

The Evolution of Artificial Intelligence in Vocational Learning Ecosystems:  
From Personalization to Ecosystem Orchestration

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ABSTRACT (10 PT)

Artificial intelligence (AI) is becoming deeply embedded in technical and vocational education and training, yet the literature on this convergence remains fragmented across separate research traditions. This study maps the intellectual structure of AI within vocational learning ecosystems and synthesizes the field's most influential contributions to clarify how AI is reorganizing these ecosystems. The study uses a hybrid design combining bibliometric science mapping with a PRISMA-based systematic review. Researchers searched the Scopus database and analyzed a dataset of 141 documents published between 2012 and 2026 for publication dynamics, geographical distribution, source distribution, citation impact, and keyword co-occurrence; the most conceptually relevant documents were then read in full for narrative synthesis. The field is young but growing rapidly: 104 documents (73.8 percent) were published between 2024 and 2026, and Indonesia is the largest single-country contributor. Co-occurrence analysis produced four thematic clusters: engineering-education and digital-infrastructure ecosystems, AI-based adaptive and personalized learning, vocational and workforce training, and sustainability and policy. Beyond mapping these clusters, this study's principal contribution is a conceptual reframing of AI's role in the field: rather than a discrete instructional tool, AI increasingly functions as an ecosystem orchestration layer that integrates digital infrastructure, adaptive and personalized learning, workforce-aligned competency development, and credentialing systems into a single structure connecting curriculum, learners, industry, and recognition mechanisms. Empirical evidence for this orchestration role, however, remains concentrated in higher education and engineering contexts; direct evidence from vocational settings, including workshops, laboratories, and work-based learning, is still scarce. The findings provide vocational institutions and policymakers with an evidence-based agenda for designing AI-enabled vocational learning ecosystems.

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INTRODUCTION

Technical and vocational education and training (TVET) is being reshaped by digital technology, and artificial intelligence (AI) is widely regarded as the most consequential driver of this change (Adel, 2024; Ang et al., 2020). Earlier generations of educational technology were largely digitization tools: they converted materials and communication into electronic form but left the underlying instructional process largely untouched. AI represents a qualitative rather than incremental

shift because it introduces systems capable of customizing content, predicting learner needs, and generating recommendations that act directly on the learning process itself, rather than merely delivering fixed content through a new medium (Fake & Dabbagh, 2023). This distinction matters specifically for vocational education, whose central purpose is to align learner competencies with the evolving needs of the world of work. Because AI can personalize learning pathways, connect curricula to real-time labour-market signals, certify skills through microcredentials, and link classroom instruction with workplace practice, it functions not merely as an instructional aid but as infrastructure capable of reorganizing how vocational competencies are developed, recognized, and deployed.

This shift is difficult to understand through the lens of a single classroom or a single tool, because its effects span institutions, industry, and recognition systems simultaneously. Ecosystem frameworks offer a better vantage point. Following Dabbagh and Castaneda (2020), who foreground the role of learner agency within personal learning environments, and Deev et al. (2021), whose convergence model blends education, technology, and sustainability, this study defines a vocational learning ecosystem as an interdependent network of learners, educators, institutions, industry partners, technology infrastructure, and recognition systems, in which competency development emerges from the interaction among these elements rather than from any single classroom or tool. Within such an ecosystem, artificial intelligence does not operate as a separate application but as a connecting and adaptive layer: the convergence of intelligent tutors, robotics, and the Internet of Things illustrates an already-orchestrated system (Adel, 2024), while large-scale educational data analytics supplies its supporting architecture (Ang et al., 2020).

Several recent reviews have already synthesized parts of this literature, yet each leaves a specific gap that motivates the present study. AbuKhousa et al. (2023) and Schoenenberger (2024) map immersive and connected-learning technologies but treat AI as one input among several rather than as an organizing layer, and neither adopts a bibliometric lens capable of showing the field's overall structure. Fake and Dabbagh (2023) offer a conceptual framework for personalized learning design, but its scope is confined to personalization and does not extend to credentialing, workforce alignment, or governance. Eljak et al. (2024) and Fortuna et al. (2025) provide systematic reviews of cloud- and AI-based learning, but both are framed around higher education in general, do not isolate vocational- or engineering-specific evidence, and do not quantify the geographical or disciplinary concentration of the literature. Taken together, existing reviews are thematically narrow, are not vocational-specific, and rely on narrative rather than bibliometric methods; none provides a field-level map of publication dynamics, geographical concentration, or thematic structure specific to artificial intelligence in vocational and engineering education. As a result, there is no complete picture of this field's intellectual structure, its geographical and disciplinary concentration, or the mechanism through which artificial intelligence generates value in the vocational realm specifically the gap this study addresses.

This study closes this gap through a hybrid design that combines bibliometric science mapping with PRISMA-based systematic synthesis: the bibliometric method displays the structure and dynamics of the field at scale, while the systematic synthesis interprets the claims and findings of the most relevant studies. Accordingly, this study addresses four research questions: (RQ1) How has scholarly production on artificial intelligence in vocational learning ecosystems developed over time, in terms of volume, document type, and citation impact? (RQ2) What is the thematic structure of this field, as revealed through keyword co-occurrence? (RQ3) Through what mechanism does artificial intelligence reorganize the vocational learning ecosystem? (RQ4) What research agenda follows from the current evidence base? These questions correspond to four objectives: to describe the development of artificial intelligence studies in the vocational learning ecosystem; to uncover the thematic structure of this field through keyword co-occurrence; to explain the mechanism through which artificial intelligence reorganizes the vocational ecosystem; and to develop a research agenda for the future. The novelty of this article lies in its vocational-ecosystem perspective, and specifically in formalizing artificial intelligence's role as an orchestration layer that integrates digital infrastructure, adaptive learning, workforce development, and credentialing systems, a conceptual contribution developed in the Discussion.

## **METHOD**

This study uses a hybrid study design. This design combines bibliometric analysis with systematic literature review. Both approaches are applied to a single dataset. Bibliometric analysis measures the performance and structure of a research field. The measurement used publication metadata and citations (Donthu et al., 2021; Zupic & Čater, 2015). Systematic studies apply transparent and repeatable procedures (Page et al., 2021). The merger of the two masks their respective weaknesses. Bibliometrics display the structure. Bibliometrics do not explain meaning. Narrative synthesis explains meaning. Narrative synthesis is difficult to apply on a large scale.

### ***Data sources and searches***

The researchers chose Scopus as the sole data source because of its broad coverage of the education, engineering, and computing literatures and its structured export of citation and keyword metadata. Records were retrieved by applying the following search string to the article title, abstract, and keyword fields: ("Artificial Intelligence" OR AI OR "Generative AI") AND ("Vocational Learning Ecosystem\*" OR "Vocational Ecosystem\*" OR "Learning Ecosystem\*") AND ("Technical and Vocational Education and Training" OR TVET OR "Vocational Education"), restricted at search time to English-language records published between 2012 and 2026 and to the document types listed in Table 1. The search was executed and the dataset downloaded on June 4, 2026, directly retrieving the 141 documents that form the analytic dataset; the researcher compiled a working list of all downloaded documents containing the author, title, year, source, keyword, and citation count for each record. Because the field is expanding quickly, re-running the same string in Scopus after the export date returns

a larger and still-growing result set, consistent with the rapid recent growth this study documents in the Results.

### ***Inclusion and exclusion criteria***

The researcher screened the retrieved records against the criteria in Table 1. Because the Scopus search string was already topic, language, and date-limited at search time, this screening operated mainly as a metadata check on the 141 retrieved records rather than a separate large-scale exclusion step. One record, Zotov et al. (2021), carries a Retracted publication status in Scopus; it was retained in the bibliometric mapping dataset ( $n = 141$ ) for completeness of the citation and keyword metadata but was excluded from full-text reading and narrative synthesis. A further record, an indexed "Compilation of References" entry from an edited volume, is back-matter rather than a substantive contribution and does not clearly satisfy the topical inclusion criterion in Table 1. The complete selection process is summarized in the PRISMA-style flow diagram (Figure M1).

