skills acquired through industry experience and informal learning environments. Artificial intelligence has increasingly been explored as a technological enabler for improving experience-based evaluation systems. AI-supported assessment mechanisms enhance objectivity, scalability, and analytical precision through machine learning, learning analytics, and automated decision-support tools that interpret complex evidence of professional competencies (Celik, 2023b; Fombona et al., 2025; Hijazi et al., 2025; Khan et al., 2025). Emerging technologies such as the Internet of Things (IoT), intelligent monitoring systems, and digital learning infrastructures further enable the collection of operational data from real

technical systems, creating new opportunities for intelligent competency evaluation and evidence-based recognition of prior learning in vocational engineering education. Despite the growing body of research on AI-enabled educational technologies, studies addressing AI applications in credit bank evaluation remain fragmented across several domains, including artificial intelligence in education, digital governance, competency assessment, and institutional policy frameworks (Celik, 2023a; Garzón et al., 2025).

Existing research often examines AI technologies and credit recognition policies separately rather than investigating their integration within competency-based vocational education systems. In particular, limited studies have systematically examined how artificial intelligence can support experience-based credit bank evaluation within the context of vocational electrical technology education, where practical competency verification, industrial training, and safety compliance play critical roles in educational outcomes. Addressing this gap is essential for developing evaluation approaches capable of aligning experiential learning with formal academic accreditation in technical and engineering-oriented vocational programs. Table 1 summarizes the key research gaps identified from previous studies and highlights how the present study contributes to addressing these gaps in the context of AI-supported experience-based credit bank evaluation.

Table 1: Research gaps in AI-supported credit bank evaluation research

Research area	Previous studies	Identified research gap	Contribution of this study
Artificial intelligence in education	Previous studies mainly focus on AI-assisted learning systems and intelligent tutoring systems.	Limited studies examine AI-supported evaluation for experience-based credit recognition.	This study investigates AI-supported evaluation mechanisms for experience-based credit bank systems in vocational engineering education.
Credit bank systems	Existing research discusses credit bank systems and recognition of prior learning frameworks.	Integration between AI technologies and credit recognition mechanisms remains underexplored.	This study synthesizes existing research to provide a conceptual synthesis of AI-supported evaluation mechanisms that integrate experiential evidence and intelligent analytics.
Vocational engineering education	Prior research emphasizes competency-based learning and vocational training systems.	Few studies examine AI-supported evaluation specifically within vocational electrical technology programs.	This study provides a conceptual synthesis tailored to vocational electrical technology education.

To address this research gap, the present study employs an integrated analytical approach combining PRISMA-based systematic review procedures with bibliometric analysis. The PRISMA framework provides a transparent and reproducible methodology for literature identification and selection (Garzón et al., 2025), while bibliometric techniques reveal citation relationships, keyword co-occurrence structures, and thematic patterns within AI-supported evaluation research (Ahmad et al., 2025; Hijazi et al., 2025).

By integrating these two analytical approaches, the study offers a comprehensive perspective on the intellectual development and thematic organization of research related to AI-supported credit bank evaluation. The study synthesizes research on Artificial Intelligence for Experience-Based Credit Bank Evaluation in Electrical Technology Programs and identifies emerging research trends and thematic structures within this interdisciplinary

field. In doing so, the research contributes to the academic discourse by clarifying how AI can support credit recognition by linking competency evidence, data-driven analysis, and institutional decision-making processes within vocational engineering education. The conceptual synthesis shows how AI-supported credit bank evaluation connects workplace electrical experience, competency analytics, and curriculum-aligned credit decisions. Because electrical technology education requires verifiable technical accuracy, strict safety compliance, and standardized operational procedures, it provides a rigorous context for examining how artificial intelligence can support reliable and transparent competency recognition mechanisms within vocational engineering and industrial technology education systems.

The conceptual synthesis of AI-supported experience-based credit bank evaluation is presented in Fig. 1.

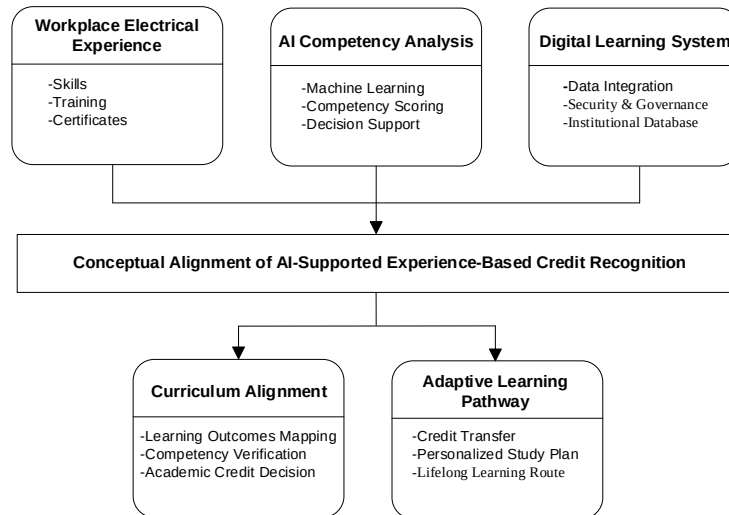


Fig. 1: Conceptual synthesis of AI-supported experience-based credit bank evaluation in vocational electrical technology education

This study contributes to the literature by integrating PRISMA-based systematic review with bibliometric mapping to conceptualize AI-supported experience-based credit bank evaluation as an evidence-based and quality-assurance-oriented evaluation approach within vocational electrical technology education. The study therefore provides a structured analytical perspective linking artificial intelligence technologies, experiential competency recognition, and institutional quality assurance in vocational engineering education.

