Trends and topics in arts education and artificial intelligence: a systematic review using a human-in-the-loop model

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Abstract: Artificial intelligence in arts education (AIAEd) has rapidly expanded, yet its conceptual evolution remains underexamined. This study systematically reviews 372 Web of Science publications using latent Dirichlet allocation and computational grounded theory to map the field's paradigmatic development. Five thematic clusters emerge: fundamental principle design, technological and interdisciplinary expansion, AI-driven educational models, intelligent behavioural evaluation, and personalised creative learning. A six-stage evolutionary analysis reveals a trajectory from early exploratory work to systematised design, discipline-specific applications, metaverse-supported visual pedagogies, and the recent shift toward generative AI and multidimensional learner modelling. The latest stage highlights creativity-oriented AI tools, affect-aware feedback, and socio-health dimensions of evaluation. Findings indicate a delayed but decisive transition from technology-centred experimentation to human-centred, creativity-enhancing AIAEd frameworks.

Keywords: Artificial intelligence in arts education; AIAEd; computational grounded theory; CGT; topic modelling; generative artificial intelligence; pedagogical design and evaluation.

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1 Introduction

1.1 Artificial intelligence education system: background and urgency

Over the past decade, artificial intelligence (AI) has moved from peripheral experimentation to a cornerstone of educational innovation. Its adaptability and capacity for personalised feedback have demonstrated measurable impacts on learning outcomes across diverse contexts (Bhutoria, 2022; Liu et al., 2025b). AI technologies now provide scalable responses to persistent pedagogical challenges, including limited teaching resources, inequitable access, and the difficulty of sustaining individualised learning in large or remote classrooms (Zafari et al., 2022). AI functions as a catalyst for educational transformation by enabling adaptive learning environments that tailor content, predict difficulties, and support real-time monitoring and intervention (Sun et al., 2025). By integrating intelligent tutoring systems, recommendation algorithms, and predictive analytics, AI can construct dynamic learning pathways that align with students' cognitive profiles. This transformation reframes the teacher's role from sole transmitters of knowledge to designers and facilitators of learning experiences (Bhutoria, 2022).

Education, long recognised as a foundation of human development and societal progress, now faces growing demands for flexibility, personalisation, and data-driven improvement. Conventional teacher-centred and theory-oriented pedagogies often struggle to meet these needs, particularly for learners who benefit from experiential and multimodal engagement (Zafari et al., 2022). In response, the artificial intelligence education system (AIEd) has emerged as a distinctive sub-domain of educational technology research that embeds algorithmic intelligence directly into teaching and learning processes. AIEd encompasses applications from adaptive assessment and intelligent feedback to curriculum design and institutional management, and its expanding research corpus reflects the urgency of re-conceptualising how education operates in an AI-mediated environment (Zafari et al., 2022). Global policy initiatives and investment patterns reinforce this trend: between 2008 and 2017, global venture capital investment in AI-based education exceeded 10.47 billion USD (Mou, 2019), and the global AIEd market is projected to reach 5.8 billion USD by 2025 (Zeng et al., 2025). These figures underscore AI's expanding role as both a technological and an economic force shaping contemporary education.

Beyond quantitative expansion, the scope of AIEd continues to diversify. Recent advances in generative AI have transformed content production by enabling automated generation of personalised exercises, formative assessments, and creative prompts (Yilmaz and Karaoglan Yilmaz, 2023). Simultaneously, the integration of virtual reality (VR) and augmented reality (AR) has produced immersive, multi-sensory learning environments that connect abstract theory with embodied practice (Marques et al., 2024). Together, these developments indicate that AIEd is evolving from an efficiency-oriented toolset toward a holistic learning ecosystem that supports creativity, accessibility, and cognitive engagement. Moreover, AI applications are increasingly regarded as partial substitutes for human instruction in addressing teacher shortages and educational inclusion (Edwards and Cheok, 2017; Guan et al., 2020). However, despite the rapid diffusion of AIEd across general education, its systematic integration within arts education remains comparatively underexplored, forming a central motivation for the present study.

1.2 The value of arts education

Arts education – also referred to as aesthetic education – focuses on developing learners' capacities to perceive, experience, appreciate, and create beauty (Denac, 2014). Beyond aesthetic sensitivity, it encompasses identity formation, emotional regulation, and interpersonal competence (Holochwost et al., 2021). Accordingly, arts education extends beyond technical skill training and functions as a holistic pedagogical process that cultivates cognitive, emotional, and moral dimensions of human development.

Arts education covers a diverse constellation of disciplines, including visual arts (painting, sculpture, collage etc.), dance (ballet, jazz, hip-hop, choreography, martial arts etc.), theatre (improvisation, classical, musical theatre etc.), and music (instrumental and vocal performance, media composition etc.). In some curricula, additional creative domains such as digital media, culinary arts, or creative writing are also integrated (Holochwost et al., 2021). Although these disciplines differ in medium and technique, they share a common emphasis on aesthetic value and human expression. Consequently, arts education should be understood as a pluralistic field shaped by disciplinary diversity rather than as a uniform pedagogical category.

Arts education plays an enduring role in shaping individuals' ideals, sentiments, and appreciation of beauty across general education (Liu et al., 2025a). From early childhood onwards, it contributes to the formation of thinking, emotional, and social competencies (Holochwost et al., 2021). Aesthetic learning supports individuals in recognising and creating beauty, thereby fostering holistic growth and moral refinement (Zhanqiang, 2023). Psychologist Erik Erikson's developmental theory further underscores its relevance to self-identity and confidence formation throughout psychosocial stages (Maree, 2022). Empirical findings reveal that engagement with the arts enhances expressive and cognitive capacities, stimulates creativity and critical thinking (Lukaka, 2023), and promotes self-esteem, empathy, and social interaction (Arslan, 2014). Together, these findings position arts education as a core contribution to psychological maturity and lifelong learning.

Despite its recognised importance, arts education faces persistent structural and methodological difficulties. Its inherent emphasis on creativity and aesthetic judgement complicates standardisation within formal education, particularly in digitally mediated contexts. In addition, disciplinary diversity leads to uneven technological adoption.

Visual-centric fields such as painting have rapidly adopted immersive tools like VR, whereas domains grounded in interpretation and performative expression – such as music – have not achieved comparable digital sophistication. Such disparities underscore the need for interdisciplinary frameworks that can bridge pedagogical differences and support balanced technological development.

Under these conditions, technological augmentation of arts education becomes an educational necessity rather than an optional enhancement. Advanced AI-driven systems offer the potential to personalise aesthetic learning, simulate multimodal creative environments, and generate new forms of artistic interaction. However, due to the heterogeneity of art forms and educational contexts, existing literature remains fragmented and lacks systematic synthesis. The present review addresses this gap by employing a human-in-the-loop computational grounded theory (CGT) model to map, classify, and interpret the evolving intersections between AI and arts education. By identifying cross-domain patterns across, this study contributes both conceptual clarification and a methodological foundation for future interdisciplinary research.

1.3 Artificial intelligence arts education system

The integration of artificial intelligence into arts education has become an inevitable development within higher education worldwide. As Ke (2023) observed, AI is poised to assume a more active role in university-level art education, reshaping pedagogical design and learner engagement.This transformation is not merely technological but also disciplinary, as competence in AI-related tools is becoming an essential requirement for students in the arts (Sun et al., 2025). Cropley (2020) also argues that arts education offers a particularly suitable context for examining AI's 'human-like creativity', because artistic practice demands originality, emotion sensitivity, and contextual nuance – capacities often regarded as the frontier of artificial cognition. Accordingly, integrating AI into arts education serves dual purposes: preparing students for a digitised creative economy and providing a testbed for exploring the relationship between machine creativity and human artistry.

Although AI technologies have achieved commercially viable proficiency in artistic creation and performance (Sun et al., 2025), their educational adoption remains fragmented and inconsistent across art disciplines. The traditional 'one-size-fits-all' instructional model is ill-suited to the pluralistic and interpretive nature of the arts. Current studies demonstrate diverse applications, including painting courses (Sun et al., 2025), martial-arts pedagogy (Chen et al., 2023a), Chinese ink-painting instruction (Liu et al., 2025b), music research (Xiaoyu et al., 2024), film studies (Zeng et al., 2025), musical-theatre education (Dong et al., 2024), Indian classical music (Singh & Arora, 2025), and design learning environments (Chen et al., 2025a). However, these efforts largely remain isolated case studies rather than elements of a coherent pedagogical system, and substantial disparities persist in technological maturity across artistic domains.

Empirical findings also suggest a double-edged effect of artificial intelligence arts education (AIAEd). Some studies report that excessive reliance on AI tools may weaken students' critical thinking, creativity, and ethical awareness, raising concerns about higher-order cognition and academic-integrity (Wang et al., 2025; Basha, 2024). Conversely, other research indicates that AI can enhance sustained learning motivation through adaptive feedback and novel interactive experiences (Sun et al., 2025). These divergent results foreground a central unresolved issue: in creativity-oriented disciplines, does AI act as a catalyst or a constraint on artistic development?

Addressing this question constitutes a core objective of the present systematic review. By tracing the evolution of AI applications across multiple artistic domains, this study aims to clarify both how AI has been integrated into arts education and whether such incorporation meaningfully supports learners' creative, cognitive, and affective growth. This analysis provides a foundation for constructing a coherent theoretical and practical model of the emerging AIAEd.

