From Algorithms to Adab: A Bibliometric Analysis of AI-Driven Adaptive Learning Research and Its Implications for Islamic Education

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Abstract

AI-driven adaptive learning is expanding rapidly, yet little is known about how its research agenda has shifted since the rise of generative AI or what this shift means for Islamic education. This bibliometric study analysed 2,818 Scopus documents (2010–2027) through VOSviewer co-occurrence mapping of 1,000 keywords. Publications rose from 7 in 2010 to 1,064 in 2025, and 91% of the corpus appeared from 2023 onward. Eleven clusters formed three layers: a human-centred core of ethics, data mining, classroom implementation and generative AI (48.5% of keywords), adaptive-system architecture (21.4%), and application domains (30.1%). Overlay mapping showed a shift from adaptive systems and data mining toward large language models, data privacy and ethics. None of the mapped keywords addressed Islamic education. We argue that the concept of adab offers a framework for the ethical and epistemological questions now central to the field and propose a research agenda for madrasah and pesantren.

Keywords: adaptive learning, artificial intelligence, bibliometric analysis, generative AI, Islamic education

Introduction

Digital transformation has shifted education from a one-size-fits-all model to learning that responds to each learner's needs. *Adaptive learning* refers to instructional systems that adjust content, sequence, difficulty and feedback to a learner's characteristics and performance. The idea has a long history in adaptive hypermedia (Brusilovsky, 2001) and intelligent tutoring systems, and a meta-analysis of fifty controlled evaluations found that intelligent tutoring systems generally raise achievement compared with conventional instruction (Kulik & Fletcher, 2016).

Artificial intelligence (AI) has given adaptive learning new capabilities. Machine-learning models can trace learner knowledge, predict performance and recommend learning paths automatically (Chen, Chen, & Lin, 2020; Kabudi, Pappas, & Olsen, 2021; Gligorea et al., 2023). Hwang, Xie, Wah and Gašević (2020) identify four roles for AI in education, as intelligent tutor, intelligent tutee, learning tool or partner, and policy-making advisor. Ouyang and Jiao (2021) describe this development as a movement from AI-directed toward AI-supported and AI-empowered learning, in which the learner increasingly shares control with the system. Since the public release of ChatGPT in November 2022, large language models (LLMs) have extended these possibilities to dialogue, explanation and personalised feedback (Kasneci et al., 2023; Lo, 2023). The same development has raised new problems: algorithmic bias, data privacy, academic integrity, opaque decision-making and the changing role of the teacher (Baker & Hawn, 2022; Holmes et al., 2022; Yan et al., 2024).

Several reviews have mapped this field. Xie, Chu, Hwang and Wang (2019) reviewed technology-enhanced adaptive and personalised learning studies published between 2007 and 2017. Zawacki-Richter, Marín, Bond and Gouverneur (2019) found that research on AI in higher education paid little attention to pedagogical and ethical questions, a concern reaffirmed by a later meta-review that called for more ethics, collaboration and rigour (Bond et al., 2024). Chen, Xie, Zou and Hwang (2020) likewise identified gaps between AI applications and educational theory. Two recent bibliometric studies focus specifically on AI and adaptive learning. Kang, Liu and Zhang (2025) analysed 561 Web of Science articles from 2014 to 2024 using CiteSpace, and Rahman and Khalid (2026) analysed 2,354 Scopus publications from 2015 to 2026, reporting sharp growth after 2023 and central themes of machine learning, intelligent tutoring systems, generative AI and large language models.

These studies describe *what* the field studies, but they do not examine how the field's orientation has shifted from technical to ethical and epistemological questions, nor do they interpret their findings for any particular educational tradition. This gap matters for Islamic education. Islamic educational thought understands education not only as the transmission of knowledge (*ta'līm*) and nurture (*tarbiyah*) but also as the cultivation of *adab*, the right ordering of knowledge, conduct and character (Al-Attas, 1980; Halstead, 2004). Recent work has also proposed Islamic virtue-based ethics as a basis for evaluating AI (Raquib, Channa, Zubair, & Qadir, 2022). Whether the global literature on adaptive learning leaves room for these perspectives has not yet been examined.