2. Research objectives

The objective of this study is to systematically examine the development of research on artificial intelligence for experience-based credit bank evaluation in vocational electrical technology education. Specifically, the study aims to synthesize the existing literature related to artificial intelligence-supported evaluation systems, experience-based learning recognition, and credit bank mechanisms within vocational and engineering education contexts. In addition, the study seeks to identify the intellectual structure, thematic clusters, and emerging research trends within this interdisciplinary field through the integration of PRISMA-based systematic review procedures and bibliometric analysis. By examining recent Scopus-indexed publications, the study aims to provide a comprehensive analytical understanding of how artificial intelligence can support competency recognition, data-driven evaluation, and curriculum-aligned decision-making processes within vocational electrical technology programs.

3. Research questions

To achieve the objectives of this study, the following research questions are proposed:

- **RQ1:** What are the major research themes and intellectual structures related to artificial

intelligence-supported experience-based credit bank evaluation identified through bibliometric analysis?

- **RQ2:** How do existing studies conceptualize the integration of artificial intelligence technologies with credit bank systems and recognition of prior learning frameworks in vocational education?
- **RQ3:** What evaluation, quality-assurance, and risk-related mechanisms are emerging for implementing AI-supported experience-based credit recognition in vocational electrical technology education?

4. Literature review

An AI-based evaluation system applies artificial intelligence technologies to assess learner performance and interpret experience-based evidence within educational and professional environments (Junaidi et al., 2025; Hijazi et al., 2025; Setiyawan et al., 2025). By integrating machine learning algorithms, learning analytics, and automated data processing techniques, such systems enable more consistent, scalable, and data-driven evaluation processes while reducing subjectivity in competency assessment.

These capabilities are particularly valuable in vocational and technical education, where learner performance must often be assessed through practical tasks, workplace experience, and applied technical problem solving (Hijazi et al., 2025; Junaidi et al., 2025; Kavitha and Joshith, 2024; Khan et al., 2025; Setiyawan et al., 2025). Machine learning and intelligent analytics further support adaptive evaluation mechanisms capable of identifying patterns in learner competencies and predicting educational outcomes through data-driven modeling approaches (Padovano and Cardamone, 2024; Madanchian and Taherdoost, 2025; Markus et al., 2025).

These analytical capabilities strengthen the reliability of AI-enabled evaluation systems and contribute to the development of evidence-based

decision-making processes in competency recognition and educational assessment. Within this broader digital evaluation framework, a Credit Bank System provides an institutional mechanism for recognizing and accumulating learning outcomes acquired across multiple learning environments, including formal education, workplace training, and informal learning contexts (Angolkar et al., 2025; Celik, 2023a; Ramirez-Montoya et al., 2024).

Credit bank and Recognition of Prior Learning (RPL) frameworks allow vocational education institutions to support flexible learning pathways and lifelong learning models by translating experiential competencies into formal academic credit aligned with occupational standards and curriculum requirements (Angolkar et al., 2025; Celik, 2023a; Padovano and Cardamone, 2024). To ensure methodological rigor in synthesizing the interdisciplinary literature surrounding artificial intelligence and experience-based evaluation systems, this study adopts the PRISMA framework as a structured method for identifying, screening, and analyzing relevant scholarly publications (Garzón et al., 2025).

PRISMA enables transparent and reproducible literature selection procedures, which is particularly important when analyzing emerging research areas that integrate educational technology, artificial intelligence, and vocational learning systems. In addition, bibliometric analysis is employed to identify citation patterns, keyword co-occurrence structures, and intellectual linkages within the research domain, thereby revealing the thematic organization of studies related to AI-supported experience-based evaluation (Ahmad et al., 2025; Garzón et al., 2025; Hijazi et al., 2025).

Underlying these methodological perspectives, experience-based learning theory emphasizes authentic engagement, reflective practice, and the integration of workplace knowledge with formal educational structures. This perspective is particularly relevant in vocational education settings where professional competence is often developed through direct participation in real-world technical environments (Ahmad et al., 2025; Celik, 2023a; Garzón et al., 2025). In the context of vocational electrical technology programs, experience-based learning provides the pedagogical foundation for integrating workplace evidence, competency analytics, and institutional credit recognition mechanisms into a coherent AI-supported evaluation approach.

5. Methodology

This study applies a PRISMA-guided systematic review based on the PRISMA 2020 guidelines combined with bibliometric analysis to examine research on Artificial Intelligence for Experience-Based Credit Bank Evaluation in Electrical Technology Programs. PRISMA provides a transparent and reproducible framework for systematic literature identification and study

selection, while bibliometric techniques enable the exploration of citation relationships, keyword co-occurrence structures, and intellectual development patterns within AI-supported vocational evaluation research (Garzón et al., 2025; Setiyawan et al., 2025; Liu et al., 2025).