1.4 Existing review landscape and the need for a human-in-the-loop synthesis

A growing body of literature has attempted to synthesise research on AIEd, offering insights into its development, applications, and pedagogical implications. Prior reviews have examined AIEd from perspectives such as student learning analytics and educational technologies (Roll and Wylie, 2016; Hinojo-Lucena et al., 2019; Chan and Zary, 2019). However, many rely on single-journal bibliometric analyses or short-term cross-journal samples, which limit their capacity to capture long-term evolution and interdisciplinary complexity. Similar limitations appear in reviews addressing arts-related contexts.

Recent efforts have synthesised AI applications in the performing arts have largely adopted technical perspective, emphasisingpose recognition, gesture analysis, and neural-network-based movement classification (Shen and Chen, 2024). Other reviews focus predominantly on K-12 education, examining AI in school curricula and personalised learning (Zafari et al., 2022), or on online and distance learning using data-mining approaches(Dogan et al., 2023). Systematic reviews have similarly concentrated on higher education evaluation and feedback (Sembey et al., 2024), robot-assisted instruction and NLP integration (Younis et al., 2023), or specific AI models such as convolutional neural networks (Silva et al., 2023). While these studies demonstrate thematic diversity, they are largely domain-specific or technique-oriented and rarely trace how AI integration within arts education evolves across extended time spans or across multiple artistic disciplines.

Although some reviews employ extended timeframes and large-scale corpora – for example, Guan et al. (2020) surveyed twenty years of AI and deep-learning applications in education across 400 publications – their analyses often remain descriptive, relying on keyword frequencies or visual mapping rather than modelling latent thematic structures or semantic change. More recently, Bhutoria (2022) employed latent Dirichlet allocation (LDA) to compare AI-driven personalised learning across the United States, China, and India, demonstrating the methodological promise of combining computational modelling with interpretive validation. However, this work remains focused on personalised learning rather than the multi-modal, creativity-oriented domain of arts education.

Together, these patterns indicate two intertwined gaps: the absence of a longitudinal, multi-journal synthesis dedicated to arts education, and the lack of integrative review approaches that combine computational scalability with expert interpretation. Neither approach alone is adequate for a domain where technical innovation intersects with aesthetic judgement, creative processes, and human emotional development. Consequently, there is a pressing need for human-in-the-loop systematic reviews that integrate machine-driven topic discovery with expert interpretive refinement. Such an approach ensures both analytical scalability and conceptual depth – crucial for navigating the heterogeneous, creativity-oriented, and pedagogically diverse landscape of AIAEd.

1.5 The present research

This study addresses the lack of longitudinal and systematic synthesis of AIAEd research. Rather than offering another descriptive overview, it examines AIAEd as a developing research field and traces how its paradigms, themes, and focal concerns have evolved over time. The aim is to clarify the structural patterns and developmental trajectories of AI integration within arts education.

Accordingly, the study addresses the following research questions:

1. What are the major paradigms that have shaped the historical development of AIAEd research?
2. What are the life cycles of these paradigms, and how has AIAEd research transitioned from one paradigm to another?
3. What emerging themes are currently gaining prominence within the AIAEd research community?

To answer these questions, we conducted a longitudinal, multi-journal systematic review of 372 AIAEd publications indexed in the Web of Science. Titles and abstracts were extracted from a 22-year period (2003–2025) and analysed using a Human-In-The-Loop framework that integrates computational modelling and expert interpretation. Specifically, we employed LDA to identify latent themes within the corpus and then refined these results through iterative interpretive coding under the CGT framework. This mixed-methods design enables both scalability and conceptual depth, allowing us to trace paradigm shifts, thematic life cycles, and emerging focal areas across time. By combining algorithmic precision with human interpretive insight, this research provides both a systematic mapping of AIAEd research and a replicable analytical model for future interdisciplinary reviews. The next section outlines the methodological framework and procedures adopted in this study.

2 Method

2.1 Methodology

2.1.1 Computational grounded theory

CGT is an emerging methodological framework that integrates computational text mining techniqueswith the interpretive logic of grounded theory. While grounded theory emphasises iterative coding, categorisation, and theory construction based on qualitative data, CGT introduces computational models to assist in systematically detecting patterns and structures across large-scale corpora. This approach allows researchers to leverage the scalability and objectivity of machine learning while maintaining the contextual and theoretical sensitivity of qualitative inquiry (Nelson, 2020).

The significance of CGT lies in its ability to bridge inductive human interpretation with deductive computational analysis. In the present study, computational modelling was first applied to automatically identify latent structures in the corpus of abstracts. These machine-generated themes were then critically examined and re-interpreted through the grounded theory lens to ensure conceptual coherence and contextual validity. This process addresses a key limitation of purely computational approaches: while algorithms can detect statistical regularities in language use, they often lack the theoretical capacity to explain why certain themes emerge and how they relate to broader disciplinary discourses. By embedding the results within the grounded theory framework, the study ensures that the identified themes are not only statistically robust but also theoretically meaningful (Rabbani and Ahmed, 2025).

2.1.2 Latent Dirichlet allocation

LDA is a widely adopted unsupervised machine learning model for topic discovery in large-scale text corpora (Blei et al., 2003). LDA assumes that each document can be represented as a mixture of latent topics, and each topic is characterised by a probability distribution over words. By inferring these distributions, LDA enables researchers to uncover underlying thematic structures that are not explicitly annotated in the data. It clusters documents, topics and words according to selected parameters, enabling researchers to derive a set of interpretable themes from the corpus within a relatively short timeframe (Jelodar et al., 2019). Results obtained by Miwa et al. (2014) showed that LDA features can significantly reduce the workload involved in the screening phase of a systematic review. This statistical representation has made LDA one of the most popular techniques in natural language processing and the digital humanities (Maier et al., 2018).

In the context of this study, LDA served as the computational component of the CGT framework. It provided an initial layer of abstraction by generating candidate topics from the corpus of abstracts, which were subsequently visualised and assessed using coherence metrics (Miwa et al., 2014). However, LDA results are inherently limited. The topics it produces reflect probabilistic word co-occurrences, which do not always align with theoretically significant constructs (Törnberg and Törnberg, 2016). Furthermore, LDA cannot independently determine the interpretive meaning of a topic; its outcomes require human expertise to transform statistical clusters into conceptually grounded categories (Nikolenko et al., 2017).

For this reason, the LDA-derived themes were not treated as definitive findings but as computationally generated signals requiring further interpretation. By situating these results within the framework of computational grounded theory, the study combined the efficiency and reproducibility of machine learning with the depth and rigor of qualitative analysis. This dual strategy ensured that the final thematic interpretation was both data-driven and theoretically robust.

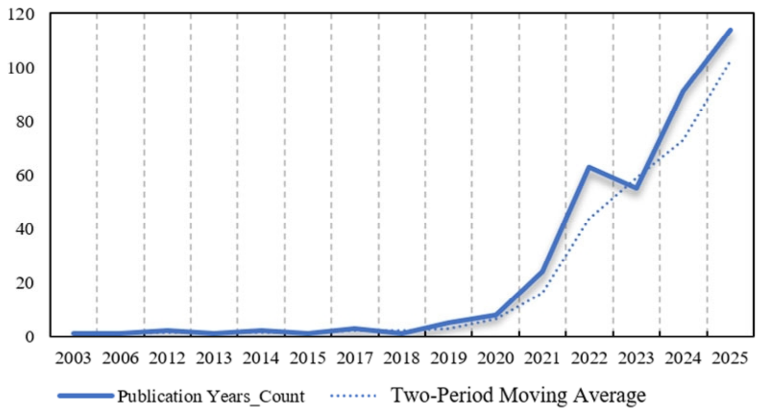
2.2 Procedure

2.2.1 Data extraction

The data collection process adhered to the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines, ensuring transparency and replicability in literature screening (Page et al., 2021). The primary goal was to construct a text database using abstracts of scientific articles, which are widely adopted in topic modelling studies for identifying thematic structures in scholarly publications (Jiang et al., 2016; Martín et al., 2019). Abstracts were selected as the textual source because they concisely summarise the objectives, methods, and findings of studies, thereby offering a reliable representation of article content for computational analysis. The screening process comprised four stages: identification, screening, eligibility assessment, and inclusion.

During the identification stage, the Web of Science (WOS) database was selected as the primary source due to its extensive cross-disciplinary coverage, consistent metadata structures, and rigorous journal selection criteria, which are essential for ensuring comparability and reliability in large-scale computational text analysis. Although other databases also index education- and technology-related literature, they differ substantially in coverage, indexing standards, and data-export functionality. To maintain dataset consistency and avoid potential biases introduced by heterogeneous metadata structures and duplicate records across platforms, this study focused on WOS as a single, well-established source. Consequently, other databases were not included in the present analysis. Within the WOS database, Boolean operators (AND/OR) were used to combine keywords related to the study's focal topics. The specific query applied was: TS = ((AI) OR TS = (artificial intelligence)) AND TS = (arts education).