This study addresses that gap through a bibliometric analysis of AI-driven adaptive learning research indexed in Scopus between 2010 and 2027. It asks three questions: how publication output has developed over this period; how the conceptual network and its themes have evolved, based on keyword co-occurrence; and which thematic clusters structure the field and what they imply for Islamic education. The article first describes the method, then presents and discusses the publication trend, the conceptual network and its evolution, and the thematic clusters, before turning to the implications for Islamic education and closing with conclusions and a research agenda.

Methods

This study used bibliometric analysis, following the systematic and reproducible review procedure described by Garza-Reyes (2015) and the guidelines for bibliometric research set out by Zupic and Čater (2015) and Donthu, Kumar, Mukherjee, Pandey and Lim (2021).

Bibliometric mapping makes the structure of a research field visible, so that its concepts can be interpreted and compared objectively. The analysis was carried out with VOSviewer version 1.6.18 (van Eck & Waltman, 2010) in five stages, shown in Figure 1.

The first stage was data identification in the Scopus database. The search was applied to article titles, abstracts and keywords with the query TITLE-ABS-KEY ("adaptive learning" AND "artificial intelligence" AND (education* OR student* OR teach* OR learner*)). The initial search returned 3,138 documents published between 1989 and 2027. The second stage was data screening. Documents were limited to five subject areas relevant to education, namely Computer Science, Social Sciences, Psychology, Arts and Humanities, and Multidisciplinary, leaving 2,856 documents. They were then limited to the period 2010–2027, yielding a final corpus of 2,818 documents. The data were exported on 30 September 2026 in CSV format.

The third stage was data cleaning with OpenRefine. Terms with the same meaning were merged, for example "ai" and "artificial intelligence", or "cognitive load" and "cognitive loads", and citation counts were checked. The fourth stage was analysis. Microsoft Excel was used for the descriptive analysis of publication years, and VOSviewer was used for keyword co-occurrence analysis. The 1,000 keywords with the highest occurrence were mapped and grouped into clusters using the VOSviewer clustering technique (Waltman, van Eck, & Noyons, 2010), and the results were displayed as network, overlay and density visualisations. The fifth stage was presentation of the results using Microsoft Excel, Tableau and VOSviewer.