The integration of PRISMA-based systematic review with bibliometric analysis offers complementary analytical perspectives because the PRISMA framework ensures methodological transparency and reproducibility in the identification and screening of relevant studies, whereas bibliometric techniques provide quantitative insights into the intellectual structure, thematic evolution, and collaborative research patterns within the scientific literature. This combined analytical approach therefore strengthens methodological rigor by linking qualitative literature synthesis with quantitative mapping of scientific knowledge in the field of artificial intelligence-supported evaluation systems.

A structured literature search was conducted in the Scopus database to identify peer-reviewed English-language publications related to artificial intelligence, credit bank systems, AI-based evaluation, and electrical technology education. The literature search was conducted on 15 January 2026 and focused on publications from 2022 to 2025 in order to capture recent developments in AI-supported evaluation systems. The Scopus database was selected because it provides extensive coverage of high-quality peer-reviewed literature across engineering, computer science, and interdisciplinary educational technology research domains, ensuring reliable indexing coverage, citation traceability, and consistency of bibliometric metadata (Markus et al., 2025).

To ensure methodological transparency and consistency in the literature selection process, predefined inclusion and exclusion criteria were applied. The inclusion criteria consisted of peer-reviewed publications indexed in the Scopus database, studies published between 2022 and 2025, and research addressing artificial intelligence, AI-supported evaluation systems, or credit bank mechanisms within vocational education or engineering education contexts. Publications were included when they discussed competency-based assessment, recognition of prior learning, or digital evaluation systems relevant to vocational electrical technology education. The exclusion criteria consisted of non-English publications, studies lacking sufficient methodological information, and publications that were not directly related to artificial intelligence-supported evaluation or experience-based credit recognition systems. Following the initial retrieval process, duplicate records were removed, and the remaining studies were screened through title, abstract, and keyword examination to determine their relevance to the research objectives. Duplicate checking was conducted before the screening stage. No duplicate records were identified in the single Scopus export;

therefore, duplicate records removed were reported as $n = 0$. Records removed before screening primarily resulted from Scopus filtering criteria, including publication year, document type, source type, and language restrictions. To enhance methodological reliability, the screening and eligibility assessment were independently conducted by two researchers, and any disagreements were resolved through discussion in order to ensure consistency in the study selection process. Studies that satisfied the preliminary screening criteria were subsequently subjected to full-text assessment in order to determine their eligibility for inclusion in the systematic review and bibliometric analysis.

The screening and selection procedure followed the four stages of the PRISMA 2020 framework, namely identification, screening, eligibility, and inclusion, ensuring transparency and reproducibility in the study selection process; the detailed flow of literature identification and selection is illustrated in Fig. 2. Bibliometric analysis was conducted using VOSviewer to map citation relationships, co-authorship networks, and keyword co-occurrence patterns. The analysis applied association strength normalization, which is widely used in bibliometric mapping to standardize co-occurrence relationships and ensure comparability between terms. A minimum occurrence threshold of three was selected to balance the inclusion of relevant keywords while minimizing noise from low-frequency terms. Although a lower threshold (e.g., two) could increase the number of included terms, it would introduce less relevant and weakly connected keywords, thereby reducing the clarity of the network visualization.

Conversely, a higher threshold (e.g., four or more) would overly restrict the dataset and risk excluding meaningful but moderately frequent terms. Following this threshold, 30 keywords were retained from an initial set of 476 after data cleaning, duplicate keyword removal, and term standardization. This filtering process was intended to focus the analysis on the most strongly connected and conceptually significant terms, thereby improving interpretability and ensuring a clear representation of the dominant thematic structures within the research field (Khan et al., 2025; Liu et al., 2025). VOSviewer was selected because it is widely used in bibliometric research for visualizing scientific knowledge structures and identifying thematic relationships among research publications, enabling clearer interpretation of intellectual linkages across research domains related to artificial intelligence, machine learning, competency analytics, and digital evaluation systems in vocational education environments. The qualitative synthesis derived from the PRISMA screening process was integrated with quantitative bibliometric evidence, enabling cross-validation of conceptual structures and improving analytical transparency while reducing interpretive bias in tracing the evolution of AI-supported credit bank evaluation within electrical technology programs (Li, 2025; Liu et al., 2025).

The search query applied in the Scopus database combined the following parameters: (TITLE-ABS-KEY ("Artificial Intelligence" AND "AI") AND PUBYEAR > 2021 AND PUBYEAR < 2026) AND (credit bank system) AND (ai-based evaluation system) AND (electrical technology) AND (LIMIT-TO (DOCTYPE , "bk") OR LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (SRCTYPE , "b") OR LIMIT-TO (SRCTYPE , "j") OR LIMIT-TO (SRCTYPE , "p")) AND (LIMIT-TO (LANGUAGE , "English")).

The search query applied in the Scopus database was intentionally designed using a focused combination of key concepts, including artificial intelligence, credit bank systems, AI-based evaluation, and electrical technology education, to ensure high thematic relevance and conceptual specificity within the dataset. While this structured query may limit the retrieval of studies that do not explicitly use these combined terms, a manual screening process based on predefined inclusion and exclusion criteria was conducted to identify relevant studies addressing AI-supported evaluation and experience-based learning recognition within vocational and engineering education contexts. This approach reflects a balance between precision and relevance, which is commonly adopted in systematic review and bibliometric studies to maintain analytical consistency and reduce noise from unrelated publications. The focused strategy ensures that the final dataset remains directly aligned with the research objectives, while the screening procedure minimizes the potential exclusion of relevant studies that may use different terminologies.