Table 1. Inclusion and exclusion criteria

| <b>Dimensions</b> | <b>Inclusions</b>                                                                            | <b>Exclusion</b>                           |
|-------------------|----------------------------------------------------------------------------------------------|--------------------------------------------|
| Topics            | Artificial intelligence or related technology in vocational learning, engineering, or skills | Technology has nothing to do with learning |
| Document type     | Articles, reviews, conference papers, books, book chapters                                   | Retracted or duplicate documents           |
| Period of project | Year 2012 to 2026                                                                            | Out of range                               |
| Language          | English                                                                                      | Not English                                |
| Source            | Scopus Indexed                                                                               | Incomplete metadata                        |

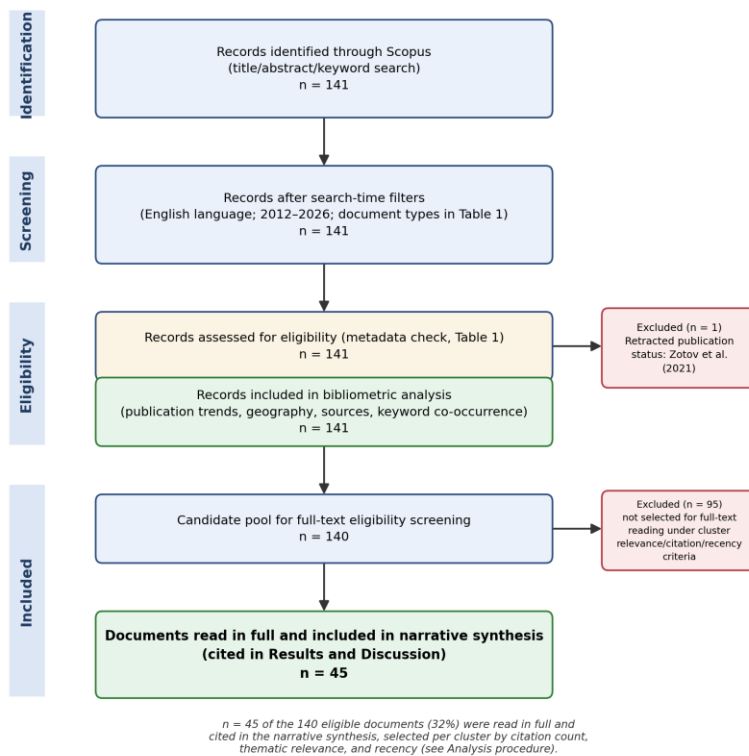


Figure M1. PRISMA-style flow diagram of the document selection process. Layout follows the standard PRISMA 2020 four-stage structure (Page et al., 2021). Counts verified against the Scopus RIS export (Export Date: 04 June 2026) and in-text citation audit. One further record (a 'Compilation of References' entry) requires author review — see main text.

Figure M1. PRISMA-style flow diagram of the document selection process, following the standard PRISMA 2020 layout and verified against the Scopus export of June 4, 2026

### Analysis procedure

The researcher analyzed the downloaded documents in two stages. The first stage assessed publication performance, including annual production, document type, citation impact, and geographic and source distribution. The second stage was science mapping. Author keywords were first normalized by consolidating morphological, spelling, and near-synonymous variants (for example, "e-learning" and "electronic learning"; "artificial intelligence" and "AI") using a manually curated VOSviewer thesaurus file, so that the co-occurrence network was not artificially fragmented by superficial term variation. Keyword co-occurrence was then computed in VOSviewer using full counting, a minimum threshold of four occurrences per keyword, and association-strength normalization for cluster detection (van Eck & Waltman, 2010), cross-checked against the bibliometrix/biblioshiny R package (Aria & Cuccurullo, 2017). The mapping formed thematic clusters based on the strength of inter-term connectivity, and the researcher additionally traced the time distribution of each term to identify growing themes (overlay and thematic-trend analysis). Within each resulting cluster, documents were prioritized for full-text reading and narrative synthesis using three explicit criteria: (a) citation count, prioritizing documents in the upper range of citations within their cluster; (b) direct thematic relevance to vocational, engineering, or skills-based learning contexts, judged from title, abstract, and keyword overlap with the cluster's representative terms; and (c) recency, to ensure that emerging but not yet highly cited 2025–2026

contributions were not systematically excluded in favor of older, more-cited work. Where a cluster's most-cited documents were topically peripheral to vocational or engineering learning, the next most relevant document by thematic fit was substituted. Of the 140 eligible documents, 45 (32 percent) were read in full and are cited in the narrative synthesis presented below (Results and Discussion), a count verified directly against the in-text citation record rather than estimated. This reading resulted in the narrative synthesis presented below.

## **RESULTS AND DISCUSSION**

### ***Publication dynamics and document types***

The dataset contains 141 documents issued from 2012 to 2026. The document received a total of 1,937 citations. The average citation reached 13.7 per document. Document production peaked today. A total of 104 documents or 73.8 percent will be issued from 2024 to 2026. 2025 will be the most productive year with 46 documents. In 2026, it will contribute 33 documents at the time of export. Figure 1 shows the annual and cumulative trajectories. The track is steeply uphill. This pattern marks a growing field. Datasets also vary in document types. Figure 2 shows the distribution. Journal articles dominated with 68 documents or 48.2 percent. The book follows with 23 documents. The conference papers totaled 20 documents. The book chapters total 19 documents. The review totals 9 documents. Books and book chapters together account for 42 documents, or 29.8 percent of the dataset a comparatively high share relative to more mature bibliometric fields, where journal articles typically dominate more decisively (Donthu et al., 2021). This pattern is consistent with, though not direct evidence for, a field that is still consolidating its conceptual vocabulary, since edited volumes and book chapters often accommodate exploratory or synthesis-oriented contributions before a topic matures into a stable stream of empirical journal articles. This interpretation should be read as tentative pending direct comparison with the document-type profiles of adjacent, more established fields such as mobile learning or learning analytics.

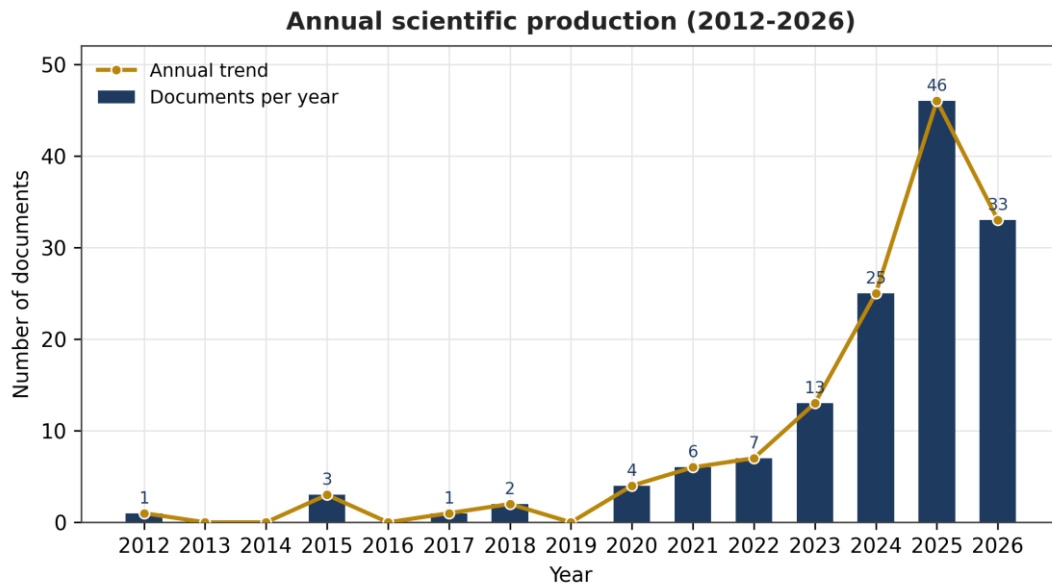


Figure 1. Annual scientific production and cumulative output, 2012–2026

### Document type distribution

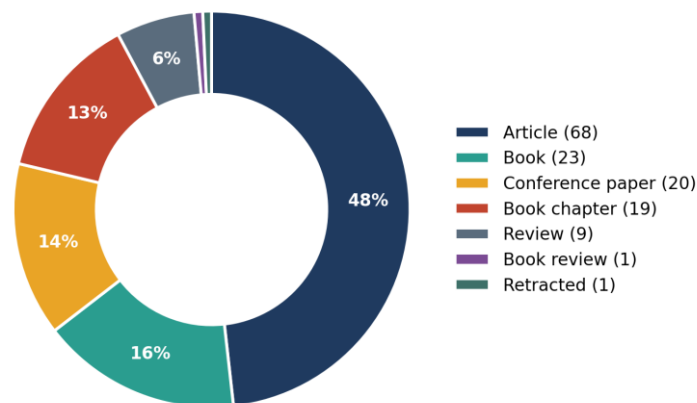


Figure 2. Distribution of document types in the dataset

### *Geographic distribution and sources*

Dataset documents come from 60 countries. 37 documents, or 26.2 percent, involved collaboration between countries. Indonesia leads with 22 documents. China followed with 15 documents. India contributed 12 documents. Figure 3 shows the country distribution. Indonesia's leading position is consistent with, though not directly explained by, its national vocational policy agenda, which has prioritized teaching-factory models and the modernization of polytechnics and vocational schools; several Indonesian studies in the dataset engage directly with this policy context (Hendric & Rosmansyah, 2025; Suyatmo et al., 2025; Wahyuni et al., 2020). However, the bibliometric analysis itself does not evaluate policy documents, funding data, or institutional investment, so this association should be read as a plausible contextual explanation rather than a demonstrated causal mechanism; confirming it would require a dedicated policy-linkage analysis, for example, tracing funding

acknowledgements or institutional affiliations against national TVET investment programs. The source of the publication is very scattered. Documents come from 124 different sources. IEEE Access is the most frequently cited source. Figure 4 shows the most productive sources. This distribution confirms the cross-disciplinary nature of this field