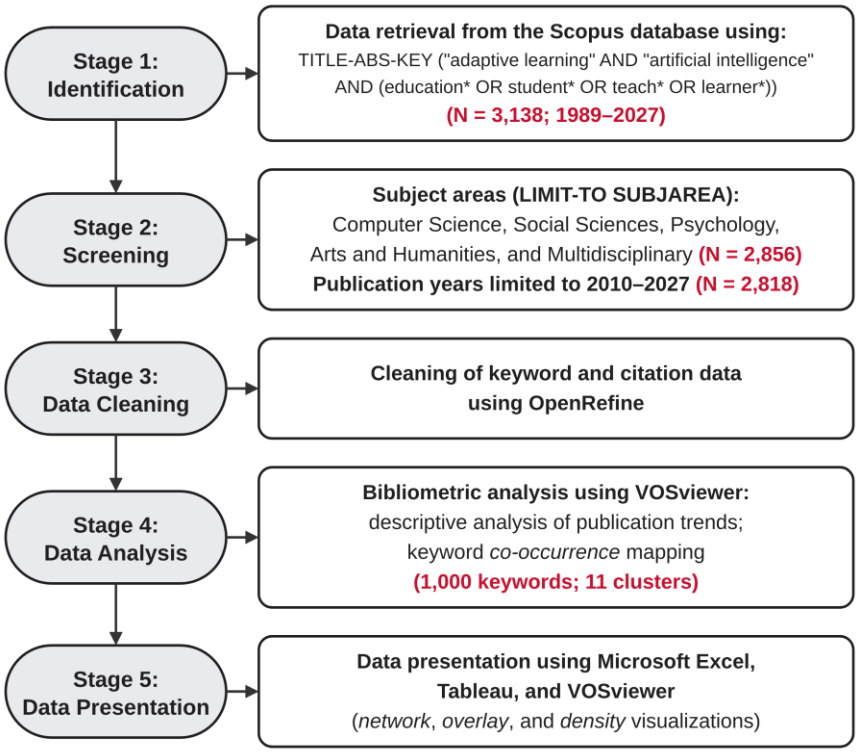


Figure 1. Stages of the bibliometric analysis

Results and Discussion

Publication Trends in AI-Driven Adaptive Learning

Research on AI-driven adaptive learning has grown very sharply. Of the 2,818 documents in the corpus, 91% were published from 2023 onward, and output peaked in 2025 with 1,064 documents (Figure 2).

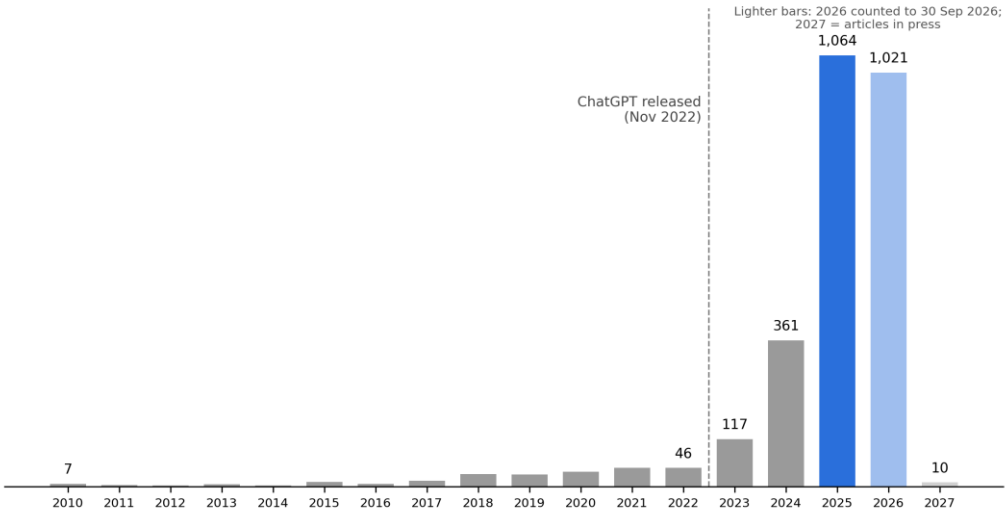


Figure 2. Number of documents per year, 2010–2027 (n = 2,818). Source: Scopus, retrieved 30 September 2026

The growth can be divided into three phases. In the initial phase (2010–2017), 3 to 14 documents were published each year, and research focused on the foundations of adaptive systems and intelligent tutoring (Brusilovsky, 2001; Kulik & Fletcher, 2016). In the phase of steady growth (2018–2022), output rose to 30–46 documents a year as online learning and learning analytics spread, including during the COVID-19 pandemic (Romero & Ventura, 2020). The acceleration phase began in 2023: output rose from 46 documents in 2022 to 117 in 2023, 361 in 2024 and 1,064 in 2025.

This acceleration coincides with the arrival of generative AI. After ChatGPT was released in November 2022, LLMs were quickly tested as tutors, feedback providers and generators of personalised material (Kasneci et al., 2023; Lo, 2023). The trend matches the independent Scopus analysis by Rahman and Khalid (2026), who also found that output grew sharply after 2023 and peaked in 2025, which strengthens confidence in the pattern. The 2026 figures should be read with care. The 1,021 documents recorded for 2026 cover publications only up to 30 September 2026, so the final total for that year is likely to exceed 2025. The ten documents dated 2027 are articles in press that were already available online.