To address the potential limitation of the focused search strategy, an expanded supplementary OR-based search was conducted to verify the coverage of the main Scopus dataset. The supplementary search combined broader terms related to artificial intelligence, credit recognition, and vocational or engineering education. The search expression included ("artificial intelligence" OR "AI" OR "machine learning" OR "learning analytics" OR "intelligent assessment") AND ("credit bank" OR "recognition of prior learning" OR "RPL" OR "prior learning assessment" OR "experience-based learning" OR "competency recognition") AND ("vocational education" OR "technical education" OR "engineering education" OR "electrical technology" OR "electrical engineering education").

The purpose of this supplementary search was not to replace the main bibliometric dataset but to reduce the risk of excluding relevant studies that used alternative terminology. Additional records were manually screened using the same inclusion and exclusion criteria applied in the main PRISMA process. This supplementary check supported the adequacy of the focused Scopus dataset while preserving methodological consistency for bibliometric analysis. While Scopus was selected due to its comprehensive indexing of peer-reviewed engineering and interdisciplinary research, the

authors acknowledge that additional databases such as Web of Science or IEEE Xplore may contain complementary literature; however, focusing on Scopus ensures consistency, citation traceability, and methodological reproducibility aligned with established bibliometric research practices within artificial intelligence and engineering education research (Markus et al., 2025; Liu et al., 2025).

6. Results

6.1. Findings from the PRISMA-based systematic review

The PRISMA-based systematic review refined a large dataset into a focused body of literature addressing AI-enabled assessment, competency recognition, and credit bank mechanisms within electrical technology programs at vocational education institutes, as illustrated in Fig. 2.

The reviewed studies show increasing scholarly attention to AI-supported evaluation for experiential learning and technical competencies, with research output rising after 2020 alongside broader adoption of AI-driven assessment in engineering education. Methodologically, most studies emphasize automated and data-driven approaches, including machine learning for competency prediction, rule-based credit awarding, and IoT-assisted verification of practical skills, while emerging applications of digital twins and multimodal learning analytics indicate early exploration of advanced assessment technologies.

Despite these advances, few studies propose structured approaches tailored to electrical technology programs, and challenges related to validation, interoperability, and ethical considerations remain, underscoring the need for more standardized and collaborative approaches to AI-based credit bank evaluation.

Fig. 2 presents the PRISMA 2020 flow diagram illustrating the study selection process, including identification, screening, eligibility assessment, and inclusion stages. During the identification stage, records were retrieved from the Scopus database, and records were removed before screening based on applied search filters.

In the screening stage, records were screened based on titles and abstracts, and irrelevant records were excluded. Reports sought for retrieval were further screened, and additional reports were excluded during this stage. In the eligibility stage, full-text articles were assessed according to predefined inclusion and exclusion criteria. Reports that did not meet the criteria were excluded with documented reasons. Finally, the included stage represents the final set of studies selected for the systematic review and bibliometric analysis. This structured selection process ensures transparency, consistency, and reproducibility in accordance with PRISMA 2020 guidelines. The annual publication trend is shown in Fig. 3. Fig. 3 shows an increasing trend in publications from 2022 to 2024, rising from

2 documents in 2022 to 25 documents in 2024, followed by 20 documents in 2025. However, the slight decline in 2025 should be interpreted cautiously because Scopus indexing for recent publications may not have been fully completed at the time of data retrieval. Therefore, the decrease in 2025 does not necessarily indicate a decline in scholarly interest, but may reflect indexing delay or database update timing. The distribution of publications by source and year is presented in Fig. 4.

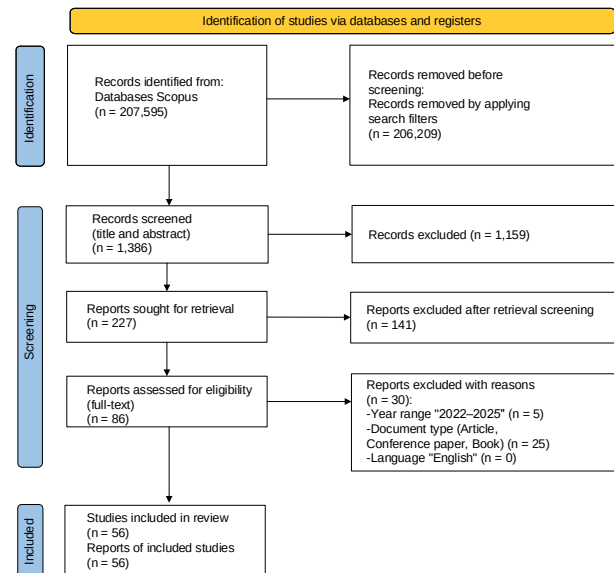


Fig. 2: PRISMA 2020 flow diagram illustrating the identification, screening, eligibility assessment, and inclusion of studies in the systematic review