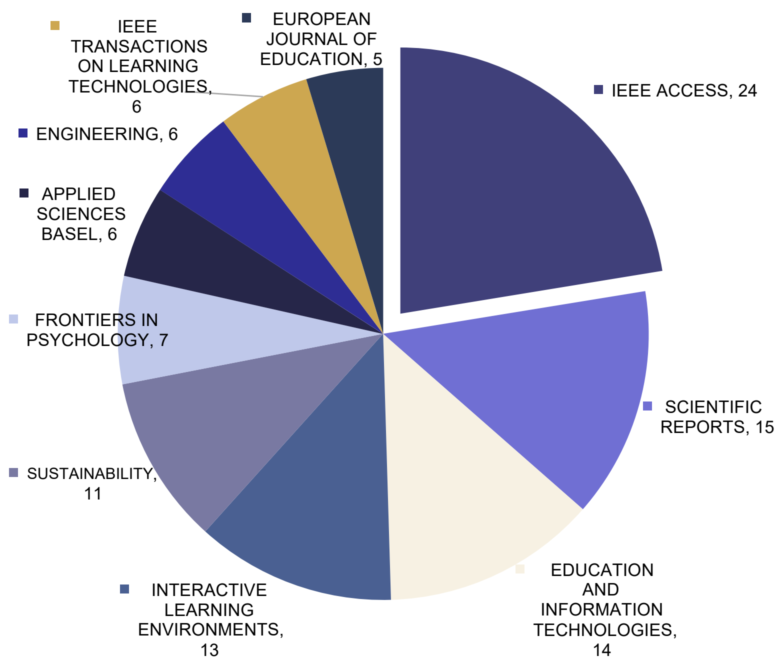
Figure 1 Public time distribution (see online version for colours)



Note: Annual publication counts of AIAEd-related studies from 2003 to 2025 (solid line) and corresponding two-period moving average (dotted line).

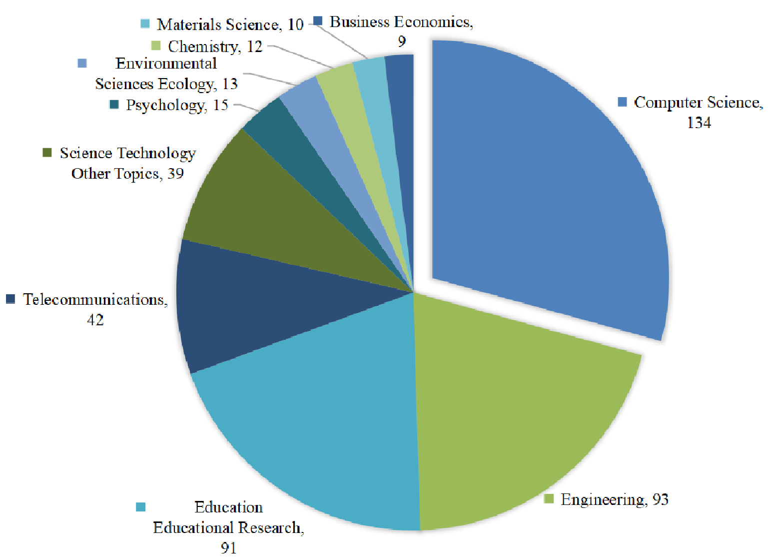
A systematic search was performed in the WOS database on 26 September 2025, yielding 727 records. After initial export, duplicates, non-English publications, and specific document types (e.g., review articles, early-access items, proceedings papers, retracted publications, editorial materials, and letters) were excluded (n = 353). A secondary eligibility check was independently conducted by two reviewers to confirm inclusion suitability for text analysis, resulting in the removal of two additional duplicate or irrelevant entries (n = 2). Following this process, the final dataset consisted of 372 eligible publications. Metadata for each article – including research area, authors, journal title, country, year of publication, source, abstract, and document type – were systematically organised and exported in CSV format for subsequent computational analysis.

Figure 2 Publication titles (see online version for colours)



Note: Distribution of AIAEd publications by source journal (number of articles per journal).

Figure 3 Research areas (see online version for colours)



Note: Distribution of AIAEd publications across Web of Science research areas (number of articles per category).

The temporal distribution revealed that the earliest relevant publication appeared in 2003. From 2003 to 2020, only 25 studies were published, reflecting the exploratory phase of this researchdomain (refer as Stage 1 later). Starting from 2021, the number of publications increased exponentially. This trend demonstrates the growing scholarly attention to the intersection of artificial intelligence and arts education (see Figure 1). This is also the reason why each year will be incorporated into the analysis as a separate phase in the subsequent sections. Publications in the dataset originated from 70 countries, with China contributing the largest share (n = 152). A total of 100 journals were represented (see Figure 2). In terms of disciplinary orientation, 71 research areas were covered, with the most frequent categories being Computer Science (n = 134), Engineering (n = 93), and Education/Educational Research (n = 91) (see Figure 3).

2.2.2 Topic modelling

All computational procedures in this study were implemented in a Python environment, where a series of scripts were executed to preprocess the text data, perform LDA modelling, and visualise thematic evolution. The overall workflow is illustrated below.

2.2.2.1 Text preprocessing

First, all abstracts were extracted from the collected corpus. Tokenisation was performed using the Natural Language Toolkit (NLTK), supplemented by a Multi-Word Expression Tokeniser to capture domain-specific compound terms. Three customised lexical resources were incorporated:

a a stopword list

b a synonym mapping dictionary to unify lexical variants

c a domain-specific vocabulary list.

After tokenisation, tokens were lower-cased, digits and non-alphabetic characters were removed, and part-of-speech tagging was applied. Verbs and stopwords were filtered out unless they appeared in the custom vocabulary. The final output consisted of preprocessed documents stored in plain text for downstream modelling. The corpus ultimately employed for subsequent research comprised a total of 373,808 characters.

2.2.2.2 Dictionary and corpus construction

A gensim dictionary was built from the preprocessed tokens, and a corpus was generated using the bag-of-words (BoW) representation. Word frequencies were further calculated, and word clouds were created to provide a descriptive overview of the dataset.

Formally, each document **d** was represented as a BoW vector:

$$\mathbf{d} = \left\{ \left(w_i, f_{i,d} \right) \right\}_{i=1}^{N}$$

where w_i denotes the i-th unique token in the dictionary and $f_{i,d}$ is its frequency in document d.

2.2.2.3 LDA model estimation and model selection

LDA was implemented via the gensim library. Multiple candidate models were fitted by varying the number of topics *K* from 1 to 20, with 20 passes and an auto-tuned hyperparameter setting for α and *η*. For each *K*, two evaluation metrics were computed:

Log-Perplexity:

$$perplexity(D) = \exp\left\{ -\frac{\sum_{d=1}^{M} \log p(w_d)}{\sum_{d=1}^{M} N_d} \right\}$$

where *D* is the document set, exp{} is an exponential function with the natural logarithm **e** as the base, $p(w_d)$ is the generation probability of document *d*, N_d represents the lexical length of document *d*, and *M* is the number of documents.

Topic coherence (c_v):

$$Coherence(V) = \sum_{(V_i, V_j \in V)} score(V_i, V_j, \in)$$

Here, *V* is a set of words describing the topic, and ϙ returns a smoothing factor for the real number to guarantee the score.

Both metrics were plotted across different values of *K*, and the final topic number was determined based on the balance between interpretability and statistical fit.

2.2.2.4 Topic visualisation and distribution extraction

Once the optimal number of topics was identified, the final LDA model was trained. Outputs included:

1. topic keywords saved in both TXT and CSV formats
2. document-topic distributions ($p(z|d)$) for each document, with the dominant topic identified per abstract
3. interactive visualisation via pyLDAvis, enabling topic interpretability inspection.

2.2.2.5 Thematic evolution and similarity analysis

To examine longitudinal changes, six staged corpora were modeled separately. For each stage, topic labels were generated using the top five keywords, and topic intensities were computed as the proportion of documents dominated by each topic.

The cosine similarity was applied to measure thematic continuity between adjacent stages:

$$\text{cosine similarity}(A, B) = \cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}}$$

Here, A_i and B_i are vector representations of the two topics *A* and *B*.

2.2.2.6 Sankey diagram construction

Finally, to visualise thematic transitions, the similarity matrices were transformed into source-target-value triplets and combined with topic intensities. A Sankey diagram was generated using Plotly, where nodes represented topics in each stage and links represented the strength of inter-stage thematic similarity. The node colour scheme differentiated stages, and link transparency reflected cosine similarity strength. The outputs from these procedures provided a multi-dimensional understanding of thematic evolution across temporal stages, serving as the foundation for the result presentation in Section 3.3.

2.2.2.7 Thematic intensity

Thematic intensity refers to the relative weight or salience a theme acquires within a particular period. It is expressed as the number of documents that the model associates with a given theme. A higher intensity indicates that more texts in the corpus converge around the same thematic cluster, suggesting that this theme occupies a central place in discourse during that stage. The formula for calculating thematic intensity is as follows:

$$T_k = \frac{\sum_{d=1}^{M} \theta_k^d}{M}$$

Here, T_k is the intensity value of the topic *k*, and θ_k^d is the probability of the topic *k* appearing in the document *d*.