Conceptual Network Structure and Thematic Evolution

The co-occurrence map of 1,000 keywords places "artificial intelligence" and "adaptive learning" as the two largest nodes at the centre of the network (Figure 3). Node size reflects how often a keyword occurs, and links show keywords that occur together in the same document. Both central nodes are connected to almost every cluster, so they act as bridges between the technical and pedagogical domains of the field.

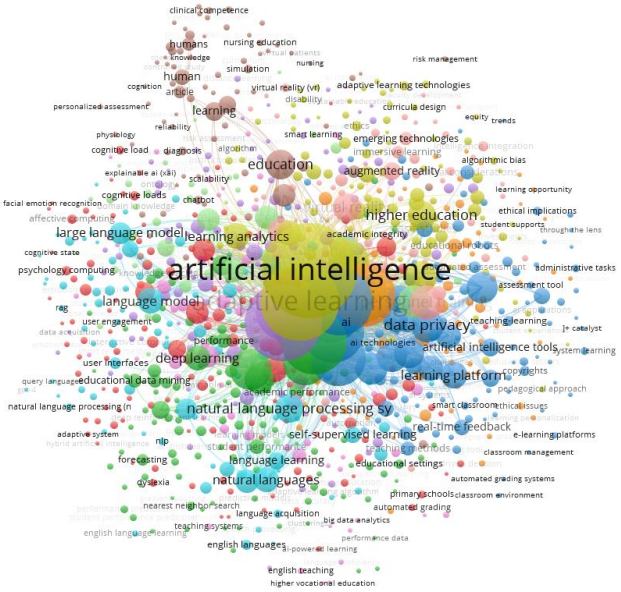


Figure 3. Network visualisation of keyword co-occurrence

Three broad groups surround the centre of the network. The first is a technical domain, with keywords such as "deep learning", "natural language processing", "large language model", "educational data mining" and "self-supervised learning". The second is a pedagogical and institutional domain, with "higher education", "learning analytics", "teaching methods", "real-time feedback" and "learning platform". The third is an ethical domain, with "data privacy", "academic integrity", "algorithmic bias" and "ethical implications". The position of "data privacy" close to the centre suggests that ethical questions are no longer peripheral but have become part of the core discussion, in line with long-standing concerns about privacy and consent in learning analytics (Slade & Prinsloo, 2013; Pardo & Siemens, 2014).

