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Mapping Sentiment Analysis in Educational Technology: OpenAlex Bibliometrics, Thematic Trends, and Research Gaps (2013-2025)

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Abstract. This study aims to map the intellectual structure, publication growth, collaboration patterns, thematic evolution, and research gaps of sentiment analysis in educational technology. The study addresses the lack of an open and integrated bibliometric synthesis that connects productivity, collaboration, topic modelling, and gap detection in this field. A bibliometric and science-mapping approach was applied using OpenAlex-indexed publications from 2013 to 2025. After deduplication and eligibility screening, 977 publications were analysed, while 768 papers with sufficient abstract text were used for Non-negative Matrix Factorisation topic modelling. The analysis included publication trend analysis, country and institutional productivity, co-authorship networks, keyword burst analysis, geographic gap analysis, and platform mention analysis. The results show that annual publications increased from 22 papers in 2013 to 123 papers in 2024, with India and China as the most productive countries. Six thematic clusters were identified: Learning Analytics, Social Media Sentiment, Emotion Recognition, MOOCs and E-learning, Transformers/LLMs, and ML Classifier Ensembles. Learning Analytics was the largest cluster, while Transformers/LLMs showed the fastest recent growth. The novelty of this study lies in its reproducible OpenAlex-based bibliometric framework, which integrates performance analysis, science mapping, thematic evolution, and research gap identification for sentiment analysis in educational technology.

Keywords: Sentiment analysis; Educational technology; Bibliometric analysis; OpenAlex; Learning analytics.

1. INTRODUCTION

The rapid proliferation of digital learning environments has generated large volumes of textual data—forum posts, course reviews, learner reflections, discussion threads, and social media commentary—that encode learners' affective and evaluative experiences. Sentiment analysis (SA), the computational identification of opinion polarity and emotional content in text, has therefore become increasingly relevant to educational technology research [1], [2], [3]. Its applications now range from student feedback and MOOC evaluation [4], [5] to classroom emotion recognition [6], affect-aware tutoring systems [7], and transformer-based educational text classification [8], [9].

Despite this empirical richness, the field still lacks a systematic, data-driven cartography of its intellectual structure. Existing reviews have usefully synthesised techniques for student feedback mining [10], MOOC sentiment analysis [11], and educational data mining applications, but they do not provide a field-level bibliometric account of productivity, collaboration, thematic evolution, and research gaps in one reproducible framework. As a consequence, several fundamental bibliometric questions remain insufficiently answered. Which countries and institutions are driving this field? How have thematic priorities shifted before and after the COVID-19 pandemic, which in 2020 triggered a global migration to online education? What is the structure of international research collaboration? And which EdTech sub-themes remain underexplored relative to their pedagogical importance?

Bibliometric analysis offers a rigorous and reproducible methodology for addressing these questions at scale. By combining performance analysis—quantitative measurement of productivity, citation impact, and geographic distribution—with science mapping techniques such as co-authorship network analysis, keyword co-occurrence mapping, and topic modelling, bibliometric methods can reveal the latent intellectual architecture of a field and identify its evolving frontiers [12], [13], [14]. Yet many bibliometric treatments of education and AI continue to rely on commercial databases such as Scopus and Web of Science, which can impose access barriers and reduce reproducibility. The present study uses OpenAlex—a fully open, API-accessible bibliographic index whose coverage has recently been compared with major commercial databases—to improve methodological transparency and support replication of the retrieval process [15].

The research gap addressed here is therefore not the absence of SA-EdTech studies, but the absence of an open, integrated bibliometric synthesis that connects publication growth, collaboration patterns, topic evolution, and gap detection. This paper contributes such a mapping by analysing OpenAlex-indexed publications from 2013 to 2025, decomposing the field into six operationally distinct sub-themes, comparing pre-pandemic and post-pandemic thematic patterns, and identifying under-served research niches including multilingual SA, platform-specific LMS studies, and sentiment-informed adaptive learning interventions. The novelty is framed as a reproducible bibliometric and science-mapping framework rather than as a new conceptual model of educational sentiment itself.

Five research questions guide the study:

1) How has the volume of publications on sentiment analysis in educational technology evolved from 2013 to 2025?
2) Who are the most prolific and influential authors, institutions, and countries in this field, and what patterns characterise their collaboration networks?
3) Which thematic clusters dominate the field, and how have their relative weights shifted between the pre-pandemic (2013–2019) and post-pandemic (2020–2025) periods?
4) What is the structure of international research collaboration in SA-EdTech, and which communities of scholars are most interconnected?
5) Which sub-themes within educational technology remain underexplored, particularly regarding multilingual contexts, Asian LMS platforms, and adaptive learning interventions?