3 Results and discussion

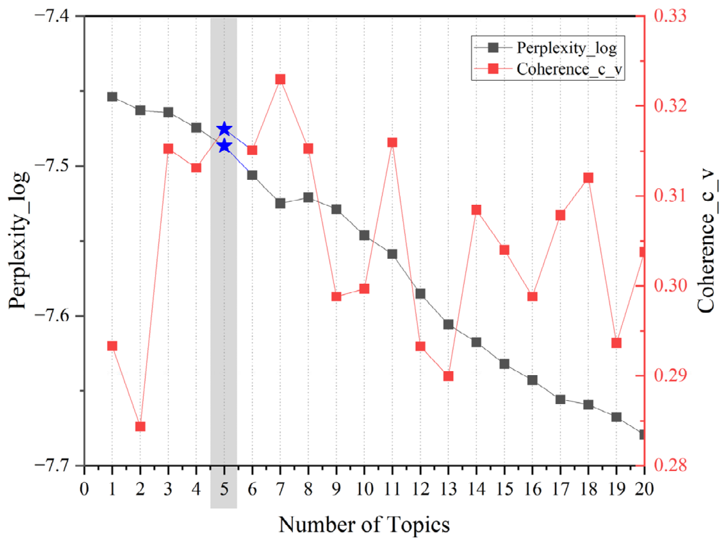
3.1 Optimal topic number

To determine the optimal number of topics for the LDA model, models with topic numbers ranging from 1 to 20 were evaluated using two widely recognised diagnostic metrics: perplexity (log-transformed) and coherence (c_v). Figure 4 presents the dual-line trend graph, where the grey line represents perplexity and the red line represents coherence. Perplexity decreased monotonically as the number of topics increased, indicating improved model fit with diminishing marginal gains beyond approximately seven topics. In contrast, coherence, which measures the semantic interpretability of topics, exhibited local maxima at three, five, and seven topics.

Through an integrative assessment of both metrics, five topics were selected as the optimal solution for subsequent analyses, as this configuration achieved a balance between model stability and interpretability while avoiding over-fragmentationof themes. This topic setting provided a parsimonious representation of the corpus-level thematic structure.

Using the same LDA optimisation procedure, optimal topic numbers were further estimated for each of the six publication stages. Results indicated that thematic structures of AIAEd research remained dynamic but stabilised within a relatively bounded range over time. Specifically, Stage 1 (2003–2020) yielded 12 topics, followed by Stage 2 (2021) with 9 topics, Stage 3 (2022) with 11 topics, Stage 4 (2023) with 11 topics, Stage 5 (2024) with 9 topics, and Stage 6 (2025) again with 11 topics. Rather than indicating linear convergence, this pattern suggests a transition toward a comparatively stable thematic configuration, fluctuating between 9 and 11 topics in later stages. The cross-stage topic transitions are visualised in Figure 6, and detailed topic compositions and representative keywords are reported in Table 1.

Figure 4 Dual-metric evaluation of the optimal number of LDA topics (see online version for colours)



Note: Dual-metric evaluation of LDA topic number selection using perplexity (log) and coherence (c_v) scores.

3.2 *Topic distribution: overall structure*

The LDA topic-modelling results revealed five dominant topics forming a coherent thematic framework, which can be organised into two interrelated paradigms that structure of AIAEd research (Figure 5). This dual structure echoes prior distinctions in AIEd research between instructional design and learning outcomes (Zafari et al., 2022). In the present study, these dimensions were empirically derived through machine-learning clustering and are conceptualised as the input and output paths of AIAEd development.

The input path encompasses studies that examine how AI is embedded within pedagogical design and instructional systems. It includes three themes: fundamental principle design (T1, 24.6%), technological development and enhancement (T2, 20.3%), and student learning-model construction (T3, 17.4%). Together, these topics reflect the structural integration of AI into curricula, teaching frameworks, and learning infrastructures, with teachers and institutions serving as primary agents of innovation. This paradigm emphasises AI-supported instructional design and system construction, aligning with broader trends in adaptive and data-driven pedagogy.

Figure 5 Heatmap of the five-topic LDA model for AIAEd research (see online version for colours)

Category	Topic 1		Topic 2		Topic 3		Topic 4		Topic 5	
topic	INPUT						OUTPUT			
1	education	0.026	artificial_intelligence	0.019	education	0.013	education	0.013	student	0.019
2	artificial_intelligence	0.022	education	0.014	artificial_intelligence	0.013	model	0.009	education	0.017
3	learn	0.021	art	0.010	student	0.008	system	0.007	artificial_intelligence	0.016
4	student	0.018	technology	0.010	research	0.008	artificial_intelligence	0.007	learn	0.012
5	technology	0.013	research	0.009	learn	0.008	behavior	0.007	art	0.012
6	study	0.011	system	0.006	model	0.008	technology	0.006	model	0.008
7	teach	0.010	health	0.006	study	0.007	effective	0.006	system	0.008
8	art	0.008	application	0.006	models	0.007	evaluation	0.006	data	0.008
9	design	0.006	visual	0.006	performance	0.006	data	0.005	performance	0.008
10	data	0.005	development	0.006	data	0.006	learn	0.004	effective	0.007

Notes: Heatmap of the five-topic LDA model for AIAEd research, displaying top keywords and their weights across input- and output-oriented topics. Red cells indicate values above the midpoint, green cells indicate values below the midpoint, and white cells represent midpoint values.

In contrast, the output path represents the learner-centred dimension of AIAEd and focuses on learning evaluation and performance outcomes. It is characterised by two themes – intelligent evaluation and learning behaviour analysis (T4, 10.9%) and personalised learning and creative performance optimisation (T5, 26.9%). These studies investigate how AI enables data-driven observation, behavioural analysis, and feedback mechanisms to support the assessment and optimisation of learning processes.

Overall, the results indicate that AIAEd research has evolved around two complementary trajectories – one teacher-oriented and the other student-oriented – mirroring the interplay between instructional design and learning assessment. Topics associated with pedagogical input account for approximately 62.3% of the corpus, indicating a stronger research emphasis on AI-driven teaching design than on evaluative mechanisms. The following subsections (3.2.1–3.2.5) examine each topic in detail, analysing their representativekeywords, conceptual orientations, and educational implications within the evolving AIAEd research landscape.

Theme 1 Fundamental principle design

The first theme (T1) captures the foundational dimension, centred on the feasibility and attitudinal acceptanceof AI-assisted practices. The highest-weightedkeywords – education (0.026), artificial intelligence (0.022), learn (0.021), and student (0.018) – suggesta pedagogicalrather than technical orientation. Supporting terms such as technology, study, teach, and art further emphasise teaching-learning processes instead of algorithmic mechanisms.

The literature encompassedwithin T1 provides the theoretical foundation for developments in the AIAEd field. Sun et al. (2025) show that AI technologies enhance college students' continuous learning intention, while Chen et al. (2023a) report that AI-based visual tools increase students' interest in martial-arts learning. In media-arts contexts, Zeng et al. (2025) demonstrate that the Artificial Intelligence Smart Sketchpad (AISS) boosts film students' motivation and engagement in character design. Predictive approaches, such as the sequential ensemble model proposed by Tian et al. (2024) further underline AI's capacity to support personalised learning through accurate engagement forecasting. From the educator perspective, Yang (2025) reveals that although university art instructors generally acknowledge AI's ease of use and pedagogical value, many lack confidence in its practical application. This pattern indicates that T1 prioritises attitudinal formation and advocacy over technical refinement.

Overall, T1 represents the formative input stage of AIAEd research. It foregrounds human-AI acceptance and pedagogical readiness, positioning AI primarily as an assistive resource for enhancing engagement and supporting personalised learning, prior to the emergence of more technically mature paradigms.

Theme 2 Technological and interdisciplinary expansion

The second theme (T2) illustrating how AI-supported artistic learning extents into broader educational and professional contexts. The dominant keywords indicate cross-domain integration and scenario diversification. In contrast to T1's focus on feasibility and acceptance, T2 represents a more mature stage, emphasising the convergence of education, art, and health-related disciplines through AI-enhanced tools.

A defining feature of this theme is the incorporation of AI-assisted visual arts into health and medical curricula, where artistic practices function as tools for reflection, empathy, and perceptual training. Weltin and Gedney-Lose (2025) conceptualised 'art as a lens' for examining social determinants of health, demonstrating improvements in emotional intelligence and non-verbal communication among health-profession students. Related studies show that immersive AI-supported visual-learning models – often incorporating machine learning and VR/AR – enhance both aesthetic engagement and applied professional competence (Ugoala et al., 2025; Wieczorek et al., 2024). AI's role in curatorial and visual-perception education further underscores its interdisciplinary potential. Xing et al. (2024) introduced an AI-based digital biophilic art curation model using computer vision, showing positive effects on wellbeing and perceptual engagement. Visual thinking strategies (VTS) have also gained prominence in health professions education; Agarwal et al. (2025) provided a detailed implementation guide, highlighting VTS's contributions to reflective practice, empathy, and critical observation – skills foundational to both artistic and clinical performance.

Beyond visual arts, AI-mediated interdisciplinary expansion has begun to include performative practices. Liu et al. (2025b) applied AI-driven diffusion models to children's traditional Chinese painting education, linking aesthetic learning with seasonal health awareness. Temsah et al. (2024) evaluated AI-generated imagery in cardiology education, emphasising the need for cautious validation, while Khoshgoftar et al. (2025) demonstrated that pantomime-based training enhances observational acuity, empathy, and ambiguity tolerance in medical students. These studies position performative arts as valuable tools for professional emotional development.

Collectively, T2 marks a transformative phase in AIAEd, where AI-enabled methods connect artistic learning with applied domains. While visual arts remain central, the growing inclusion of performative forms signals expanding interdisciplinary potential.