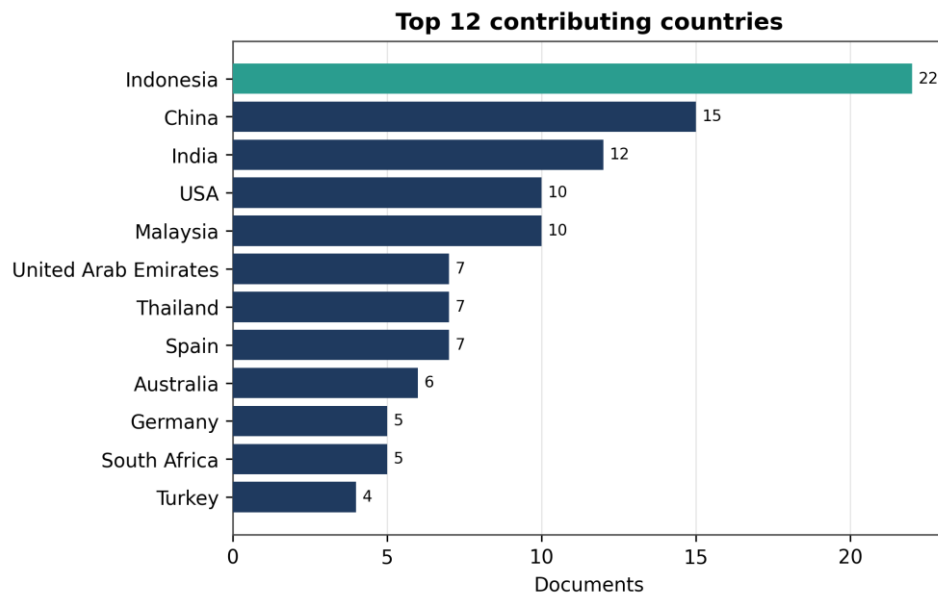


Figure 3. Top twelve contributing countries (Indonesia highlighted)

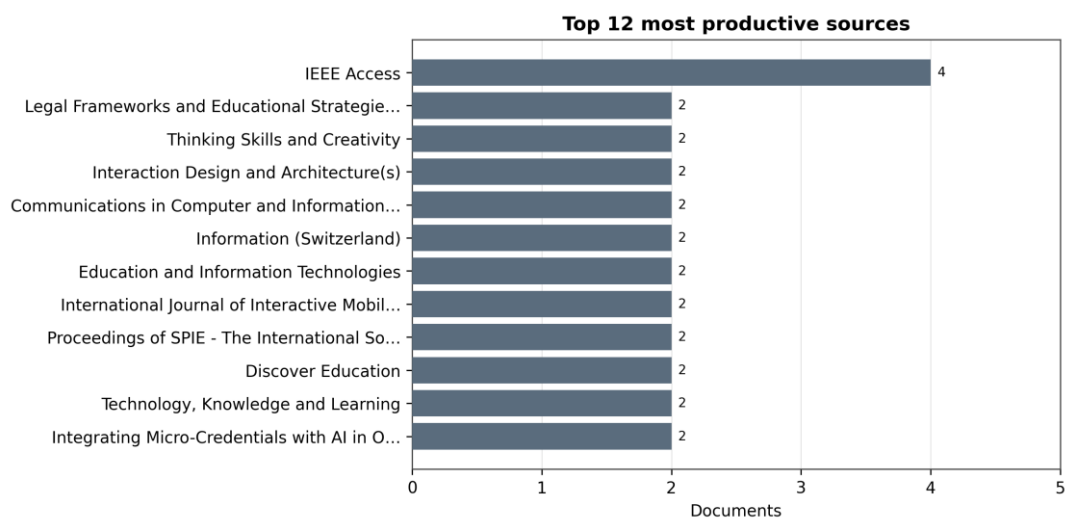


Figure 4. Top twelve most productive sources

### ***Influential documents and keyword structures***

Table 2 shows the twelve most cited documents. The most cited document discusses cloud computing in education (González-Martínez et al., 2015). The document supports the infrastructure aspect. A synthesis of blended learning adoption has also been widely cited (Anthony et al., 2022). The initial evaluation of the recommendation system complements the personalization aspect (Erdt et al.,

2015). The latest work marks a new direction that addresses the convergence of intelligent tutors, robotics, and IoT (Adel, 2024). Another work discusses large-scale educational data analytics (Ang et al., 2020). Figure 5 shows the most frequently appearing keywords, namely e-learning, engineering education, artificial intelligence, learning systems, and educational computing. The terms vocational education and higher education also stand out. The term ecosystem appears repeatedly in the dataset and supports the ecosystem perspective in this study.

Table 2. The twelve most cited documents in the dataset

| No. | Citation | Year | Title (concise)                                               |
|-----|----------|------|---------------------------------------------------------------|
| 1   | 272      | 2015 | Cloud computing and education: A state-of-the-art survey      |
| 2   | 234      | 2022 | Blended Learning Adoption and Implementation in Higher Edu... |
| 3   | 127      | 2015 | Evaluating Recommender Systems for Technology Enhanced Lea... |
| 4   | 125      | 2024 | The Convergence of Intelligent Tutoring, Robotics, and IoT... |
| 5   | 124      | 2020 | Big Educational Data Analytics: Survey, Architecture and C... |
| 6   | 116      | 2022 | Thai undergraduate science, technology, engineering, arts,... |
| 7   | 96       | 2018 | Shaping the university of the future: Using technology to ... |
| 8   | 86       | 2020 | The PLE as a framework for developing agency in lifelong l... |
| 9   | 79       | 2012 | Equity considerations for open educational resources in th... |
| 10  | 50       | 2023 | Envisioning Architecture of Metaverse Intensive Learning E... |
| 11  | 45       | 2025 | Equity in K–12 STEM Education: Framing Decisions for the F... |
| 12  | 43       | 2024 | Advancing Lifelong Learning in the Digital Age: A Narrativ... |

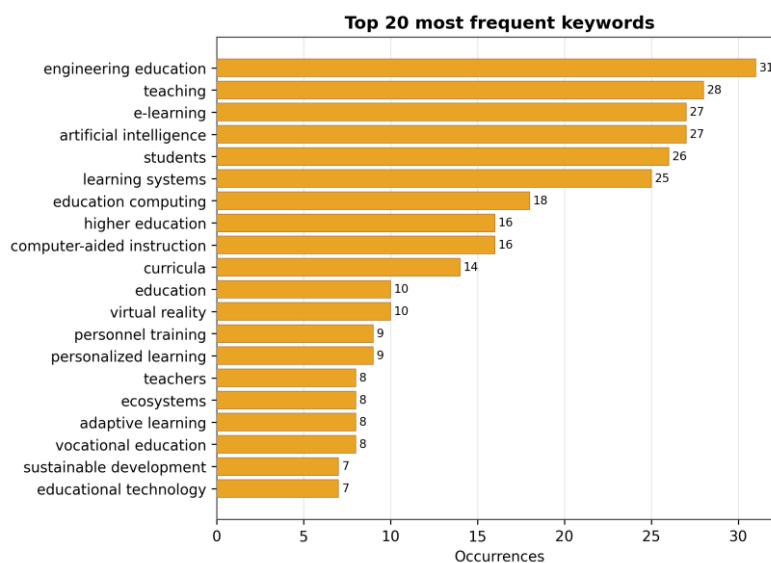


Figure 5. Twenty most frequent keywords

### ***Thematic clusters and trends***

Community detection results in four interpretable clusters. Figure 6 and Table 3 show the results. The largest clusters link engineering education, e-learning, learning systems, educational computing, immersive technology, and ecosystems. This cluster is a cluster of the engineering education and digital infrastructure ecosystem. The second cluster links artificial intelligence with adaptive and

personalized learning. This cluster also contains learning analytics, predictive analytics, gamification, and data privacy. The third cluster links vocational education with workforce training and apprenticeships. The fourth cluster links sustainable development with public policy. The four clusters are not independent literatures but functionally interdependent, bridged principally through the nodes of artificial intelligence and engineering education. Publications in the personalization/analytics cluster and in the vocational/workforce cluster both route through these two high-degree terms rather than connecting directly to one another, which suggests that digital-infrastructure and engineering-education scholarship functions as the technical substrate on which AI-based personalization is built, and that this substrate in turn feeds largely through infrastructure and analytics work rather than direct citation ties into the smaller vocational-training and sustainability/policy clusters. This bridging pattern provides early, network-level evidence for the layered relationship among infrastructure, intelligence, skills, and governance that this Discussion develops conceptually below.