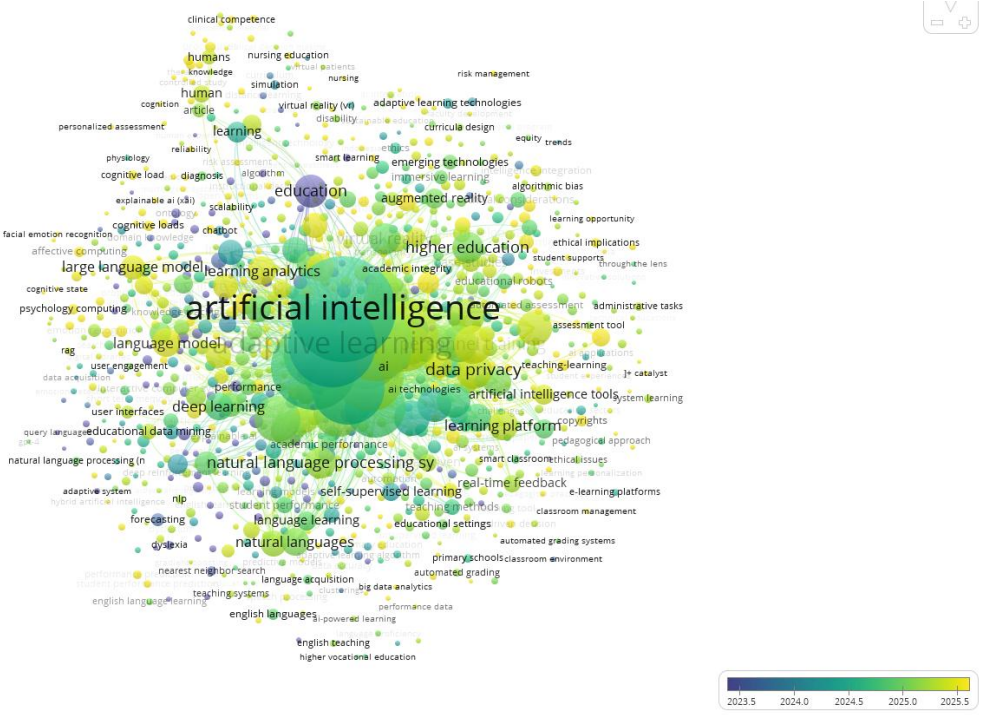


Figure 4. Overlay visualisation of keywords by average publication year

The overlay visualisation in Figure 4 colours each keyword by its average year of publication, from purple (around 2023.5) to yellow (around 2025.5). This narrow range reflects the trend in Figure 2, since most documents were published from 2023 onward. Earlier keywords, shown in purple and blue, include "education", "adaptive system" and "forecasting". The central nodes "artificial intelligence" and "adaptive learning", together with "learning analytics", appear in blue-green. The most recent keywords, shown in yellow, include "large language model", "data privacy", "artificial intelligence tools", "assessment tool", "automated assessment" and "ethical implications".

This shift in colour points to an evolution in two directions. Technologically, the focus has moved from rule-based adaptive systems and data mining toward LLMs and generative AI. Conceptually, it has moved from the question of how a system adapts toward the question of how that adaptation is evaluated, overseen and justified. The second shift echoes the call by Zawacki-Richter et al. (2019) and Bond et al. (2024) for greater pedagogical and ethical reflection, as well as UNESCO's (2023) guidance for a human-centred approach to generative AI in education.

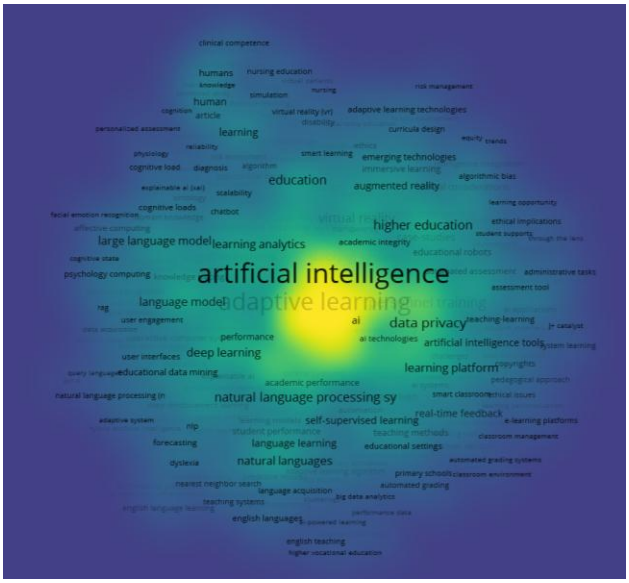


Figure 5. Density visualisation of keywords

The density visualisation in Figure 5 confirms that research is concentrated on the pairing of "artificial intelligence" and "adaptive learning". Surrounding areas such as "learning analytics", "deep learning", "data privacy" and "higher education" show moderate density, while peripheral themes such as "dyslexia", "nursing education", "early childhood education" and "primary schools" remain sparsely studied and can be read as opportunities for further research. Taken together, these findings answer the first two research questions. AI-driven adaptive learning has grown rapidly since 2023, its network is centred on AI and adaptive learning, and its themes have evolved from a technical focus toward generative AI, automated assessment and ethical considerations.

Main Thematic Clusters

The co-occurrence analysis grouped the 1,000 keywords into 11 clusters. The four largest clusters (C1–C4) contain 485 keywords, or 48.5% of all items (Table 1). The theme names in the table are the authors' interpretation of the dominant keywords in each cluster.