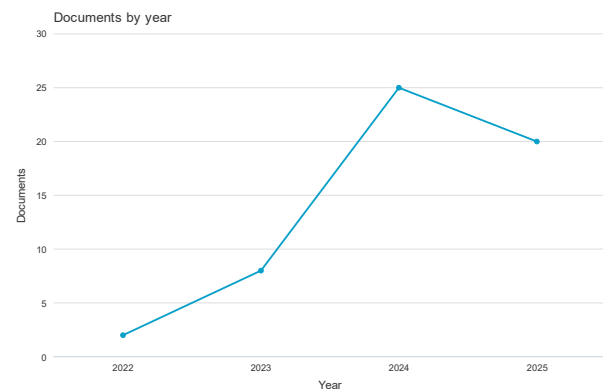


Fig. 3: Number of publications per year related to AI-supported credit bank evaluation

Fig. 4 presents the number of documents by source. IEEE Access shows the highest contribution in 2023 (3 documents). Journal of Innovation and Knowledge appears in 2025 (2 documents), while Annals of Data Science (2024), Acta Logistica (2023), and Applied Energy (2022 and 2025) each contributed one document per respective year. This indicates a distribution of publications across multiple international journals. The country-level publication distribution is shown in Fig. 5.

Fig. 5 illustrates the distribution of publications by country or territory. India shows the highest number of publications, followed by China, Saudi

Arabia, the United Arab Emirates, and the United Kingdom. This pattern indicates that AI-supported evaluation and competency-based education research has attracted international attention across both Asian and non-Asian research contexts. However, the dominance of India should be interpreted descriptively rather than causally, as the present bibliometric data do not provide sufficient evidence to explain the underlying national-level factors driving this publication pattern. The subject-area distribution of publications is presented in Fig. 6.

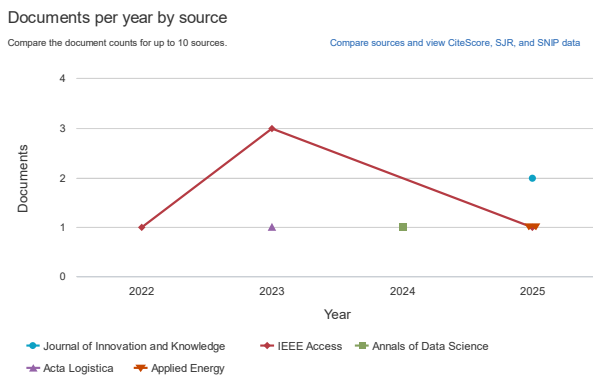


Fig. 4: Distribution of publications by source and year

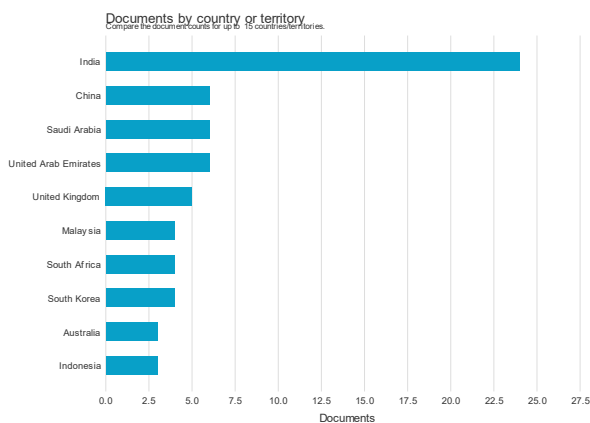


Fig. 5: Publications by country

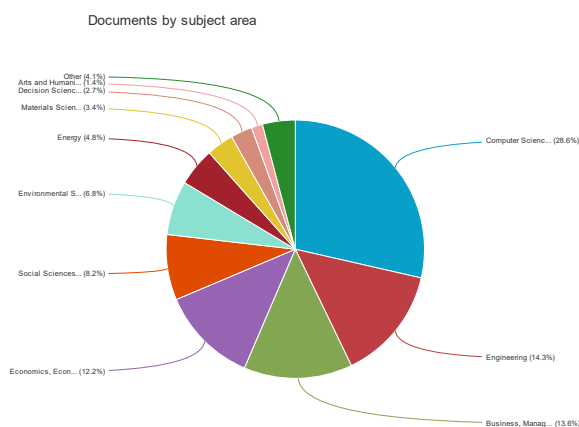


Fig. 6: Distribution of publications by subject area

Fig. 6 presents the distribution of documents by subject area. Computer Science accounts for the largest share (28.6%), followed by Engineering

(14.3%), Business, Management and Accounting (13.6%), and Economics, Econometrics and Finance (12.2%). Other contributing fields include Social Sciences (8.2%), Environmental Science (6.8%), Energy (4.8%), Materials Science (3.4%), Decision Sciences (2.7%), Arts and Humanities (1.4%), and other areas (4.1%).

This distribution highlights a strong emphasis on technology and engineering, complemented by business and social dimensions. Beyond descriptive distribution patterns, the dominance of computer science and engineering subject areas indicates that research on AI-supported credit bank evaluation remains predominantly technology-centered. This concentration suggests the necessity for deeper pedagogical integration, particularly within vocational curriculum studies, to ensure that technological innovation is systematically aligned with instructional design and competency-based educational frameworks.

6.2. Bibliometric analysis results

Fig. 7 presents the bibliometric mapping of research on Artificial Intelligence for Experience-Based Credit Bank Evaluation in Electrical Technology Programs, illustrating the thematic structures that organize AI-supported assessment and credit recognition research within vocational education.