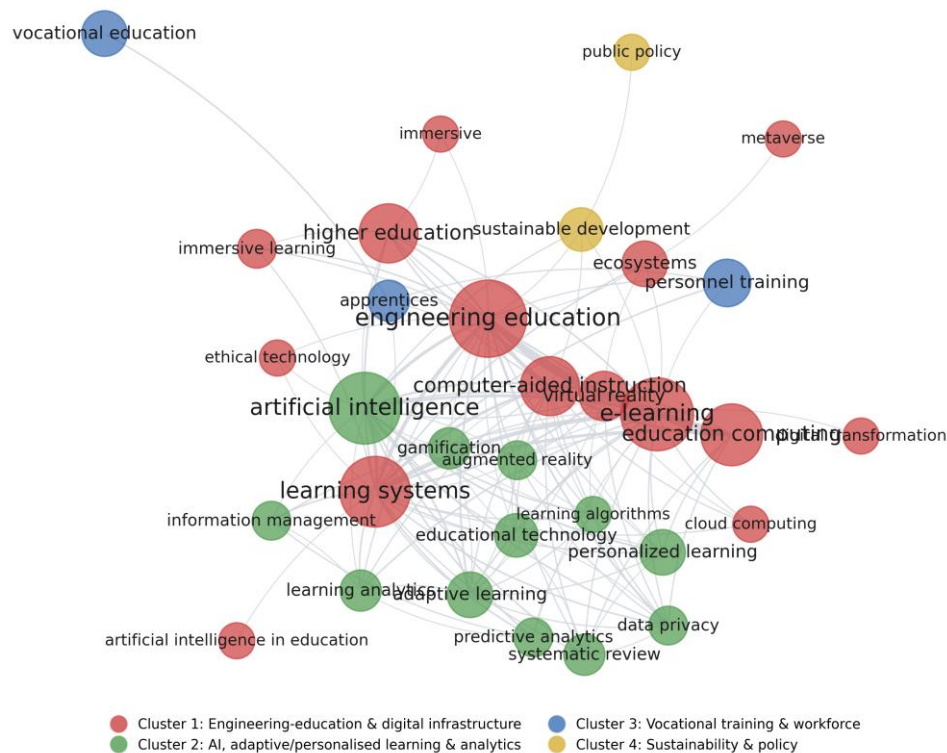


Figure 6. Network visualisation of the keyword co-occurrence map; nodes are sized by occurrence and coloured by thematic cluster

Table 3. Thematic clusters and their interpretation

| Cluster                                                       | Representative terms                                                                                                              | Interpretation                                                            |
|---------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------|
| 1. Engineering-education and digital-infrastructure ecosystem | engineering education, e-learning, learning systems, education computing, virtual reality, ecosystems, cloud computing, metaverse | Infrastructural and immersive foundations of digital vocational provision |

| Cluster                                                 | Representative terms                                                                                                                    | Interpretation                                                  |
|---------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------|
| 2. AI, adaptive and personalised learning and analytics | artificial intelligence, personalised learning, adaptive learning, learning analytics, predictive analytics, gamification, data privacy | Data-driven adaptation, personalisation and intelligent support |
| 3. Vocational training and workforce                    | vocational education, personnel training, apprentices                                                                                   | Skills formation and labour-market alignment                    |
| 4. Sustainability and policy                            | sustainable development, public policy                                                                                                  | Governance, equity and sustainability of provision              |

Overlay visualization adds time information. Figure 7 colorizes each term according to the average year of publication. The terms cloud computing and learning analytics are on the older side. The terms digital transformation, data privacy, learning algorithms, and predictive analytics are the latest fronts. These findings show a growth boost from data and governance issues. The density visualization reinforces that finding. Figure 8 shows the scientific focus. Attention is focused on the core of engineering education, artificial intelligence, e-learning, and learning systems. The terms vocational, sustainability, and policy are on the periphery. This pattern emphasizes the limitations of research in the vocational realm.

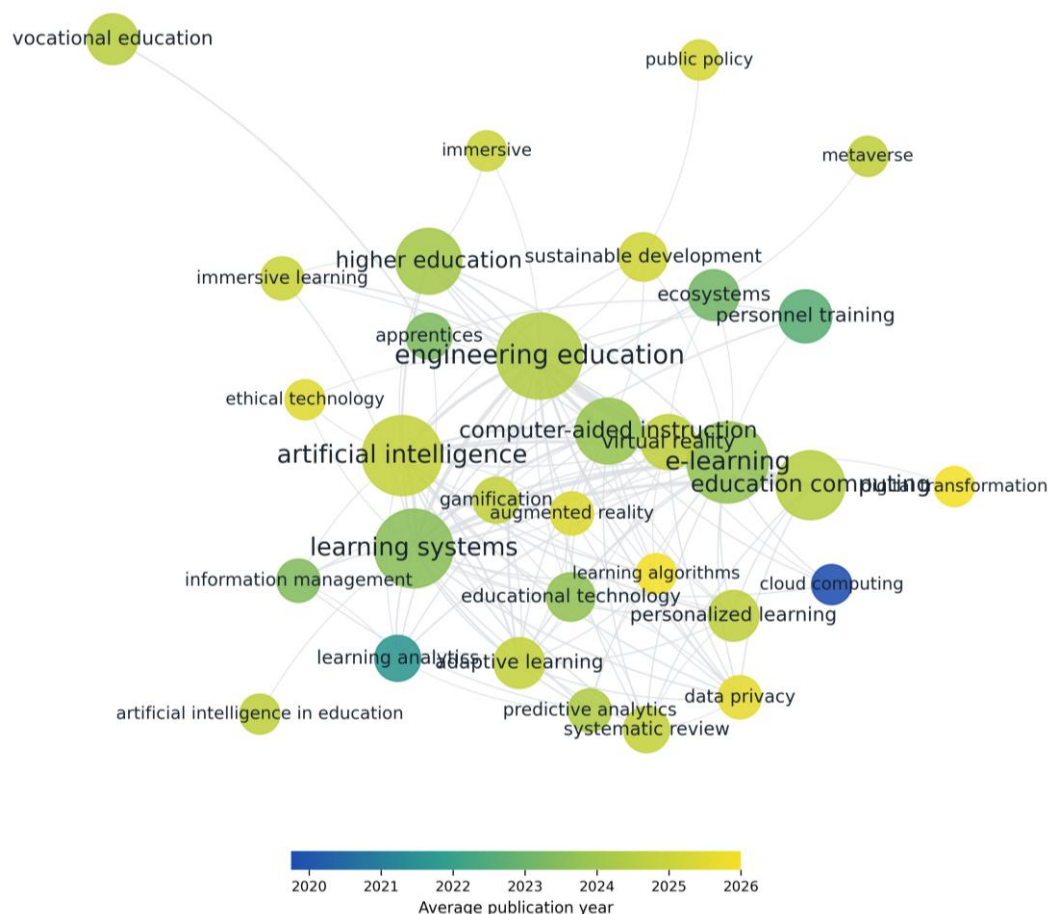


Figure 7. Overlay visualisation of the keyword map, with nodes coloured by average publication year

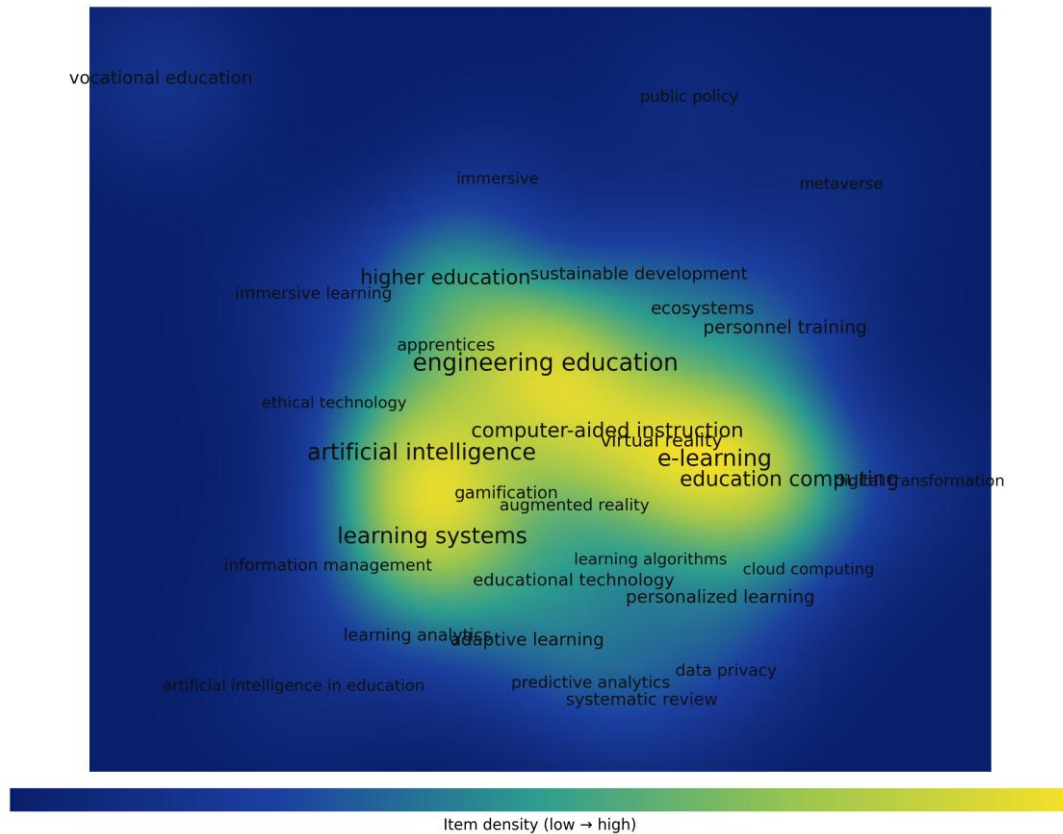


Figure 8. Density visualisation of the keyword map; brighter regions indicate higher item density

Rounding through theme groups all the time strengthens the overlay results. Figure 9 shows the theme's trends. The theme of infrastructure and artificial intelligence has grown the fastest since 2023. The theme of vocational and labor grew more slowly. Sustainability and policy themes emerge consistently despite small volumes.