Table 1. Eleven thematic clusters in AI-driven adaptive learning research

Cluster	Items	Theme	Dominant keywords
C1	133	Human-centred AI: ethics, cognition and affect	ai ethics, explainable ai, affective computing, emotion recognition, cognitive load, eye tracking, human-ai collaboration, self-regulated learning, transparency, dyslexia
C2	131	Educational data mining and performance prediction	educational data mining, machine learning, deep learning, knowledge tracing, student performance prediction, random forest, recommender systems, adaptive assessment, agentic ai
C3	116	AI in classroom practice and institutions	automated grading, automated assessment, personalized learning, smart classroom, student engagement, student retention, data privacy, ethical concerns, policy makers
C4	105	Generative AI, equity and curriculum design	generative ai, chatgpt, academic integrity, ai literacy, algorithmic bias, digital divide, equity, inclusive education, curriculum design, teacher education
C5	102	Adaptive e-learning and learner modelling	adaptive e-learning, learner model, bayesian knowledge tracing, item response theory, learning styles, learning paths, ontology, learning objects, moodle
C6	84	LLMs, chatbots and NLP for language learning	large language models, gpt-4, chatbots, conversational ai, prompt engineering, retrieval-augmented generation, speech recognition, english language learning
C7	80	AI in STEM, programming and early childhood	computational thinking, computer programming, educational robots, mathematics education, stem education, early childhood education, mobile learning
C8	78	Health-professions education and experimental studies	medical education, nursing education, clinical competence, simulation, virtual patients, randomized controlled trial, motivation, critical thinking, indonesia
C9	67	Big data, knowledge graphs and recommendation	big data analytics, knowledge graph, recommendation algorithms, reinforcement learning, differentiated instruction, personalized teaching, blended learning
C10	59	Immersive technologies and gamification	augmented reality, virtual reality, metaverse, extended reality, immersive learning, gamification, serious games, experiential learning
C11	45	Intelligent tutoring and multi-agent architecture	intelligent tutoring systems, intelligent agents, multi-agent systems, case based reasoning, student modeling, internet of things, smart campus

The eleven clusters can be read as three layers. The first layer is a **core of issues** (C1–C4, 485 keywords). C1, the largest cluster, places people at the centre: AI ethics, explainable AI, cognitive load, emotion and self-regulation, reflecting calls for AI whose decisions learners and teachers can understand (Khosravi et al., 2022). C2 contains the analytical foundations of

adaptive learning, namely educational data mining, knowledge tracing and performance prediction (Corbett & Anderson, 1994; Romero & Ventura, 2020). C3 covers the use of AI in classrooms and institutions, including automated assessment, student retention and data privacy. C4 captures the effects of generative AI, such as academic integrity, AI literacy, algorithmic bias and the digital divide (Baker & Hawn, 2022; Kasneci et al., 2023).

The second layer is the "architecture of adaptive systems" (C5, C9 and C11, 214 keywords). It continues the tradition of adaptive hypermedia and intelligent tutoring through learner modelling, ontologies, knowledge graphs, recommender systems and multi-agent designs (Brusilovsky, 2001; Kulik & Fletcher, 2016). Learning styles now appear only as part of C5. This marginal position is consistent with evidence that matching instruction to learning styles has little empirical support (Pashler, McDaniel, Rohrer, & Bjork, 2008), and with the field's move toward modelling learners' knowledge and performance directly from data.

The third layer consists of "application domains" (C6, C7, C8 and C10, 301 keywords): language learning with LLMs, STEM and programming, health-professions education, and immersive technologies. The appearance of the keyword "indonesia" in C8 shows that research from the Indonesian context is beginning to register, although it remains confined to particular domains. These findings answer the third research question. Research on AI-driven adaptive learning no longer asks only how systems are built, but also for whom they work and by which values they are directed. A core layer dominated by human, ethical and equity concerns indicates that the field is moving toward the very questions of ethics, epistemology and social transformation that frame this conference.