This theme demonstratesa shift from isolated pedagogical applications toward system-level enhancement, positioning AI as a conduit for cross-domain learning and the cultivation of creative and humanistic capacities.

Theme 3 AI-driven educational models and methodological innovations

The function of T3 is support teaching design and decision-making. The dominant keywords indicate a model-centred and analytics-oriented research trajectory. Unlike T1 and T2, T3 marks a system-oriented research trajectory positioning educators as primary users of AI frameworks.

Although many studies within this theme are not exclusively arts-focused, their implications for AIAEd are substantial. AI-driven models provide the methodological infrastructure upon which creativity-dependent learning can be supported. As Hwang and Wu (2025) observed in graphic design education, the generative AI era requires pedagogical goals that prioritise creative inquiry and aesthetic reasoning, rather than efficiency solely.

Technological advancement forms the core of this theme. Chauhan and Agrawal (2024) proposed cloud-fog computing architectures to address resource limitations in distributed learning systems, while recent work highlights the transformative role of generative AI and large language models (LLMs) – including ChatGPT, Gemini, Claude, and LLaMA – in improving accessibility and adaptability in educational design (De Silva et al., 2025; Lang et al., 2025). Reinforcement learning frameworks like COBRA (Haider et al., 2025) enhance system reliability, and LLM-graph neural network integration improves contextual reasoning and domain-specific knowledge representation (Yu et al., 2025). These developments support AI systems capable of incorporating human feedback and modelling complex problem-solving processes relevant to artistic learning.

T3 also incorporates the methodological expansion of AI within STEAM education. Building on earlier evidence of STEM's positive effects on creativity and collaboration (Song, 2017; Ahmad et al., 2020), recent studies explicitly positions STEAM as a bridge between technological and artistic domains. Wu et al. (2025) demonstratedthat AI-enhanced, game-based STEAM models improve motivation and creative engagement, while Chang et al. (2024) reported gains in AI conceptual understanding and creative emotion through hands-on STEAM activities. Dong et al. (2024) further illustrated this integration through a robotics-based musical theatre programme that merged engineering principles with performing arts.

In parallel, model-driven decision-supportsystems have been developed assist educators, including predictive frameworks for student retention (Davazdahemami et al., 2025), automated text-feedback analysis (Nawaz et al., 2022), and adaptive exercise-recommendation systems applicable to arts contexts (Liu et al., 2025a). These innovations link data-driven modelling with personalisedinstruction and adaptive learning design.

Overall, T3 represents the methodological backbone of AIAEd's input pathway. While originating outside the arts, these AI frameworks underpin the development of intelligent creative learning environments. The rise of generative AI and LLMs represents a pivotal turning point, enabling pedagogical design that better accommodate creativity, inclusivity, and learner adaptability. As part of the broader STEM and STEAM landscape, AIAEd inherits methodological foundation while extending them to address the distinctive cognitive and emotional demands of artistic practice.

Theme 4 Intelligent evaluation and learning behaviour analysis

The fourth theme (T4) addresses AI-based learning behaviour analysis and intelligent educational evaluation, representing the empirical, outcome-oriented dimension of AIAEd. The key terms highlight a methodological emphasis on assessment, monitoring, and feedback within digital learning environments. Although T4 comprises the smallest corpus (n = 38), it signals crucial shift from pedagogical design toward evidence-based evaluation, functioning as the empirical counterpart to the input-oriented themes. Two major research strands emerge.

The first focus on learning behaviour and cognitive processes, and affective states. Pang et al. (2025) applied interpretable machine learning to martial-arts performance assessment, ensuring fairness through movement-feature alignment and temporal-bias mitigation. Rong et al. (2022) demonstrated that AI-VR environments enhance creativity and concentration in arts learning. Affective analytics further extend this line of inquiry: Imran et al. (2025) achieved high-accuracy emotion classification, while Sáez-Velasco et al. (2025) and Shen et al. (2024) revealed how students' attitudes toward generative AI shape perceived creativity, autonomy, and concerns about authorship and professional identity.

The second strand emphasises system-level pedagogical evaluation and feedback mechanisms. Saini et al. (2025) introduced the artificially intelligent smart teacher feedback system (AISTFS), enabling real-time reflective teaching through gesture-based analysis. ChatGPT-driven feedback systems were shown to enhance learning outcomes, motivation, and self-efficacy (Chen et al., 2025a), while multimodal AI applications in music and art education improved performance, engagement, and creativity (Wang, 2025; Huang et al., 2024b).

In summary, T4 represents the evaluation-oriented output path of AIAEd, where behavioural analytics and system-level assessment converge to ensure accountability and continuous refinement. Despite a relatively limited evidence base, this theme signals the emergence of intelligent assessment ecosystems capable of capturing the emotional, cognitive, and creative processes fundamental to artistic learning.

Theme 5 Personalised learning and creative performance optimisation

The fifth theme (T5), the most prevalent cluster (26.9%), focuses on AI-supported personalised learning and creative performance optimisation. The dominant keywords indicate a distinctly student-centred orientation, marking a shift from instructor- or system-focused paradigms (T1–T4) toward learner autonomy, adaptive pathways, creativity enhancement. Research within this theme can be organised into three interrelated strands.

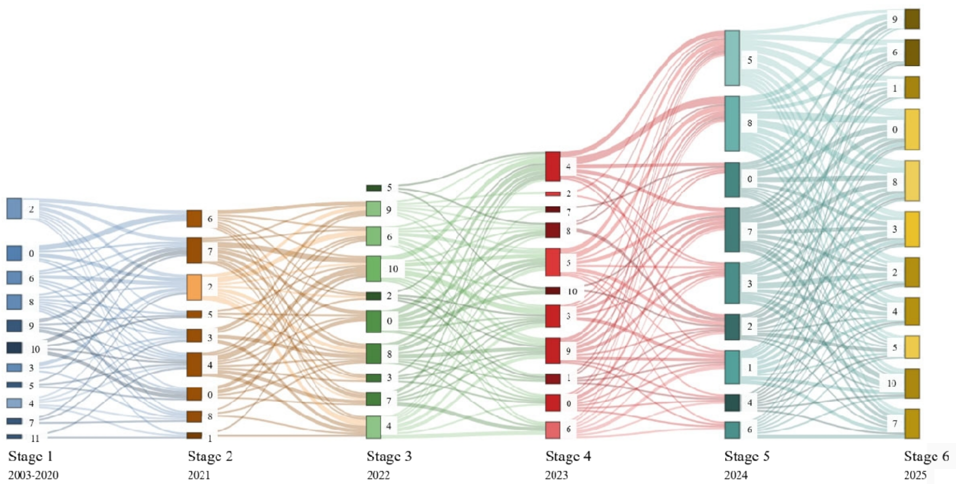
The first strand concerns learner adaptation and AI knowledge-acceptance models. With the rise of generative AI, studies have documented fundamental changes in learning practices and assessment cultures (Kolade et al., 2024). Emotional and affective AI systems play a prominent role in artistic contexts, supporting responsive and personalised learning experiences (Akalya Devi et al., 2023). Personalised AI tutoring models further demonstrate how AI can scaffold individual learning trajectories, from incremental knowledge acquisition to studio-based creative training (Kim and Kim, 2020; Yi, 2024). Across these studies, creativity is consistently framed as the core competence of arts education, with scholars emphasising human-centred and collaborative human-AI pedagogies rather than automation (Tong and Lee, 2023; Corazza et al., 2025).

The second strand focuses on AI-based student modelling, performance prediction, and adaptive feedback. While predictive analytics have shown promise in enhancing motivation and artistic performance, challenges related to data noise, explainability, and bias remain salient, particularly in open-ended creative domains (Liang et al., 2022; Pan et al., 2025). Recent systems demonstrate that deep-learning and multimodal approaches can significantly improve achievement, engagement, self-efficacy, and emotional involvement in arts learning environments (Chiu et al., 2024; Fang and Jiang, 2024). Pedagogical agents grounded in social and para-social interaction theories further extend personalised support, fostering both learning efficiency and socio-cognitive development (Fang et al., 2025).

The third strand addresses AI-assisted learning material identification and resource recommendation, enabling adaptive access to artistic content. While early systems were largely generic (e.g., Wei et al., 2021), more recent arts-specific applications integrate disciplinary knowledge into recommendation processes. Examples include interpretable music-classification models aligned with musicological understanding (Singh and Arora, 2025) and NLP-based systems supporting culturally informed music learning in Chinese folk traditions (Huang and Song, 2022). These approaches lay the foundation for AI-guided creativity support tools that enhance repertoire exploration, cultural literacy, and personalised artistic development.

In summary, T5 embodies the student-centred output dimension of AIAEd and reflects a mature phase in the field's evolution. The theme illustrates a broader shift from system-driven technologies to learner-driven creativity ecosystems, reaffirming the centrality of students' experiences, competencies, attitudes, and creative potential in shaping the future direction of AIAEd research.

Figure 6 Sankey diagram of multi-stage LDA topic evolution (2003–2025) (see online version for colours)



Note: Nodes denote topics (indexed as in Table 1), colours indicate stages, and link width represents cosine similarity between topics across consecutive stages.