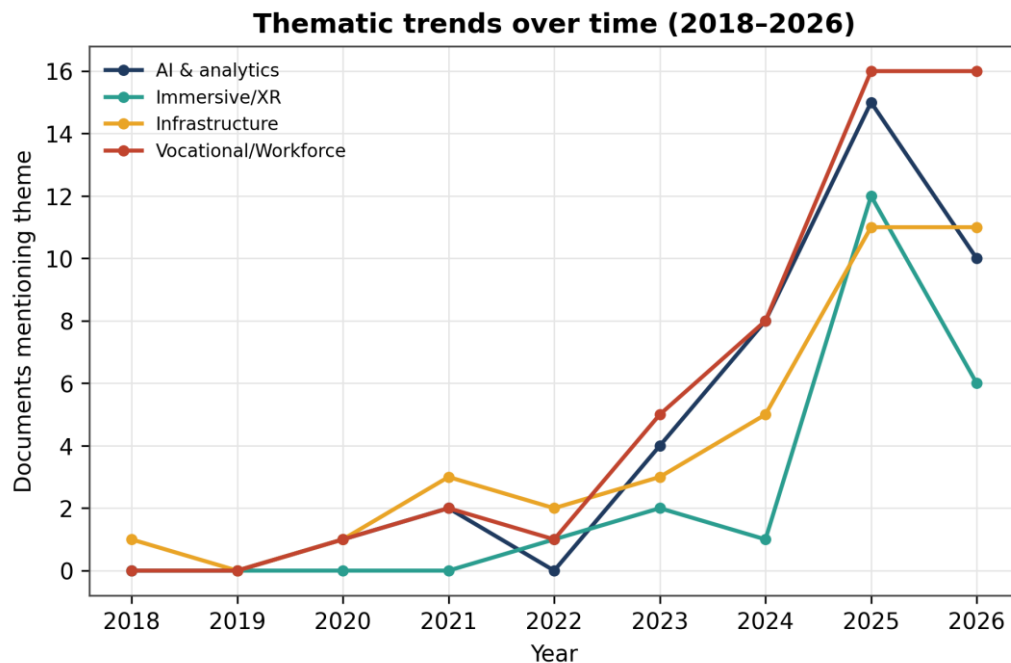


Figure 9. Thematic trends over time, 2018–2026

### ***Adaptive and personalized learning based on artificial intelligence***

Adaptive intelligence clusters are at the core of this field. Personalization isn't just a feature. Personalization is a designed experience. The experience aligns the material, tempo, and feedback with each learner. Fake and Dabbagh (2023) propose a framework for designing such experiences. The framework highlights the profile and learning path. The global synthesis affirms the promise as well as the inequality of personalization. Fortuna et al. (2025) report evidence of improved learning outcomes. The study also noted the issue of transparency and equality. Stošić et al. (2025) recorded opportunities and risks in a balanced manner. Analytics and recommendations drive personalization. Initial work on recommendation systems builds evaluation practices (Erdt et al., 2015). Implementation now includes API-based educational services (Pérez-Jorge et al., 2025). Other applications include adaptive blended environments based on data mining (Gupta et al., 2023). Personalization is increasingly combined with gamification in the fields of STEAM and engineering (Babu et al., 2025; Kassenkhan et al., 2026). Gamified programming environments show concrete paths from data to individual challenges (Maskeliūnas et al., 2023). The value of adaptation for vocational education lies in narrowing the distance of learning readiness. However, there is still little evidence in workshops or vocational work practices.

### ***Ecosystem of education, engineering and digital infrastructure***

The largest cluster discusses the foundations of technology. This foundation supports artificial intelligence-based vocational learning. Cloud computing is the main enabler. The survey of cloud computing in education marks this foundation (González-Martínez et al., 2015). Cloud e-learning platforms for mechatronics are becoming vocational-engineering applications (Chao et al., 2015). Recent reviews discuss cloud-based e-learning environments (Eljak et al., 2024). Immersive technology is attached to this foundation. The metaverse learning architecture is one example (AbuKhoua et al., 2023). VR-based distance learning models are developing in Indonesian universities (Hendric & Rosmansyah, 2025). Cloud-based immersive mobile tools are also emerging (Semerikov et al., 2025). Mixed reality remote learning complements this trend (Goagoses et al., 2025). The HyFlex-VR design adds a variety of approaches (Mahande et al., 2026). Knowledge representation infrastructure provides a semantic framework. Knowledge graphs organize structured domains (Li & Lu, 2025). Analytical modeling organizes less defined domains (Santamaría-Bonfil et al., 2021). Read together, these three technology streams describe a layered digital-infrastructure architecture rather than a loose collection of tools. The base layer is computational and storage infrastructure, principally cloud computing, which supplies the scalability and accessibility needed to deliver vocational content and services at scale (González-Martínez et al., 2015; Chao et al., 2015; Eljak et al., 2024). The second layer is experiential infrastructure: immersive and mixed-reality technologies that reproduce authentic, hands-on vocational tasks that would otherwise require physical workshops or equipment (AbuKhoua et al., 2023; Hendric & Rosmansyah, 2025; Semerikov et al., 2025; Goagoses et al., 2025; Mahande et al., 2026). The third

layer is semantic infrastructure: knowledge graphs and analytical models that structure otherwise unstructured skill and competency domains so that AI systems can reason over them (Li & Lu, 2025; Santamaría-Bonfil et al., 2021). Each layer depends on the one beneath it immersive experiences require cloud delivery, and semantic reasoning requires both to supply well-structured, accessible content and this dependency structure, rather than the word "ecosystem" alone, is what justifies treating engineering-education and digital-infrastructure scholarship as a single architectural stack underpinning AI-based vocational learning.

### ***Vocational training, microcredentials, and workforce alignment***

This cluster links artificial intelligence with the main goal of vocational. The goal is to produce work-ready competencies. The study noted the competency gap of vocational teachers (Wahyuni et al., 2020). Another study examined lecturer behavior and self-efficacy in preparing industry-ready graduates (Suyatmo et al., 2025). The review discusses the open source software ecosystem for vocational (Raffi et al., 2025). Skill recognition is a rapidly evolving theme. Microcredentials are increasingly combined with artificial intelligence in open and distance education (Durak & Çankaya, 2024; Harizan & Ally, 2025; Md Harizan & Ally, 2024). The connected learning perspective places portable credentials within the ecosystem (Schoenenberger, 2024). Trust in credentials relates to governance technology. Blockchain-based accreditation and verification support that trust (de Alwis et al., 2025; Lin et al., 2021). Artificial intelligence-based platforms support the development of the teacher profession (Sakhipov et al., 2023). The platform of industrial and educational integration expands the agenda of alignment (Fan, 2026). Artificial intelligence-based decision-making frameworks support sustainable entrepreneurship (Rong, 2024). This cluster most clearly shows the peculiarities of vocational. However, this cluster is also the smallest.

### ***Sustainability, ethics and governance***

The fourth cluster is compact in size. This cluster marks a critical conversation that is beginning to mature. Convergence models link education and artificial intelligence with sustainability (Deev et al., 2021). Recent work discusses generative artificial intelligence for sustainable development in higher education (Meletiadou, 2025). Another work discusses digital transformation towards a green organizational culture (Genga & Babalola, 2025). Place-based sustainability learning has also emerged (Abdallah, 2024). Ethical and governance issues are present throughout the cluster. The case study discusses ethical artificial intelligence in engineering education (Merl et al., 2025). The analysis addresses the cultural and ethical dimensions of LMS adoption (Ajani et al., 2026). A systematic study discusses privacy and innovation in neuroeducation (Oubagine et al., 2025). The study discusses changes in the role of teachers in artificial intelligence-based classrooms (August-Mowers, 2026). Other studies discuss safety and well-being in technology-laden institutions (Aldous & Ismail, 2024; Ismail & Aldous, 2025). Governance is an important element of a healthy learning ecosystem.

### ***Cross-cluster synthesis: patterns, inconsistencies, and implications***

Read across the four clusters rather than one at a time, several cross-cutting patterns, tensions, and implications emerge that individual cluster summaries do not capture in isolation.

*Recurring patterns.* Three patterns recur across otherwise distinct clusters. First, artificial intelligence is consistently described as a layer that connects rather than replaces existing structures: connecting infrastructure to learners in the personalization cluster (Fake & Dabbagh, 2023), connecting credentials to industry in the vocational cluster (Schoenenberger, 2024; de Alwis et al., 2025), and connecting policy to practice in the sustainability cluster (Deev et al., 2021). Second, almost every cluster reports evidence concentrated in higher education, with vocational- and TVET-specific evidence appearing as a secondary or illustrative case rather than the primary object of study. Third, governance and trust mechanisms, such as blockchain verification, data-privacy safeguards, and ethical review, tend to appear only after a technology stream has already matured, suggesting that governance research systematically lags technical implementation by several years in this field.

*Inconsistencies.* The literature is not fully consistent. Personalization studies report both efficiency gains and equity risks arising from the same underlying mechanism, adaptive algorithms, without converging on when personalization helps versus harms under-resourced learners (Fortuna et al., 2025; Stošić et al., 2025). Similarly, some sustainability-cluster studies treat artificial intelligence as inherently supportive of sustainable development (Meletiadou, 2025), while others frame it as an additional governance and equity risk requiring safeguards (Aldous & Ismail, 2024; Ajani et al., 2026), a tension this literature has not yet resolved empirically.

*Theoretical, practical, and emerging-direction implications.* Collectively, the four clusters support reframing artificial intelligence's role in vocational education from a discrete instructional tool to an orchestration layer, a claim this study formalizes in the conceptual model presented below. For vocational institutions, the clustering carries a practical implication: infrastructure investment in cloud and immersive systems alone is insufficient without parallel investment in credential-recognition mechanisms and governance capacity, since the smallest cluster, vocational training and workforce alignment, is precisely where infrastructure and governance must converge on concrete, certifiable competencies. Finally, the overlay and thematic-trend analysis (Figures 7–9) point to data privacy, learning algorithms, and predictive analytics as the fastest-growing but least vocational-specific themes in the dataset, marking a priority area for future vocational-context research.