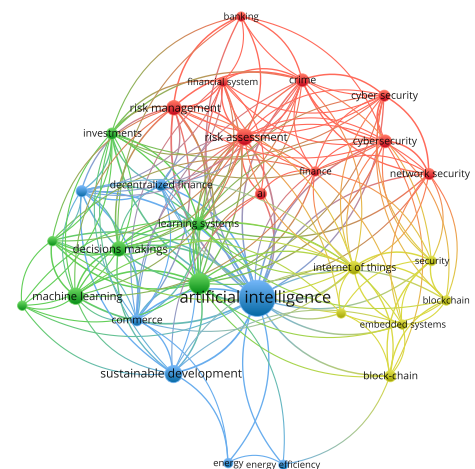


Fig. 7: Bibliometric keyword co-occurrence network for AI-supported experience-based credit bank evaluation

Metadata from Scopus-indexed articles were extracted and standardized to ensure consistency of author keywords. After duplicate keyword removal and term harmonization, a minimum occurrence threshold of three was applied, resulting in 30 keywords retained from an initial set of 476 for subsequent co-occurrence analysis, as illustrated in the bibliometric network. The keyword co-occurrence analysis identified four thematic clusters representing risk, cybersecurity, and financial systems; learning systems, machine learning, and decision-making; digital technologies such as the Internet of Things and blockchain; and

sustainability-related and contextual factors shaping AI-enabled evaluation approaches.

Citation and co-citation analysis further revealed strong intellectual linkages among studies focusing on artificial intelligence, learning systems, cybersecurity, and digital infrastructures, with highly cited works emphasizing risk assessment, secure data processing, and verification mechanisms across interdisciplinary research domains. In addition, the bibliometric network indicates active international collaboration among researchers working on artificial intelligence, machine learning, cybersecurity, and decision-support systems, reflecting shared scholarly efforts to develop reliable and transparent AI-supported credit recognition mechanisms.

By integrating PRISMA findings with bibliometric mapping, artificial intelligence emerges as the central thematic core, closely connected with learning systems, cybersecurity, and digital infrastructures, while emerging trends highlight increasing attention to secure evaluation environments, distributed technologies, and sustainability-oriented perspectives. Beyond descriptive trend reporting, the bibliometric distribution patterns indicate structural asymmetry in research development. The concentration of publications in computer science and engineering domains, coupled with limited representation in pedagogical and curriculum-focused studies, suggests a maturity imbalance in the field. This imbalance implies that technological optimization has advanced more rapidly than instructional integration, reinforcing the necessity of an engineering pedagogy-oriented interpretive framework to contextualize AI-supported credit bank systems within competency-based vocational education. The simplified thematic clustering structure is shown in Fig. 8.

Fig. 8 illustrates the thematic clustering of keywords identified through bibliometric analysis, revealing two primary clusters. The first cluster includes terms such as risk assessment, cybersecurity, and crime, which indicate concerns related to security, data protection, and system reliability within AI-supported evaluation environments. The second cluster is centered on artificial intelligence, machine learning, decision-making, and the Internet of Things, representing the technological and analytical components of AI-enabled evaluation systems.

It should be noted that the interpretation of keyword relationships is based on co-occurrence patterns rather than direct causal associations. The term "crime" appears as part of the network structure and is interpreted cautiously as a security-related concept rather than implying broader governance or ethical frameworks. Therefore, the clustering results are presented descriptively to reflect thematic groupings observed in the data without extending beyond the empirical evidence.

Table 2 presents the ten most strongly connected terms selected from the bibliometric keyword

network in order to improve interpretability and maintain visualization clarity in the network structure. This keyword selection follows established bibliometric reporting practices. The bibliometric analysis conceptualizes AI-enabled credit bank evaluation as an integrated evaluation system grounded in Scopus-indexed literature. By focusing on the ten most strongly connected keywords, the analysis highlights the most influential conceptual relationships shaping the research domain.

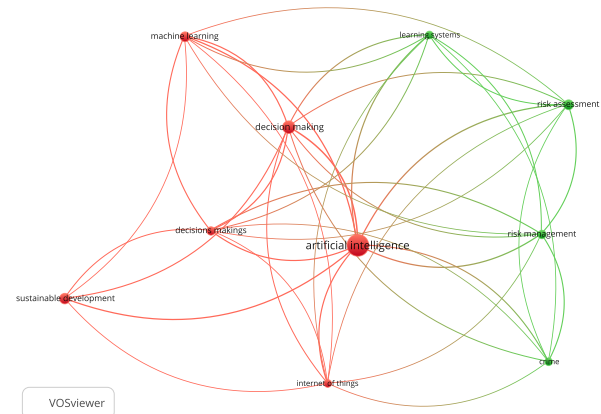


Fig. 8: Thematic clustering of AI-supported credit bank evaluation research

7. Discussion

This section interprets the PRISMA-based screening results and bibliometric findings from an engineering pedagogy perspective, positioning artificial intelligence not merely as a technological tool but as an embedded component of experience-based credit bank evaluation in vocational electrical technology education. By integrating systematic review procedures with bibliometric mapping, the analysis identifies two dominant thematic structures illustrated in Fig. 8: security- and risk-related evaluation concerns and technology-supported data-driven evaluation mechanisms (Kavitha and Joshith, 2024; Liu et al., 2025; Madanchian and Taherdoost, 2025; Ramirez-Montoya et al., 2024).