Table 1 Result of multi-group LDA topic modelling (see online version for colours)

Stage	*Category*	*Index*	*Topic*	*Intensity*
Stage 1 (2003–2020)	Pedagogical design	0	Human-machine interaction in art and education	0.125
		1	Sustainable art creation and educational technology integration	0.042
		2	Educational robotics and AI in engineering education	0.125
		3	VR- and AI-driven learning environment design	0.125
		4	AI-based gamified learning and system development	0.167
		5	AI support for sensorimotor and artistic skill learning	0.042
		6	AI-driven educational processes and safety	0.125
		11	AI and cyber-physical system integration in education	0.042
	Pedagogical performance evaluation	7	AI in community arts education and youth development	0.125
		8	AI music learning systems and learner analysis	0.042
		9	Data-driven models for student performance prediction	0.000
		10	AI-Based learning environment and student performance analysis	0.042
Stage 2 (2021)	Pedagogical design	0	Learning resource recommendation and team collaboration	0.091
		1	Online content classification and language learning systems	0.045
		2	AI applications and VR-based teaching	0.318
		3	Innovative pedagogical design with AI integration	0.091
		4	Chinese educational datasets and learning analytics	0.091
		5	AI-STEAM curriculum and sustainable teaching design	0.091
		6	Human-robot system design in arts education	0.091
		8	Constructionism and AI learning for children	0.091
	Pedagogical performance evaluation	7	Student performance and learning quality evaluation	0.091
Stage 3 (2022)	Pedagogical design	2	Creative education and posthumanist perspectives	0.091
		3	Clustering algorithms in surgical education training	0.018
		4	AI and digital teaching systems in higher education	0.018
		6	AI and technological development in music education	0.055
		7	Martial arts education and machine learning models	0.182
		8	AI-enhanced creativity in arts education with VR	0.018
		9	Software- and system-driven art education models	0.145
		10	Animation and AI-supported educational system design	0.073
	Pedagogical performance evaluation	0	Learner ability and analytics models	0.073
		5	Video event analysis and educational safety data	0.182
	Irrelevant theme	1	-	0.145

Notes: Results of multi-group LDA topic modelling across six developmental stages of AIAEd, including topic category, index, thematic label, and intensity for each stage. Values above the stage mean are highlighted in red.

Table 1 Result of multi-group LDA topic modelling (see online version for colours) (continued)

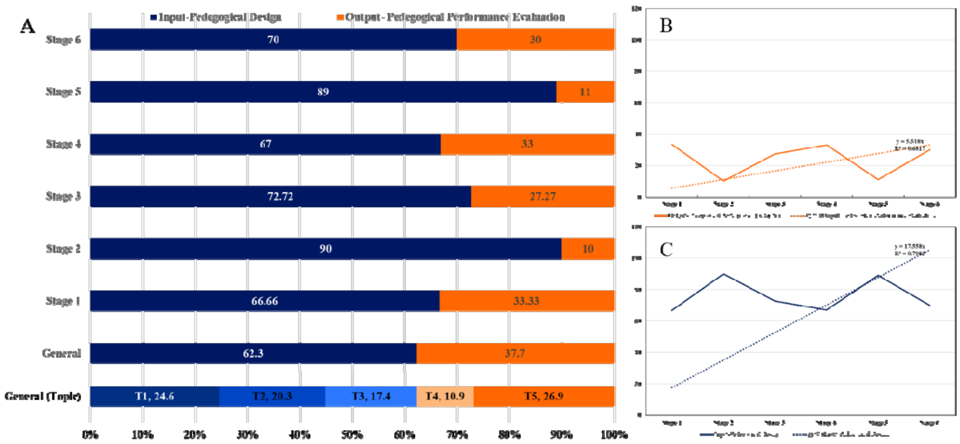
Stage	Category	Index	Topic	Intensity
Stage 4 (2023)		2	Metaverse and visual arts education concepts	0.10
		3	Goal-oriented models and educational systems	0.06
		4	Data-driven learning environments and future education	0.12
		5	AI-supported visual and experimental teaching	0.10
		6	Martial arts education and AI system design	0.10
		10	Multimodal fusion of metaverse and speech in higher education	0.12
		0	AI learning and performance evaluation under uncertainty	0.16
		1	Student performance and behavioural feature modelling	0.04
		9	AI detection and accuracy analysis in classroom environments	0.06
		7	-	0.10
		8	-	0.04
		0	Educational modelling of learning environments and student behaviours	0.088
		1	Task-oriented AI educational systems	0.143
		2	Aesthetic perception and AI data representations	0.055
		3	AI applications in arts and cross-domain education	0.110
		5	AI learning systems in arts and metaverse education	0.022
		6	Chatbots and knowledge construction in education	0.209
		7	Online and human-AI interactive learning applications	0.110
		8	ChatGPT-driven educational tools and learning innovation	0.088
	Pedagogical performance evaluation	4	AI-driven organisational performance and engagement analysis	0.176
		0	Student learning and creative AI tools in education	0.138
		1	ChatGPT and student feature modelling	0.069
		2	Visual and anxiety perspectives in AI education	0.077
		3	General AI applications in arts and education	0.123
		5	Generative AI and design in arts education	0.077
		7	AI-driven feedback in higher education environments	0.138
		9	Creativity, motivation, and STEAM education practices	0.038
		6	Academic performance and learning effectiveness models	0.077
		8	Social and health evaluation of learning performance	0.154
		10	AI classification and accuracy models for student performance	0.038
	Irrelevant theme	4	-	0.069

Notes: Results of multi-group LDA topic modelling across six developmental stages of AIAEd, including topic category, index, thematic label, and intensity for each stage. Values above the stage mean are highlighted in red.

3.3 Stage-based thematic evolution

To address the second research question – What are the life cycles of these paradigms, and how has AIAEd research transitioned from one paradigm to another? – we conducted six independentrounds of LDA modelling correspondingto six publication stage (Stage 1–6), based on the optimal topic numbers identified for each stage. Thematic evolution was traced derived using cosine-similarity analysis and visualised through a Sankey diagram (Figure 6), with detailed topic distribution reported in Table 1.

Figure 7 Distribution and growth trends of input- and output-oriented themes across AIAEd developmental stages (a) proportional distribution of pedagogical input-oriented and learner-centred output-oriented themes across six developmental stages and general distribution (b) linear trend of input-oriented theme intensity over time (c) linear trend of output-oriented theme intensity over time (see online version for colours)



The results reveal a general tendency toward thematic consolidation and structural rebalancing over time. Stage 1 exhibited a relatively fragmented landscape with 12 topics, whereas subsequent stages stabilised around 9–11 topics (Stage 2 = 9; Stage 3 = 11; Stage 4 = 11; Stage 5 = 9; Stage 6 = 11). Despite this numerical convergence, topic intensity increased across stage, reaching its peak in 2025, indicating a progressive concentration and maturation of core research paradigms within AIAEd. Figure 7(a) shows that pedagogicalinput–orientedthemesdominate acrossall stages,whereas Figures 7(b) and 7(c) indicate positive linear growth trends for both input and output pathways. Relative to the overall pattern, output-oriented themes exhibit greater developmental potential.

The following sections provide a detailed account of the thematic composition, evolution trajectories, and pedagogical implications of each stage.

Stage 1 (2003–2020): Early exploration and conceptual formation

Stage 1 comprised 12 distinct topics, representing the most thematically diverse period in the dataset. Topic intensities were relatively uniform (M = 0.083), with no single dominant paradigm. The pedagogical design category (66%) reflecting early explorations into human-machineinteraction, robotics,VR-supportedlearning, gamification,and cyber-physical systems. The remaining one-third (33%) centred on Pedagogical Performance Evaluation, including community arts education, AI-assisted music learning, and initial data-driven attempts to model student performance. The prominence of broad learner groups – such as community participants, youth, and general student populations – suggests that early AIAEd research prioritised exploratory applicability over discipline-specific innovation.

This stage was dominated by conceptual advocacy, public-attitude debate, and philosophical reflection on AI's cultural and educational implications. Discussions of AI across work, art, and education became increasingly optimistic, while ethical concerns and anxieties surrounding automation persisted (Cools et al., 2024; Aleksander, 2017). Within arts education, scholars emphasised both AI's transformative potential and the risks of eroding aesthetic agency, calling for critical frameworks to guide cultural integration (Gao and Wang, 2019). Alongside these debates, early prototyping efforts emerged, including preliminary AI-supported creative experiments and rudimentary deep-learning-based performance classification.

Overall, Stage 1 represents the exploratory and formative phase of AIAEd, marked by conceptual speculation, cautious technological optimism, and tentative system development, laying the foundation for the more structured and discipline-oriented paradigms observed in later stages.

Stage 2 (2021): Early consolidation and systematisation

Stage 2 yielded nine topics, reflecting a clear transition from the exploratory diversity of Stage 1 toward early thematic consolidation. Topic intensities remained relatively even ($M = 0.11$), with no dominant paradigm. Research was overwhelmingly concentrated on Pedagogical Design (90%), covering learning-resource recommendation, online and VR-supported instruction, chatbot-assisted teaching, AI-driven pedagogical innovation, educational dataset construction, AI-STEAM curricula, and constructionist approaches to children's learning. Only one topic addressed performance evaluation, focusing on student achievement modelling, indicating that evaluative frameworks were still at a nascent stage.