Implications for Islamic Education

None of the 1,000 mapped keywords refers directly to Islam, *madrasah*, *pesantren* or religious education. Research on AI-driven adaptive learning in Islamic educational settings is therefore not yet large enough to form a node of its own in the global literature indexed by Scopus. This gap matters because each of the three layers identified above touches directly on ethical, epistemological and social questions in Islamic education.

From an ethical perspective, clusters C1 and C4 show that transparency, human oversight, data privacy and academic integrity are now core issues (Holmes et al., 2022). In Islamic education these issues can be read through the concepts of *adab* and *ta'dīb*, which describe education as the cultivation of right conduct and the proper placing of knowledge (Al-Attas, 1980). Raquib et al., (2022) similarly argue that Islamic virtue ethics can guide the design and use of AI. An adaptive system that selects content and assesses learners should therefore keep the teacher in the role of educator rather than reducing the teacher to a supervisor of the machine, and should treat learner data as a trust (*amānah*).

From an epistemological perspective, clusters C2, C5 and C11 model learner knowledge as mastery that can be measured and predicted, for instance through knowledge tracing and performance prediction. Islamic educational thought also regards knowledge as the formation of character and *adab*, which cannot be fully captured by interaction data (Halstead, 2004). This tension raises the question of what may legitimately be personalised by a machine and what should remain the domain of the educator. The rise of LLMs in cluster C6 adds a further question about the authority and reliability of religious knowledge generated by AI (Yan et al., 2024).

From the perspective of social transformation, cluster C4 highlights equity, the digital divide and inclusive education. These issues are pressing for the many *madrasah* and *pesantren* located in areas with limited digital infrastructure. AI-driven adaptive learning could narrow quality gaps, but it could also widen them if only well-resourced institutions can use it (Baker & Hawn, 2022).

These findings point to a research agenda for Islamic education. Studies are needed that develop and test AI-driven adaptive learning for Islamic Religious Education and Arabic, drawing on the advances in LLMs and natural language processing seen in cluster C6. Ethical frameworks for adaptive learning grounded in *adab*, in *amānah* in the handling of data and in the role of the teacher as educator are also needed. Further work should examine the readiness of *madrasah* teachers and lecturers in Islamic higher education to design curricula that use adaptive systems, as well as equity of access in *madrasah* and *pesantren* with limited infrastructure. Finally, a follow-up bibliometric study could trace the Islamic education literature specifically, including databases beyond Scopus.

Conclusion

This bibliometric analysis of 2,818 Scopus documents from 2010 to 2027 yields three main findings. First, research on AI-driven adaptive learning has grown very rapidly, from 7 documents in 2010 to 1,064 in 2025, with 91% of the corpus published from 2023 onward, a surge that coincides with the arrival of generative AI. Second, the conceptual network is centred on "artificial intelligence" and "adaptive learning", and the focus has shifted from adaptive systems and data mining toward LLMs, automated assessment, data privacy and ethics. Third, eleven thematic clusters form three layers: a core of human, ethical and equity issues (48.5% of keywords), the architecture of adaptive systems (21.4%) and application domains (30.1%).

The absence of keywords related to Islamic education reveals a clear research gap. Islamic education has conceptual resources, such as *adab* and *ta'dīb*, that speak directly to the ethical and epistemological questions now dominating the field. Further research should develop and test AI-driven adaptive learning for Islamic Religious Education and Arabic, build an ethical framework for it, and ensure equitable access in *madrasah* and *pesantren*.

This study has several limitations. The data come only from Scopus, the query did not include synonyms such as *personalised learning* or *intelligent tutoring system*, and the 2026 data do not yet cover a full year. Future studies could broaden the query, add databases such as Web of Science or Garuda, and complement the keyword mapping with citation and co-authorship analyses.

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