The interaction between these thematic clusters indicates that AI-supported credit bank evaluation can be understood as an integrated evaluation approach in which analytical intelligence, cybersecurity, institutional accountability, and risk management function as interrelated dimensions rather than isolated components (Liu et al., 2025; Madanchian and Taherdoost, 2025; Rashidi et al., 2026).

This convergence suggests that governance models from domains such as cybersecurity and digital decision systems offer relevant insights for educational evaluation, particularly in terms of algorithmic accountability, data integrity, and risk mitigation (Ahmad et al., 2025; Khan et al., 2025). Such interdisciplinary integration strengthens the accountability and quality-assurance foundations of AI-enabled evaluation systems in vocational

education (Ramirez-Montoya et al., 2024; Ahmad et al., 2025). The findings further highlight the pedagogical role of the conceptual structure presented in Fig. 1, indicating that AI-supported

credit bank evaluation extends beyond automated scoring and functions as an instructional alignment system within competency-based engineering education.

Table 2: Extracted keywords for systematic review and bibliometric screening

Keywords	Description	References
Crime	This term is interpreted as a security-related concept associated with cybersecurity risks, data protection issues, and system vulnerabilities within AI-supported evaluation environments. Cybersecurity is addressed as a foundational requirement for protecting learner data, ensuring system reliability, and sustaining confidence in AI-driven credit recognition platforms within vocational education environments.	Ahmad et al. (2025), Khan et al. (2025), Ziemba et al. (2024), and Liu et al. (2025)
Cybersecurity	Learning systems are conceptualized as digitally mediated environments that integrate AI and analytics to support personalized learning pathways and evidence-based evaluation of experiential competencies.	Ahmad et al. (2025), Khan et al. (2025), Liu et al. (2025), and Madanchian and Taherdoost (2025)
Learning system	Risk assessment refers to systematic processes for identifying and evaluating uncertainties associated with AI-based educational decisions, including bias, validity, and transparency in experience-based credit evaluation.	Ahmad et al. (2025), Hijazi et al. (2025), Liu et al. (2025), Junaidi et al. (2025), and Ramirez-Montoya et al. (2024)
Risk assessment	Risk management emphasizes institutional strategies and policy mechanisms designed to mitigate ethical, technical, and organizational risks arising from the deployment of AI in vocational credit bank systems.	Ahmad et al. (2025), Khan et al. (2025), Liu et al. (2025), and Madanchian and Taherdoost (2025)
Risk management	Artificial intelligence is positioned as a transformative technology enabling intelligent assessment, adaptive learning, and data-informed recognition of prior learning in vocational electrical technology programs.	Liu et al. (2025), Ahmad et al. (2025), Khan et al. (2025), and Ziemba et al. (2024)
Artificial intelligence	Decision making highlights the role of AI-supported analytics in enhancing the consistency, fairness, and evidence-based nature of credit allocation decisions within vocational education institutions.	Ahmad et al. (2025), Hijazi et al. (2025), Li (2025), and Madanchian and Taherdoost (2025)
Decision making	The Internet of Things is considered as a complementary data source that enriches experiential evidence by capturing real-time performance and operational data relevant to vocational skill assessment.	Ahmad et al. (2025), Hijazi et al. (2025), Liu et al. (2025), Madanchian and Taherdoost (2025), and Ramirez-Montoya et al. (2024)
Internet of Things	Machine learning is discussed as a core AI technique that enables pattern recognition, predictive assessment, and scalable evaluation of learner competencies derived from prior learning experiences.	Madanchian and Taherdoost (2025), Mohanraj and Pichai (2025), Li (2025), Padovano and Cardamone (2024), and Hijazi et al. (2025)
Machine learning	Sustainable development frames the long-term societal and institutional value of AI-enabled credit bank systems in supporting inclusive education, workforce resilience, and alignment with SDGs.	Ahmad et al. (2025), Angolkar et al. (2025), Fombona et al. (2025), Markus et al. (2025), and Ziemba et al. (2024)
Sustainable development		

By linking workplace-acquired electrical competencies—such as certifications, performance records, and practical skill demonstrations—with AI-based analytical models and curriculum standards, institutions can validate professional capability while maintaining academic rigor, fairness, and transparency (Angolkar et al., 2025; Hijazi et al., 2025; Liu et al., 2025; Pokorny, 2024).

This alignment is particularly critical in electrical technology programs, where safety compliance, operational reliability, and technical proficiency are essential. From an implementation perspective, the findings support a structured validation model comprising three interrelated stages: (1) systematic collection and verification of experiential competency evidence, (2) AI-supported analytical evaluation using machine learning and pattern recognition to enhance consistency and reduce bias, and (3) curriculum-aligned academic credit decisions governed by institutional quality assurance frameworks (Ahmad et al., 2025; Celik, 2023a; Madanchian and Taherdoost, 2025).