Substantively, this stage was characterised by the rapid uptake of VR- and AI-enhanced instructional environments, with immersive and simulation-based learning emerging as a central methodological orientation. In parallel, the construction of educational databases gained prominence, providing essential infrastructure for subsequent data-driven AIAEd research. Early feasibility studies of AI-supported STEAM learning also appeared on this stage, marking initial efforts to connect artistic creativity with computational thinking. On the evaluative side, preliminary AI-assisted grouping and assessment approaches began to surface in visual-arts instruction, though their scope remained limited.

Overall, Stage 2 represents the initial systematisation phase of AIAEd. Pedagogical design became more structured and technologically grounded, while learning evaluation remained underdeveloped, preparing the ground for model-driven instruction and learner-centred analytics in subsequent stages.

Stage 3 (2022): Expansion into discipline-specific applications and creative paradigms

Stage 3 comprised eleven topics, with Pedagogical Design remaining dominant (N = 8). Compared with stages 1–2, topic intensities become more differentiated, indicating the emergence of clear priority directions rather than exploratory dispersion. Pedagogical design expanded into discipline-specific applications, including creative education informed by posthumanist perspectives, AI-enhanced music and martial-arts instruction, VR-supported arts learning, and system-driven digital art education models. During this stage, art education, music education, and martial arts education emerged as particularly active domains (Xu and Jiang, 2022; Liu, 2022; Ye et al., 2022). Performance-evaluation themes remained limited (N = 2), focusing primarily on learner ability modelling and video-based analytics, while one topic was excluded as irrelevant.

Turning point and criteria. Stage 3 marked a substantive shift from general pedagogical exploration to concrete disciplinary embedding. This transition is evidenced by

1 the emergence of high-intensity, domain-grounded topics

2 the alignment of AI functions with art-specific pedagogical logics (e.g., creativity theory, embodied skill training, and curriculum-level system design).

Three topics exceeded the average intensity and defined the intellectual centre. T2 (0.091) reframed creativity through posthumanist perspectives that reconsider human-machine boundaries in artistic learning (Rousell et al., 2022), supported by early HCI-based creativity modelling (Fan and Zhong, 2022). T7 (0.182), the most prominent topic, consolidated martial arts as a core AIAEd domain by linking AI-based motion analysis to embodied skill pedagogy (Ye et al., 2022). T9 (0.145) captured the growing institutionalisation of system-level AI integration within arts curricula, particularly in design and digital art education (Chen et al., 2022).

Alongside these central lines, immersive learning continued to gain momentum in creative-education contexts (Rong et al., 2022). and AI-enabled visual communication with big-data-driven pedagogical innovation also appeared (Hao, 2022). Overall, Stage 3 constitutes an expansion phase in which AIAEd shifted from general-purpose experimentation toward discipline-specific applications and creativity-oriented paradigms, while evaluation remained secondary and method-focusedrather than pedagogically comprehensive.

Stage 4 (2023): Metaverse-driven visual pedagogies and the rise of uncertainty-aware evaluation

Stage 4 comprised eleven topics, nine of which were pedagogically relevant, with Pedagogical Design remaining dominant (≈67%). Compared with Stage 3, thematic emphasis became more concentrated around visual-computational pedagogies, including metaverse-oriented visual arts education, system- and goal-driven instructional models, data-driven learning environments, AI-supported visual and experimental teaching, and multimodal fusion between metaverse infrastructures and speech-based interaction in higher education. Visual-AI technologies continued as the central technical backbone, extending from immersive learning toward metaverse-enhanced perception and visual-style modelling.

A key development in pedagogical design was the consolidation of generative-visual systems within arts curricula. Stable-diffusion and related generative-visual systems were shown to possess pedagogical value (Dehouche and Dehouche, 2023), and were increasingly adopted in design education (Fan and Li, 2023; Zhao, 2023) as well as in cultural-arts learning pathways such as Tibetan Thangka style fusion (Chen et al., 2023b). In parallel, Visual-AI algorithms further penetrated embodied-arts domains, strengthening martial-arts engagement and movement precision (Chen et al., 2023a; Hui, 2023). Together, these patterns indicate that visual-centric AI applications became structurally embedded rather than experimentally deployed.

The most salient transition of Stage 4 occurred within Pedagogical Performance Evaluation, which reached its first substantive peak. The most intensive topic – AI learning and performance evaluation under uncertainty (0.16) – marked a conceptual transition from earlier accuracy-centred evaluation toward uncertainty-aware and affect-sensitive evaluation. This transition is reflected in evidence demonstrating reliable AI-supported assessment in authentic learning contexts (Aloisi, 2023), alongside VUCA-based immersive learning framework (Devassy et al., 2023) and fuzzy ordinal models for noisy academic prediction (Gámez-Granados et al., 2023). Emotional and socio-cognitive dimensions were further incorporated through multimodal emotion AI systems (Akalya Devi et al., 2023) and empathy-oriented robotic companions that increased learner acceptance (Han et al., 2023).

In addition, 2023 marked the first substantive emergence of the metaverse in AIAEd. Metaverse-driven themes integrated VR/AR, multimodal interfaces, and immersive visualisation into higher-arts education, exemplified by metaverse-based visual-arts evaluation frameworks (Hu, 2023). Collectively, Stage 4 represents a pivotal year in which AIAEd consolidated its reliance on visual-computational technologies while broadened its evaluative paradigms to incorporate uncertainty, emotion, and multimodal immersive experience.

Stage 5 (2024): Generative AI and metaverse in arts education

Stage 5 comprised nine topics, with pedagogical design remaining dominant (89%). Compared with Stage 4, thematic emphasis shifted from immersive-environment construction toward generative-AI-centred pedagogical innovation. Core themes included modelling of learning environments, task-oriented AI systems, aesthetic data representation, cross-domain AI applications, metaverse-based art instruction, chatbot-supported knowledge construction, and ChatGPT-enabled educational tools. Performance evaluation remained marginal, represented by a single topic with limited pedagogical relevance. The defining characteristic of this stage was the decisive entrance of generative AI – particularly ChatGPT – as a central pedagogical and discursive anchor in arts education.

Within pedagogical design, technological refinement continued through deep-learning enhancements (Chiu et al., 2024), big-data applications in art education (Huang et al., 2024b), IoT-supported AI art-teaching systems (Fang and Jiang, 2024), and hybrid ResNet-TCN architectures for attention recognition in online classrooms (Tu et al., 2024). In parallel, the metaverse persisted from Stage 4 but moved toward more grounded educational implementation. Evidence from Wu et al. (2024) shows that collaboration within educational metaverse depends on environmental facilitation and learners' self-efficacy.

A major transition occurred as generative AI began to eclipse the metaverse as the dominant paradigm. The most intensive topics, T6 (0.209) and T8 (0.088), reflected the rapid diffusion of generative-AI-driven educational tools. Public engagement with AI-generated content positioned GAI as a major driver of educational innovation (Chalupa and Nesměrák, 2024). Empirical studies reported benefits in gamified instruction (Huang et al., 2024a) and STEAM learning, where AIGC tools reduced gender disparities in art practice (Lee et al., 2024). Yet concerns surrounding authorship, privacy, and job displacement intensified among art- and design-major students (Shen et al., 2024), echoing broader ethical debates about intellectual property and labour futures (Wang, 2024).

By 2024, the earlier launch of ChatGPT had translated into structural changes in AIAEd trajectories, reshaping lifelong-learning and assessment frameworks (Kolade et al., 2024). Applications such as face-biometric evaluation (Deandres-Tame et al., 2024) illustrated the growing relevance of generative AI to arts-education assessment. Collectively, Stage 5 represents a paradigm-shift phase in which human-AI interaction, creativity-oriented pedagogy, and generative media displaced immersive-environment technologies as the primary drivers of AIAEd development.

Stage 6 (2025): Integration of creative AI tools and multidimensional learner evaluation

The sixth stage (2025, K = 11) represents the most expanded and structurally differentiated phase of AIAEd development. Among the ten valid topics, four exceeded the stage average intensity (M = 0.091) – student learning and creative AI tools in education (T0 = 0.138), general AI applications in arts and education (T3 = 0.123), AI-driven feedback in higher education (T7 = 0.138), and social and health evaluation of learning performance (T8 = 0.154). Unlike Stage 5, which was dominated by pedagogical design, Stage 6 displayed a more balanced distribution between pedagogical design and performance evaluation with broader cross-domain applications.

Pedagogical design in Stage 6 was shaped by the consolidation of generative AI – especially ChatGPT – into mainstream educational practice. Topics related to creative AI tool use (T0), ChatGPT-based learner modelling (T1), and generative AI for arts and design education (T5) reflected a shift toward creativity-oriented, affect-sensitive, and STEAM-aligned pedagogical innovation (Fang et al., 2025; Wu et al., 2025). Technical refinement moved from system construction toward fine-grained pedagogical functions, including explainable quality assessment for martial-arts movement (Pang et al., 2025), AI-driven gesture-based feedback for educators (Saini et al., 2025), and comprehensive AI-supported exercise recommendation (Liu et al., 2025a).

In parallel, Stage 6 displayed a more reflective orientation toward the pedagogical consequences of generative AI. De Silva et al. (2025) emphasised the need for sustained AI literacy and intentional integration, while Hwang and Wu (2025) argued that visual design education requires new goals and instructional methods in the GAI era. Teacher attitudes emerged as a central implementation factor, influencing educators' self-efficacy and adoption behaviours (Yang, 2025).