### ***Towards an artificial intelligence-based vocational learning ecosystem***

The bibliometric structure and the thematic synthesis above converge on a single picture: the four clusters are not parallel, independent literatures but interdependent layers of one vocational learning ecosystem, connected by artificial intelligence as the orchestrating mechanism. Digital infrastructure underpins adaptive intelligence; adaptive intelligence, in turn, serves the vocational goals of skill formation and competency recognition; and sustainability, ethics, and governance considerations

condition all of the layers beneath them. Within this structure, artificial intelligence functions simultaneously as an adaptation engine, a learning analyzer, and an achievement validator, connecting layers that the cluster-by-cluster literature above largely treats in isolation. Artificial intelligence is moving personalization from teachers to distributed systems: such systems read learner data and adjust material and pace, then extend the ecosystem beyond the institution through portable credentials and industrial signals (de Alwis et al., 2025; Fan, 2026; Schoenenberger, 2024), and can deepen the authenticity of learning environments through immersive infrastructure and the cloud (AbuKhoussa et al., 2023; Chao et al., 2015; Hendric & Rosmansyah, 2025).

To formalize this argument beyond narrative description, this study proposes an explicit conceptual model, the AI-Orchestrated Vocational Learning Ecosystem (AI-VLE) model, comprising six interlocking components identified through the bibliometric and narrative synthesis above (Figure 10): (1) *Digital Infrastructure*, the cloud, immersive, and semantic infrastructure stack described earlier, which supplies the technical substrate for all other components; (2) *Adaptive Intelligence*, the AI-driven personalization, analytics, and recommendation mechanisms that translate infrastructure into individualized learning experience (Fake & Dabbagh, 2023; Fortuna et al., 2025); (3) *Authentic Competency Development*, the immersive and work-based learning environments through which vocational competencies are practiced under realistic conditions (AbuKhoussa et al., 2023; Chao et al., 2015; Hendric & Rosmansyah, 2025); (4) *Credentialing Systems*, the recognition mechanisms, including blockchain-verified microcredentials, that formalize competencies gained through the first three components and make them portable across institutions (de Alwis et al., 2025; Schoenenberger, 2024; Md Harizan & Ally, 2024); (5) *Workforce Alignment*, the mechanisms, including industrial data signals and platform integration, that connect credentialed competencies to actual labour-market demand (Fan, 2026; Rong, 2024; Sakhipov et al., 2023); and (6) *Governance and Sustainability*, the reflective, cross-cutting layer of privacy, ethics, and policy safeguards that conditions how the other five components operate (Deev et al., 2021; Merl et al., 2025; Ajani et al., 2026). In this model, artificial intelligence's evolving orchestration role is what allows Components 1–3 to feed forward into Components 4–5, while Component 6 loops back across all five to constrain and legitimate the system as a whole; it is this pattern of dependency and feedback among components, rather than any single technology, that constitutes an orchestrated ecosystem rather than a mere collection of educational technologies.

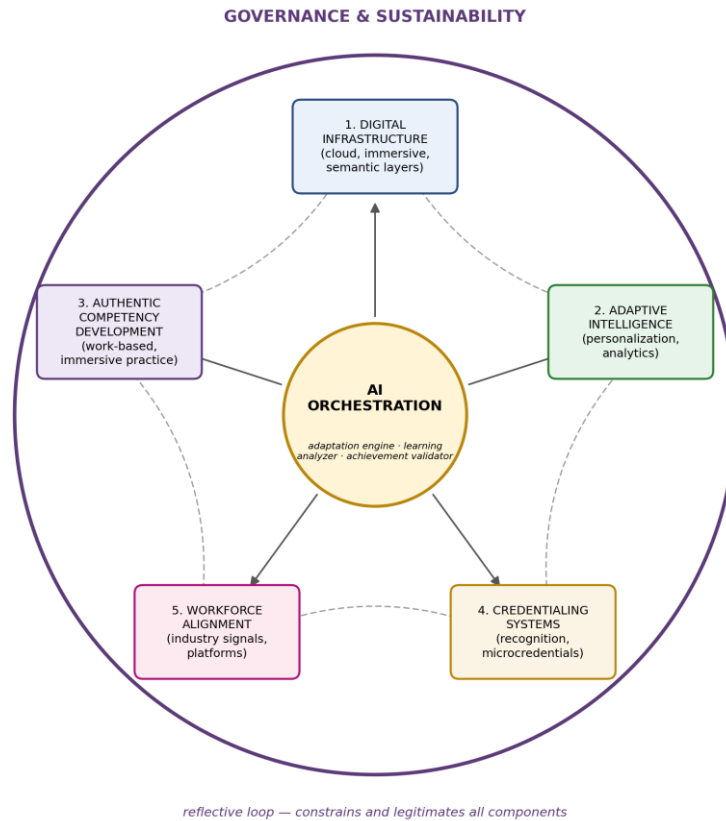


Figure 10. The AI-Orchestrated Vocational Learning Ecosystem (AI-VLE) model, showing artificial intelligence's orchestrating relationship with each component. Solid arrows: AI's orchestrating relationship with each component. Dashed outer arrows: the feed-forward sequence 1→2→4→5→3→1 from infrastructure through intelligence, credentialing, and workforce alignment.

Figure 10. The AI-Orchestrated Vocational Learning Ecosystem (AI-VLE) model, showing artificial intelligence's orchestrating relationship with six interlocking components and the reflective governance loop

Read against this model, the bibliometric profile carries a strategic message: the field's current center of gravity sits in Components 1–2 (digital infrastructure and adaptive intelligence), which are also the largest clusters in the co-occurrence map, while Components 4 and 5 (credentialing and workforce alignment) correspond to the smallest cluster identified in this study. The literature has therefore built the infrastructure and intelligence layers of the model well ahead of the credentialing and workforce-alignment layers, and has not yet been extensively applied to conditions distinctive of vocational education: psychomotor skill acquisition, work-based learning, and formal competency certification. The contribution of Indonesian and other Asian scholarship is comparatively strong in exactly this underdeveloped area (Hendric & Rosmansyah, 2025; Rachmadi et al., 2025; Suyatmo et al., 2025; Wahyudi et al., 2025; Wahyuni et al., 2020), pointing to a plausible direction for the field's future vocational-specific growth.

## CONCLUSION

This study maps and synthesizes a fast-growing field at the intersection of artificial intelligence and vocational learning ecosystems. The literature is young, cross-disciplinary, and expanding rapidly, organized into four interconnected clusters that together describe a layered system of digital infrastructure, adaptive intelligence, skill formation, and governance.

*Theoretical contribution.* Beyond mapping this structure, the principal theoretical contribution of this study is the AI-Orchestrated Vocational Learning Ecosystem (AI-VLE) model developed in the Discussion, which formalizes artificial intelligence's shift from a discrete instructional tool to an orchestration layer connecting learners, curriculum, the world of work, and credentialing systems. This reframing extends earlier ecosystem and convergence models (Dabbagh & Castaneda, 2020; Deev et al., 2021) by specifying the mechanisms, personalization, immersive infrastructure, and microcredentialing through which artificial intelligence performs this orchestrating function.

*Practical implications.* For vocational institutions, the findings indicate that infrastructure and intelligence investments are already comparatively mature in the literature, whereas credentialing and workforce-alignment mechanisms remain underdeveloped; institutions seeking to adopt artificial intelligence should therefore prioritize interoperable, portable credentialing systems and direct industry-data linkages rather than infrastructure alone.

*Policy implications.* For policymakers, the concentration of vocational-specific evidence in a small number of national contexts, Indonesia prominent among them, suggests that policy frameworks explicitly linking artificial intelligence adoption to teaching-factory and technopark models may accelerate translation of infrastructure and intelligence research into vocational practice, provided they are paired with governance safeguards for data privacy, algorithmic transparency, and equitable access.

*Recommendations for future research.* Five priorities follow from the evidence base: (1) generating direct empirical evidence from workshops, laboratories, and work-based learning settings, where research remains scarce; (2) examining the recognition and cross-institutional portability of AI-based credentials; (3) testing artificial intelligence's orchestration role empirically within teaching-factory and technopark models; (4) developing and validating a privacy, transparency, and equity governance framework specific to vocational AI applications; and (5) pursuing longitudinal designs capable of tracking competency outcomes over time rather than relying on cross-sectional bibliometric snapshots.

This research has limitations. This study used only one English-language database, so relevant work indexed elsewhere may be underrepresented. Most of the documents are very new, which means the citation indicator does not yet reflect their final impact. Keyword-based mapping also inherits the inconsistency of terms; the researcher mitigated this problem through keyword normalization but could not eliminate it entirely. Notwithstanding these limitations, this study offers vocational institutions and policymakers an integrated, evidence-based map of the field and a conceptual model, the AI-VLE framework, to guide the design of artificial intelligence-based vocational learning ecosystems.