Sentiment analysis, also referred to as opinion mining, covers NLP techniques for identifying polarity, subjectivity, and emotional content in text [2], [3]. The field progressed from early document-level machine learning classification [16] to sentence- and aspect-level analysis [17], then from lexicon-based approaches such as SentiWordNet [18] and VADER [19] to supervised classifiers [20], deep learning models [21], [22], and transformer-based pre-trained language models [8]. Sentiment Analysis in Educational Technology Contexts The application of SA to education has moved from early studies of student feedback, Facebook data, and MOOC discussion forums [1], [4], [23] toward larger-scale deep learning, multimodal affective computing, ChatGPT-related discourse, and affect-

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aware learning analytics [5], [7], [24], [25], [26]. This trajectory shows a shift from descriptive sentiment classification toward systems that may support monitoring, intervention, and adaptive learning.

Despite the volume of empirical SA-EdTech studies, the literature remains fragmented. Kastrati et al. [10] mapped SA techniques for student feedback, while Dalipi et al. [11] reviewed MOOC feedback sentiment analysis. Adjacent bibliometric studies have mapped AI in higher education [27], [28], but they do not jointly examine SA-EdTech productivity, collaboration, topic evolution, OpenAlex retrieval, and regional/platform gaps across 2013–2025. The present study therefore builds on and extends these foundations by combining, for the first time, a comprehensive performance analysis with NMF-based topic modelling, co-authorship network analysis, and geographic gap detection within the OpenAlex ecosystem.

2. METHODS

2.1. Study Design and Analytical Framework

This study adopts a bibliometric design combining performance analysis and science mapping [12]. Performance analysis quantifies output and impact by authors, institutions, countries, and sources, while science mapping uses network analysis and topic modelling to reveal thematic and collaborative structure [13], [14]. Together, these approaches answer who contributes, what themes dominate, and how the field is connected. The analytical workflow followed six steps: OpenAlex retrieval using paired SA and EdTech terms; deduplication by OpenAlex work identifier; descriptive performance analysis; co-authorship and country-network construction; NMF topic modelling of eligible abstracts; and synthesis of citation impact, keyword bursts, regional thematic gaps, and platform mention counts.

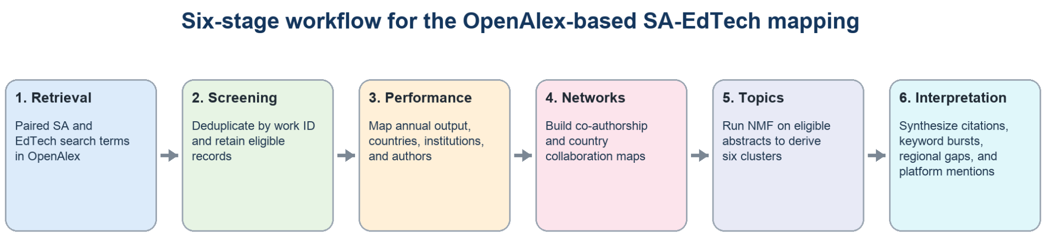

Figure 1. Workflow for OpenAlex-based SA-EdTech Mapping

2.2. Data Source: OpenAlex

Data were retrieved exclusively from OpenAlex, a fully open and continuously updated bibliographic index. The retrieval was conducted through the OpenAlex REST API on 9 March 2026, producing a reproducible database snapshot for the present analysis. OpenAlex provides programmatic access to scholarly works across disciplines and has recently been benchmarked against major commercial databases, making it suitable for transparent bibliometric research [15]. All retrieval scripts are archived in the study's supplementary materials to enable full reproduction of the dataset.

2.3. Search Strategy and Eligibility Criteria

The search query was constructed to capture publications at the intersection of sentiment analysis and educational technology. Four SA-related terms—"sentiment analysis", "opinion mining", "emotion recognition", and "affective computing"—were paired with seven educational technology terms: "educational technology", "e-learning", "MOOC", "LMS", "learning analytics", "intelligent tutoring", and "computer-assisted learning". Each of the 28 term pairs was submitted to OpenAlex using AND logic in the filter parameter: title_and_abstract.search: "SA_TERM", title_and_abstract.search: "EDTECH_TERM", publication_year: 2013-2025. Cursor pagination was used to retrieve all records returned for each query pair. The temporal scope was restricted to 2013–2025 because 2013 marks the period in which MOOC platforms achieved mainstream adoption and early high-citation SA-in-education papers appeared in indexed literature [1], [4].

The final corpus retained OpenAlex records that matched at least one SA–EdTech query pair within the 2013–2025 publication-year range and contained sufficient bibliographic metadata for descriptive analysis. Topic modelling was restricted to records with reconstructable abstract text. Because OpenAlex is dynamic and the latest indexed year can continue to change after retrieval, 2025 was treated as a latest-year snapshot in trend interpretation rather than as a stable complete-year comparator.