Performance Evaluation expanded markedly and became a co-dominant paradigm in this stage. For the first time, socio-emotional and health-related learning states became central evaluative dimensions (T8 = 0.154). Assessment frameworks moved beyond academic performance modelling (T6) toward multidimensional analyses capturing emotional readiness, psychological states, and technology acceptance. Studies demonstrated that students' attitudes toward AI shape educational effectiveness (Sáez-Velasco et al., 2025), sustained learning intention (Sun et al., 2025), and, in fine arts education, a chained mediation linking AI use → self-efficacy → achievement emotions → academic engagement (Zhang et al., 2025).

A further hallmark of Stage 6 was the systematic integration of arts with health and medical education, reflecting the expansion toward wellbeing-oriented evaluation. Arts were increasingly used 'as a lens for reflecting on social determinants of health' and incorporated into medical, cardiology, nursing, and health-professions training (Khoshgoftar et al., 2025; Ugoala et al., 2025; Weltin and Gedney-Lose, 2025; Agarwal et al., 2025). Together, these patterns indicate that Stage 6 marks a maturation phase in which creative AI tools and multidimensional learner evaluation converge to support holistic, human-centred AIAEd ecosystems.

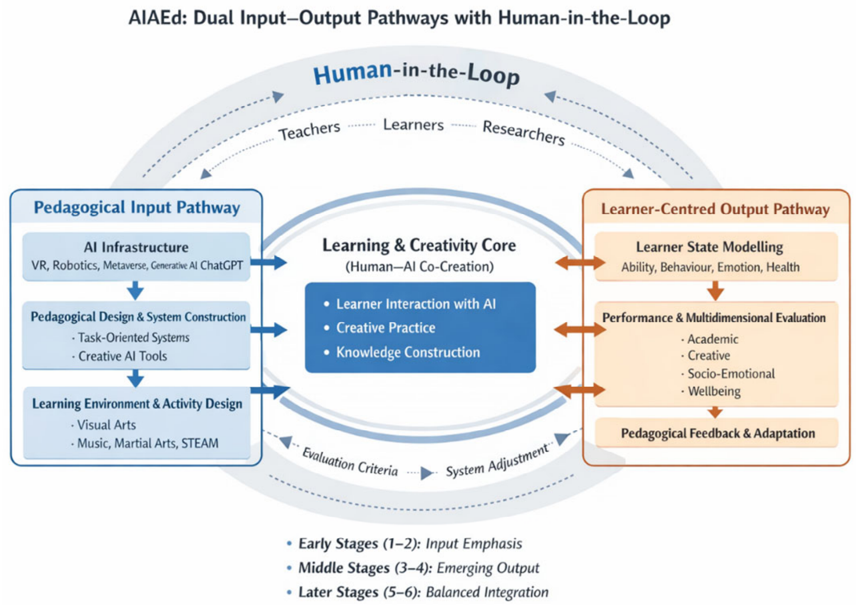
3.4 Cross-stage evolution: emerging trajectories in AIAEd research

Figure 8 shows a conceptual framework of AIAEd that organises the field into dual pedagogical input-output pathways connected through a human-in-the-loop feedback mechanism. Across the six developmental stages, AIAEd demonstrates a clear transition from technology-centred experimentation to learner-centred, creativity-oriented, and context-sensitive pedagogical models. Longitudinal similarity analyses highlight how specific paradigms transformed across phases. For example, the strongest early continuity emerged between T0 (Stage 1) and T6 (Stage 2) (cosine similarity = 0.599), both rooted in human-machine interaction in artistic learning. Immersive-learning themes showed similar stability: T2 (Stage 2) and T4 (Stage 3) both addressed VR-supported instruction, with later work shifting emphasis toward higher-education contexts. Performance-evaluation themes also evolved progressively: T7 (Stage 2) transitioned to T10 (Stage 3), where animation-enhanced instructional systems expanded assessment capabilities.

A pivotal turning point occurred in Stage 3, when discipline-specific and creativity-oriented topics begin to exert downstream influence. The strongest Stage 3 topic (T10) connects directly to Stage 4 themes of goal-oriented system design (T3) and data-driven future-learning environments (T4), indicating a consolidation of system-level pedagogical frameworks. These analytics-based paradigms subsequently provide the conceptual pathway for Stage 5's ChatGPT-driven learning innovation (T8; similarity = 0.80), marking the entry of generative AI as a structural anchor in AIAEd.

From Stage 5 onward, generative-AI-centred themes expand from instructional-design tools to drivers of student learning and evaluation. In Stage 6, ChatGPT-linked paradigms (T0; similarity = 0.80) extended into social, psychological, and health-related learning evaluation (T8; similarity = 0.80). Parallel convergence is observed for metaverse-based themes (T5, Stage 5), whose data-intensive logic aligns with generative-AI ecosystems rather than functioning as an independent dominant paradigm. Together, these continuity patterns confirm that generative-AI infrastructures, rather than immersive environments alone, have become the dominant technological backbone of contemporary AIAEd.

Figure 8 Dual input-output conceptual framework of AIAEd with a human-in-the-loop mechanism (see online version for colours)



Notes: Conceptual framework of AIAEd showing dual pedagogical pathways: the pedagogical input pathway (left), the learning and creativity core (centre), and the learner-centred output pathway (right), interconnected through a human-in-the-loop mechanism.

These cross-stage transitions correspond to three macro-level shifts in the field. First, early stages (Stages 1–2) are characterised by fundamental principle design (T1) and technological development (T2), reflecting initial concerns with feasibility, human-machine interaction, robotics, and VR-supported instruction. Second, middle stages (Stages 3–4) demonstrate a delayed but decisive move toward student learning model construction and intelligent behavioural evaluation, accompanied by discipline-specific embedding and multimodal learning environments. Third, later stages (Stages 5–6) are defined by personalised learning and creative performance optimisation, driven primarily by generative AI and dialogic human-AI interaction.

Within this later period, learner agency, affect-aware modelling, and multidimensional feedback systems become central organising principles. Research increasingly foregrounds emotional-social dimensions of learning, adaptive creativity support, and personalised developmental trajectories. At the same time, new cross-domain directions gain visibility, particularly arts-in-health education, affective computing, and socio-psychological evaluation of learning outcomes. Together, these evolutionary dynamics suggest that the future of AIAEd lies not in the accumulation of novel technologies, but in the construction of human-centred, creativity-driven, and ethically grounded AI ecosystems capable of supporting holistic artistic literacy and learner development.

4 Conclusions

This study provides the first longitudinal, multi-stage, human-in-the-loop computational review of AIAEd based on 372 publications published between 2003 and 2025. By integrating LDA–Computational Grounded Theory workflow, we systematically mapped the field's thematic composition and evolutionary trajectories. Five enduring paradigmatic clusters were identified – fundamental principle design, technological development and enhancement, student learning model construction, intelligent evaluation of learning behaviour, and personalised learning with creative performance optimisation – revealing a dual structure of pedagogical input-oriented design and learner-centred output-oriented evaluation. Across six developmental stages, AIAEd demonstrates a systematic shift from early technology-centred exploration toward discipline-specific applications, followed by the consolidation of generative-AI-driven pedagogies characterised by multimodal feedback, affect-aware learner modelling, and human-AI co-creative practices. In parallel, input-oriented pedagogical design themes remain structurally dominant, while learner-centred output-oriented evaluation themes show steady growth and increasing strategic significance for the field.

Looking forward, the imbalances identified between dominant input-oriented pedagogical design and comparatively weaker output-oriented evaluation, together with the coexistence of rapid adoption and persistent anxiety surrounding AI-driven tools, suggest that future AIAEd development should prioritise capacity building for teachers and learners alongside coordinated institutional support. For teachers, the central developmental shift is from operating AI tools to orchestrating human-AI co-creative pedagogy, including designing AI-supported creative tasks, interpreting multimodal learner data, and providing process-oriented, affect-aware formative feedback. For learners, future AIAEd environments should foster critical AI literacy and creative agency, guiding students to articulate intent, make aesthetic decisions, and reflect on the division of labour between human contribution and machine assistance. At the institutional and policy levels, these trends call for balanced investment in infrastructures that support both instructional design and learner-centred evaluation, the establishment of clear guidelines on authorship, data governance, and acceptable generative-AI use, and sustained professional development focused on pedagogical integration and assessment literacy rather than short-term tool training. Collectively, these directions translate the field's paradigm shift toward human-centred, creativity-oriented, and multidimensional evaluation into actionable pathways

5 Limitation

Despite efforts to ensure methodological rigour and analytical completeness, this study has several limitations. First, LDA-based topic modelling is inherently sensitive to corpus composition, preprocessing, and parameter selection; therefore, the identified topics should be interpreted as probabilistic thematic patterns rather than fixed or exhaustive classifications. Although coherence-perplexity optimisation and human-in-the-loop validation were employed to enhance interpretability, this methodological constraint should be acknowledged. Second, following common practice in large-scale bibliometric and topic-modelling studies, the analysis was conducted on titles and abstracts rather than full texts. While abstracts capture core research aims, methods, and contributions, they may omit methodological nuances, theoretical subtleties, and contextual details present in full articles. Future research could extend the present methodological framework by incorporating additional natural language processing techniques and full-text or mixed abstract-full-text corpora.

Declarations

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