This staged approach demonstrates that AI functions as a pedagogically grounded evaluation mechanism that integrates experiential learning, recognition of prior learning, and formal accreditation systems (Angolkar et al., 2025; Pokorny, 2024; Zhang, 2025). Overall, AI-enabled

credit bank evaluation can be understood as a pedagogical bridge connecting competency verification, curriculum design, quality-assurance mechanisms, and analytical technologies. This integration supports transparent, scalable, and learner-centered assessment practices aligned with competency-based engineering education and sustainable development goals (Ahmad et al., 2025; Fombona et al., 2025; Markus et al., 2025; Ziemba et al., 2024). The contribution of this study therefore lies in synthesizing how evaluation mechanisms with accountability and quality-assurance considerations can be aligned with competency-based curricula, providing a structured perspective for developing intelligent and accountable evaluation systems in vocational engineering education.

8. Implications and future research

From a practical perspective, the findings support the development of AI-supported evaluation systems that integrate analytical technologies with structured competency recognition processes. Vocational education institutions, particularly in electrical technology programs, can apply these insights to enhance transparency, scalability, and consistency in experience-based credit evaluation. The results highlight the importance of combining AI

analytics with governance mechanisms such as cybersecurity protection, risk management, and structured decision-support systems to ensure reliability and accountability (Kavitha and Joshith, 2024; Liu et al., 2025). This integration is especially important in electrical technology education, where competency assessment must consider safety standards, technical precision, and operational performance. At the institutional level, AI-supported evaluation systems can improve the efficiency and objectivity of competency recognition through data-driven analysis and automated decision-support

mechanisms (Hijazi et al., 2025; Li, 2025; Liu et al., 2025).

The integration of Recognition of Prior Learning (RPL) frameworks within competency-based curricula further enables institutions to align experiential learning outcomes with academic standards while maintaining fairness and transparency (Angolkar et al., 2025; Pokorny, 2024; Zhang, 2025). Future research directions identified from the PRISMA-based systematic review and bibliometric analysis are summarized in Table 3.

Table 3: Future research directions for AI-supported experience-based credit bank evaluation in vocational electrical technology education

Research area	Current research limitation	Future research direction
AI-supported competency evaluation	Existing studies mainly focus on conceptual models and literature synthesis rather than empirical validation.	Future studies should develop and experimentally validate AI-supported credit bank evaluation systems within real vocational electrical technology programs and industrial training environments.
Integration of AI with credit bank systems	Current research discusses artificial intelligence and credit bank mechanisms separately, with limited integrated evaluation models.	Future research should design intelligent evaluation approaches that integrate machine learning, learning analytics, and experience-based credit recognition systems.
Vocational electrical technology education	Most AI-in-education research focuses on general higher education rather than technical and engineering-oriented vocational programs.	Further studies should investigate AI-supported competency recognition models specifically tailored to vocational electrical technology education and industrial workforce development.
Governance, ethics, and cybersecurity	Limited research addresses governance mechanisms, risk management, and ethical considerations in AI-based credit evaluation systems.	Future research should examine governance approaches incorporating cybersecurity, algorithmic transparency, and ethical AI implementation in vocational education assessment systems.

These directions provide a structured roadmap for advancing AI-supported evaluation systems in vocational electrical technology education. Despite the methodological rigor of the PRISMA-based review and bibliometric analysis, several limitations should be acknowledged. The study is limited to the Scopus database and focuses on conceptual synthesis rather than empirical implementation. Although an expanded supplementary OR-based search was conducted to verify coverage and reduce terminology-related exclusion, the final bibliometric dataset remained based on Scopus-indexed records to preserve metadata consistency and methodological reproducibility.

Future research should therefore validate AI-supported evaluation systems through real-world applications in vocational education environments. Additionally, future studies should expand data sources by incorporating multiple databases such as Web of Science and IEEE Xplore to enhance research coverage. Further investigation is also required to develop integrated evaluation architectures that balance technological capability with governance, trust, and sustainability. By addressing these directions, future research can contribute to the development of intelligent, secure, and pedagogically grounded evaluation systems aligned with competency-based engineering education.

9. Conclusion

This study provides a systematic and bibliometric synthesis of research on artificial intelligence (AI) in experience-based credit bank evaluation within vocational electrical technology education. Using a PRISMA-based approach combined with bibliometric analysis, the study identifies key research trends, thematic structures, and conceptual relationships in

the field. The findings indicate that AI plays a central role in supporting competency-based evaluation by linking analytical technologies with experiential learning evidence and institutional quality-assurance considerations.

The identified thematic structure highlights the coexistence of security- and risk-related evaluation concerns alongside technology-driven analytical and decision-support processes. This relationship reflects the growing need to integrate data-driven evaluation methods with accountability, security, and educational requirements. In the context of vocational electrical technology education, the results emphasize the importance of aligning AI-supported evaluation with domain-specific requirements, including safety compliance, technical performance, and operational reliability. These factors are essential for ensuring that competency recognition processes are both academically valid and practically relevant. Overall, the study offers a structured understanding of how AI can support experience-based credit evaluation in vocational education. Future research should focus on empirical validation, real-world implementation, and the development of context-specific evaluation practices to enhance the effectiveness and applicability of AI-supported systems.

List of abbreviations

AI	Artificial intelligence
IEEE	Institute of electrical and electronics engineers
IoT	Internet of Things
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
RQ	Research question
RPL	Recognition of prior learning
SDGs	Sustainable development goals

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Compliance with ethical standards

Conflict of interest

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