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## REFERENCES

- Abdallah, A.K. (2024). Local to global: Place-based learning in sustainability education. In *Legal Frameworks and Educational Strategies for Sustainable Development*. IGI Global. <https://doi.org/10.4018/979-8-3693-2987-0.ch013>
- AbuKhoua, E., El-Tahawy, M.S., & Atif, Y. (2023). Envisioning Architecture of Metaverse Intensive Learning Experience (MiLex): Career Readiness in the 21st Century and Collective Intelligence Development Scenario. *Future Internet*, 15(2). <https://doi.org/10.3390/fi15020053>
- Adel, A. (2024). The Convergence of Intelligent Tutoring, Robotics, and IoT in Smart Education for the Transition from Industry 4.0 to 5.0. *Smart Cities*, 7(1), 325–369. <https://doi.org/10.3390/smartcities7010014>
- Ajani, O.A., Gamede, B.T., & Govender, S. (2026). Cultural and ethical dimensions of learning management system adoption in rural universities: Exploring data privacy, algorithmic bias, and contextual realities. *Multidisciplinary Science Journal*, 8(3). <https://doi.org/10.31893/multiscience.2026142>
- Aldous, S.M., & Ismail, G.A. (2024). Safeguarding the future: Integrating student safety into sustainable education practices. In *Legal Frameworks and Educational Strategies for Sustainable Development*. IGI Global. <https://doi.org/10.4018/979-8-3693-2987-0.ch018>
- Ammu, A.L., & Panchikkil, S. (2026). AI-Driven AR/VR Technologies for Adaptive Learning in Language Education. In *AI Innovations in Language Education and Communication*. CRC Press. <https://doi.org/10.1201/9781003659921-8>
- Ang, K.L.-M., Ge, F.L., & Seng, K.P. (2020). Big Educational Data Analytics: Survey, Architecture and Challenges. *IEEE Access*, 8, 116392–116414. <https://doi.org/10.1109/ACCESS.2020.2994561>
- Anthony, B., Kamaludin, A., Romli, A., Raffei, A.F.M., Phon, D.N.A.L.E., Abdullah, A., & Ming, G.L. (2022). Blended Learning Adoption and Implementation in Higher Education: A Theoretical and Systematic Review. *Technology, Knowledge and Learning*, 27(2), 531–578. <https://doi.org/10.1007/s10758-020-09477-z>
- Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, 11(4), 959–975. <https://doi.org/10.1016/j.joi.2017.08.007>
- August-Mowers, C.M. (2026). The Future of Education Technology: The Future of Teachers' Roles in a Tech-Driven World. In *Human-AI Collaboration and the Evolving Role of Educators*. IGI Global. <https://doi.org/10.4018/979-8-3373-4521-5.ch017>
- Babu, C.V.S., Nithika Scree, R., & Varshini, R. (2025). The role of artificial intelligence in personalized steam education: Enhancing student-centered learning. In *Integrating Personalized Learning Methods Into STEAM Education*. IGI Global. <https://doi.org/10.4018/979-8-3693-7718-5.ch008>
- Chao, K.-M., James, A.E., Nanos, A.G., Chen, J.-H., Stan, S.-D., Muntean, I., Figliolini, G., Rea, P., Bouzgarrou, C.B., Vitliemov, P., Cooper, J., & Van Capelle, J. (2015). Cloud E-learning for Mechatronics: CLEM. *Future Generation Computer Systems*, 48, 46–59. <https://doi.org/10.1016/j.future.2014.10.033>
- Conde, M.Á., García-Peñalvo, F.J., Fidalgo-Blanco, Á., & Sein-Echaluce, M.L. (2017). Can we apply learning analytics tools in challenge based learning contexts?. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. [https://doi.org/10.1007/978-3-319-58515-4\\_19](https://doi.org/10.1007/978-3-319-58515-4_19)
- Dabbagh, N., & Castaneda, L. (2020). The PLE as a framework for developing agency in lifelong learning. *Educational Technology Research and Development*, 68(6), 3041–3055. <https://doi.org/10.1007/s11423-020-09831-z>
- de Alwis, A., Shrestha, A., & Sarker, T. (2025). Exploring Governance for accreditation in the education sector using blockchain technology: a systematic literature review. *Discover Education*, 4(1). <https://doi.org/10.1007/s44217-025-00449-y>
- Deev, M., Gamidullaeva, L., Finogeev, A., Finogeev, A., & Vasin, S. (2021). The convergence model of education for sustainability in the transition to digital economy. *Sustainability (Switzerland)*, 13(20). <https://doi.org/10.3390/su132011441>
- Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, 133, 285–296. <https://doi.org/10.1016/j.jbusres.2021.04.070>

- Durak, G., & Çankaya, S. (2024). *Integrating Micro-Credentials with AI in Open Education*. IGI Global. <https://doi.org/10.4018/979-8-3693-5488-9>
- Eljak, H., Ibrahim, A.O., Saeed, F., Hashem, I.A.T., Abdelmaboud, A., Syed, H.J., Abulfaraj, A.W., Ismail, M.A.B., & Elsafi, A. (2024). E-Learning-Based Cloud Computing Environment: A Systematic Review, Challenges, and Opportunities. *IEEE Access*, 12, 7329–7355. <https://doi.org/10.1109/ACCESS.2023.3339250>
- Erdt, M., Fernández, A., & Rensing, C. (2015). Evaluating Recommender Systems for Technology Enhanced Learning: A Quantitative Survey. *IEEE Transactions on Learning Technologies*, 8(4), 326–344. <https://doi.org/10.1109/TLT.2015.2438867>
- Fake, H., & Dabbagh, N. (2023). *Designing Personalized Learning Experiences: A Framework for Higher Education and Workforce Training*. Taylor and Francis. <https://doi.org/10.4324/9781003121008>
- Fan, T. (2026). Intelligent education platform for industry-education integration: Technical architecture and key algorithms. *Proceedings of SPIE - The International Society for Optical Engineering*. <https://doi.org/10.1117/12.3104436>
- Fortuna, A., Prasetya, F., Samala, A.D., Rawas, S., Criollo-C, S., Kaya, D., Raihan, M., Andriani, W., Safitri, D., & Nabawi, R.A. (2025). Artificial intelligence in personalized learning: A global systematic review of current advancements and shaping future opportunities. *Social Sciences and Humanities Open*, 12. <https://doi.org/10.1016/j.ssaho.2025.102114>
- Funda, V., & Piderit, R. (2024). A review of the application of artificial intelligence in South African Higher Education. *2024 Conference on Information Communication Technology and Society, ICTAS 2024 - Proceedings*. <https://doi.org/10.1109/ICTAS59620.2024.10507113>
- Genga, C.A., & Babalola, S.S. (2025). Digital Transformation: The Need for a Sustainable Green Culture in African Higher Education Institutions. *Journal of Educational Technology Development and Exchange*, 18(1), 109–130. <https://doi.org/10.18785/jetde.1801.07>
- Goagoses, N., Winschiers-Theophilus, H., Auala, S., Pope, N., Rötkönen, E., Itenge, H., Suero Montero, C., Suovuo, T., & Sutinen, E. (2025). Teachers and Students Envisioning Mixed Reality Remote Learning: A Qualitative Exploration on Fostering Academic Engagement. *Technology, Knowledge and Learning*, 30(2), 685–709. <https://doi.org/10.1007/s10758-024-09797-4>
- González-Martínez, J.A., Bote-Lorenzo, M.L., Gómez-Sánchez, E., & Cano-Parra, R. (2015). Cloud computing and education: A state-of-the-art survey. *Computers and Education*, 80, 132–151. <https://doi.org/10.1016/j.compedu.2014.08.017>
- Gupta, V., Wadgaonkar, N., Divase, H., Anthony, A., & Sweta, S. (2023). Impact of adaptive blended e-learning in area of educational data mining in technical education. *AIP Conference Proceedings*. <https://doi.org/10.1063/5.0148293>
- Harizan, S.H.M., & Ally, M. (2025). ARTIFICIAL INTELLIGENCE IN MICRO-CREDENTIALS FOR OPEN AND DISTANCE LEARNING: A TECHNOLOGICALLY ENHANCED SYSTEMATIC REVIEW. *Turkish Online Journal of Distance Education*, 26(3), 1–24. <https://doi.org/10.17718/tojde.1552001>
- Hendric, S.W.L.H., & Rosmansyah, Y. (2025). Immersive Learning Model for University (ILMU): A Novel VR-Based Distance Learning in Higher Education. *IEEE Access*, 13, 156734–156754. <https://doi.org/10.1109/ACCESS.2025.3606957>
- Ismail, G.A., & Aldous, S.M. (2025). AI-Driven health and safety management in school facilities. In *Convergence of AI, Education, and Business for Sustainability*. IGI Global. <https://doi.org/10.4018/979-8-3373-1917-9.ch002>
- Kassenkhan, A., Serbin, V., Beisembekova, R., Abshukirova, A., & Mendekina, B. (2026). AI-Supported Gamification in E-Learning: A Systematic Review of Adaptive Architectures and Cognitive Outcomes. *Information (Switzerland)*, 17(3). <https://doi.org/10.3390/info17030282>
- Li, G., & Lu, Y. (2025). Construction and Application of a Formula-Augmented Knowledge Graph for Adaptive Vocational Education in Power Grid Planning. *Proceedings of 2025 International Conference on Educational Technology and Artificial Intelligence, ETAIC 2025*. <https://doi.org/10.1145/3766557.3766637>
- Lin, J., Li, B., Cui, L., & Miao, C. (2021). Practices of Using Blockchain Technology in e-Learning. *ACM International Conference Proceeding Series*. <https://doi.org/10.1145/3503181.3503191>
- Mahande, R.D., Abdal, N.M., Nasir, N., & Rahmi, U. (2026). Design and effectiveness of the HyFlex-VR learning model for emancipated learning in higher education. *Journal of Applied Research in Higher Education*, 18(3), 951–972. <https://doi.org/10.1108/JARHE-12-2024-0713>

- Maskeliūnas, R., Damaševičius, R., Blažauskas, T., Swacha, J., Queirós, R., & Paiva, J.C. (2023). FGPE+: The Mobile FGPE Environment and the Pareto-Optimized Gamified Programming Exercise Selection Model—An Empirical Evaluation. *Computers*, 12(7). <https://doi.org/10.3390/computers12070144>
- Md Harizan, S.H., & Ally, M. (2024). Artificial Intelligence in Micro-Credentials for Open and Distance Learning: A Technologically-Enhanced Systematic Review. In *Integrating Micro-Credentials with AI in Open Education*. IGI Global. <https://doi.org/10.4018/979-8-3693-5488-9.ch0014>
- Meletiadou, E. (2025). *Generative AI approaches to sustainable development in higher education*. IGI Global. <https://doi.org/10.4018/979-8-3693-5623-4>
- Merl, C., Guralnick, D., Dolezal, D., Posekany, A., & Koppensteiner, G. (2025). Ethical AI in Engineering Education: A Case Study on Mindset, Behaviors, and AI Literacy. In *Standards-Based AI Innovation for the Learning Ecosystem*. IGI Global. <https://doi.org/10.4018/979-8-3373-2235-3.ch004>
- Mogano, T.M., & Minty, R. (2026). Barriers and Enablers in the Adoption of Homework Intelligent Tutoring Systems among University Students in Disadvantaged South African Areas. *International Journal of Learning, Teaching and Educational Research*, 25(1), 872–901. <https://doi.org/10.26803/ijlter.25.1.40>
- Mukhamediyeva, K., Nurbekova, Z., Nurgazinova, G., & Aimicheva, G. (2025). Enhancing engineering thinking skills of pre-service IT teachers through cross-cutting educational technologies and stem projects. *International Journal of Education and Practice*, 13(2), 669–687. <https://doi.org/10.18488/61.v13i2.4126>
- Oubagine, R., Laaouina, L., Jeghal, A., & Tairi, H. (2025). Neuroeducation and Artificial Intelligence: A Systematic Review of Innovative Approaches for Personalized E-learning. *2025 4th International Conference on Embedded Systems and Artificial Intelligence, ESAI 2025*. <https://doi.org/10.1109/ESAI67033.2025.11438800>
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, 372, n71. <https://doi.org/10.1136/bmj.n71>
- Papadakis, S. (2026). *Virtual Tutors and AI-Powered Instructional Tools in K-12 Settings*. IGI Global. <https://doi.org/10.4018/979-8-3373-2637-5>
- Patras, Y.E., Japar, M., Rahmawati, Y., & Hidayat, R. (2025). Integration of Culturally Responsive Teaching Approach, Local Wisdom, and Gamification in Pancasila Education to Develop Students' Multicultural Competence. *Educational Process: International Journal*, 14. <https://doi.org/10.22521/edupij.2025.14.45>
- Pérez-Jorge, D., González-Afonso, M.C., Santos-Álvarez, A.G., Plasencia-Carballo, Z., & Perdomo-López, C.D.L.Á. (2025). The Impact of AI-Driven Application Programming Interfaces (APIs) on Educational Information Management. *Information (Switzerland)*, 16(7). <https://doi.org/10.3390/info16070540>
- Rachmadi, P., Situmorang, R., Sukardjo, M., Indrajit, R.E., & Gautama, E. (2025). Enhancing Entrepreneurial Competencies and Student Engagement through Gamification in Learning Management Systems. *APTISI Transactions on Technopreneurship*, 7(2), 593–604. <https://doi.org/10.34306/att.v7i2.589>
- Raffi, M.L.M., Hussain, M.A.M., Mustafa, W.A., Zabidi, M.N.A., Mardiansyah, A., & Subari, K. (2025). A Systematic Review of Open-Source Software for Technical and Vocational Education and Training (TVET). *Journal of Advanced Research in Applied Sciences and Engineering Technology*, 49(2), 75–89. <https://doi.org/10.37934/araset.49.2.7589>
- Rong, C. (2024). An AI-Driven Decision Framework for Promoting Sustainable Entrepreneurship in Vocational Colleges. *Decision Making: Applications in Management and Engineering*, 7(2), 748–769. <https://doi.org/10.31181/dmame7220251481>
- Sakhipov, A., Baidildinov, T., Yermaganbetova, M., & Ualiyev, N. (2023). Design of an Educational Platform for Professional Development of Teachers with Elements of Blockchain Technology. *International Journal of Advanced Computer Science and Applications*, 14(7), 519–527. <https://doi.org/10.14569/IJACSA.2023.0140757>
- Santamaría-Bonfil, G., Díaz-Rodríguez, H.D., Arroyo-Figueroa, G., & Batres, R. (2021). Knowledge modelling for ill-defined domains using learning analytics: Lineworkers case. *Advances in Intelligent Systems and Computing*. [https://doi.org/10.1007/978-3-030-57799-5\\_42](https://doi.org/10.1007/978-3-030-57799-5_42)
- Schoenenberger, H. (2024). *Connected Learning: Origins, Opportunities, and Perspectives of Contemporary Educational Design: A Machine-Generated Literature Overview*. Springer Nature. <https://doi.org/10.1007/978-3-031-37813-3>
- Semerikov, S.O., Vakaliuk, T.A., Mintii, I.S., Hamaniuk, V.A., Bondarenko, O.V., Nechypurenko, P.P., Shokaliuk, S.V., & Moiseienko, N.V. (2025). Immersive cloud-based mobile learning tools in higher education: a systematic review of integration frameworks and implementation strategies. *CEUR Workshop Proceedings*.

- Stošić, L., Radonjić, A., Krčadinac, O., Baltezarević, B., & Mikhailova, O. (2025). Personalized Learning through Artificial Intelligence: Opportunities, Risks, and Policy Perspectives. *International Journal of Cognitive Research in Science, Engineering and Education*, 13(2), 541–549. <https://doi.org/10.23947/2334-8496-2025-13-2-541-549>
- Suyatmo, S., Prayitno, H., Wirawan, W.A., Pratiwi, D.I., & Waluyo, B. (2025). Preparing industry-ready graduates: Interplay of lecturer behavior, self-motivation, and soft skill development in vocational education. *Acta Psychologica*, 261. <https://doi.org/10.1016/j.actpsy.2025.105892>
- van Eck, N. J., & Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics*, 84(2), 523–538. <https://doi.org/10.1007/s11192-009-0146-3>
- Wahyudi, M.N.A., Budiyo, C.W., Widiastuti, I., & Pambudi, N.A. (2025). Beyond Points and Badges: Deepening Engagement in MOOCs through Gamification. *International Journal of Interactive Mobile Technologies*, 19(1), 18–33. <https://doi.org/10.3991/ijim.v19i01.51705>
- Wahyuni, D.S., Agustini, K., Sindu, I.G.P., & Sugihartini, N. (2020). Analysis on vocational high school teacher competency gaps: Implication for VHS teacher training needs. *Journal of Physics: Conference Series*. <https://doi.org/10.1088/1742-6596/1516/1/012051>
- Wang, J., Ye, X., Liu, D., & Qin, Q. (2025). A Bibliometric Analysis of Visualizing the Knowledge Mapping for Metaverse in Education. *2025 11th International Conference on Education and Training Technologies, ICETT 2025*. <https://doi.org/10.1109/ICETT66247.2025.11136937>
- Wannapiroon, N., & Pimdee, P. (2022). Thai undergraduate science, technology, engineering, arts, and math (STEAM) creative thinking and innovation skill development: a conceptual model using a digital virtual classroom learning environment. *Education and Information Technologies*, 27(4), 5689–5716. <https://doi.org/10.1007/s10639-021-10849-w>
- Watrianthos, R., Ahmad, S.T., & Muskhir, M. (2023). Charting the Growth and Structure of Early ChatGPT-Education Research: A Bibliometric Study. *Journal of Information Technology Education: Innovations in Practice*, 22, 235–253. <https://doi.org/10.28945/5221>
- Yang, L., Ding, D., & Han, R. (2026). Research on the Digital-Intelligent Construction of Digital Communication Teaching Based on the EduCoder Platform. *Proceedings of 2025 4th International Conference on Artificial Intelligence and Education, ICAIE 2025*. <https://doi.org/10.1145/3797552.3797591>
- Zotov, V., Ibrahim, I., Petunina, I., & Lazareva, Y. (2021). Engagement of Students in Data Visualization for the Purpose of E-Learning Improvement. *International Journal of Emerging Technologies in Learning*, 16(2), 46–63. <https://doi.org/10.3991/ijet.v16i02.18745>
- Zupic, I., & Čater, T. (2015). Bibliometric methods in management and organization. *Organizational Research Methods*, 18(3), 429–472. <https://doi.org/10.1177/1094428114562629>