2.4. Data Preprocessing

Following API retrieval, raw records were deduplicated by OpenAlex work identifier (W-number). Authorship affiliation metadata was disambiguated using OpenAlex's native institution and country assignment. For records with missing country assignments, country-level imputation was performed based on the first author's institutional affiliation where available. A total of 977 papers met all eligibility criteria after deduplication and field completeness checks, representing the final analytical corpus. Of these, 768 papers (78.6%) possessed sufficient abstract text for topic modelling.

2.5. Bibliometric and Analytical Methods

Performance analysis computed annual publication counts, country- and institution-level productivity rankings, top-author identification, and citation impact metrics (total citations, citations per year normalised by publication age). Citation data were drawn from OpenAlex's cited-by-count field, which aggregates inbound citations across the OpenAlex corpus as of the retrieval date. Co-authorship network analysis constructed undirected weighted graphs in which nodes represent authors and edges represent co-authored publications. The full author network comprised 2,996 nodes and 29,087 edges; the visualised subgraph retained authors with three or more publications (n = 80 nodes, 62 edges). Louvain community detection [29], degree centrality, and betweenness centrality were used to identify collaboration communities and bridge authors. Topic modelling applied Non-negative Matrix Factorisation (NMF) [30] to TF-IDF-weighted abstracts. The number of topics was set to k = 6 based on reconstruction error (26.1350), semantic separability, and interpretability: smaller models merged MOOCs, learning analytics, and social media, while larger models split transformer and classifier terms into less stable sub-clusters. Parameters were minimum document frequency = 5, maximum document frequency = 0.90, maximum features = 5,000, and unigrams/bigrams.

Keyword burst analysis compared keyword frequencies between the early period (2013–2019) and the recent period (2023–2025) to identify terms with the largest relative frequency increases, operationalised as the difference in keyword proportion between the two periods (burst score = p_recent - p_early).

Geographic gap analysis compared topic distributions across country groupings (Western: USA, UK, Australia; Asian: China, India, Indonesia) to quantify systematic thematic differences between regional research communities. Platform-specific research was assessed by counting explicit mentions of named LMS and MOOC platforms (Moodle, Canvas, Blackboard, Coursera, edX) versus generic terms (LMS, MOOC) in titles and abstracts.

2.6. Research Ethics

This study is conducted exclusively on publicly available bibliographic metadata retrieved from an open API. No human participants, primary data collection, or personally identifiable information were involved. The study therefore requires no ethical approval beyond standard research integrity practices.

3. RESULTS AND DISCUSSION

3.1. Publication Growth Trends (RQ1)

The analytical corpus of 977 publications demonstrates a sustained upward trajectory over the 2013–2025 observation window (Figure 2). To avoid overstating growth from the latest indexed year, the complete-year trend is interpreted primarily through 2024: annual output rose from 22 papers in 2013 to 123 papers in 2024, a 459% increase and an approximate CAGR of 16.9%. The OpenAlex retrieval snapshot also contained 225 publications for 2025; this figure is reported as the latest indexed count but is not used as the basis for complete-year growth calculations because OpenAlex records can continue to update after retrieval.

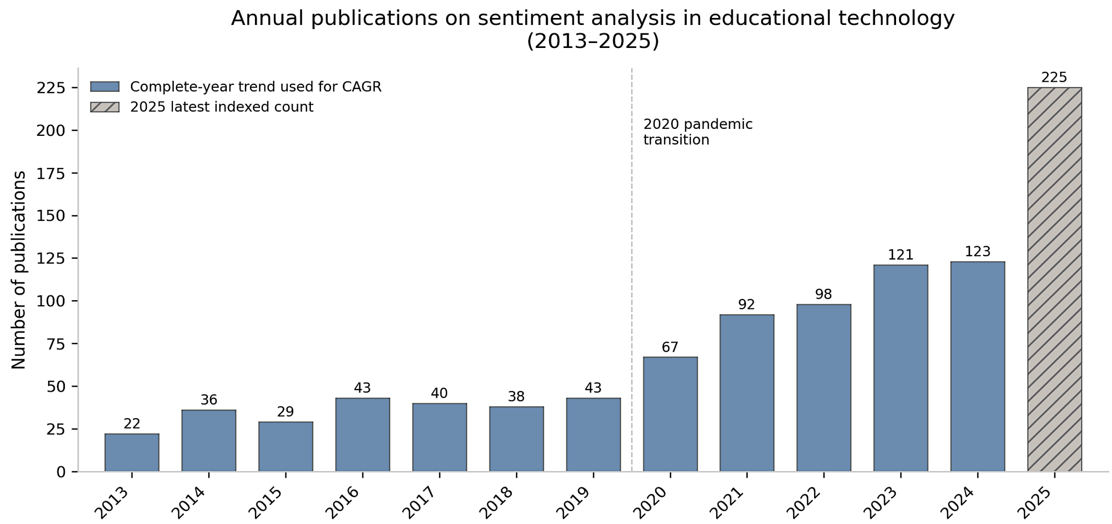

Figure 2. Annual publication counts for sentiment analysis in educational technology retrieved from OpenAlex, 2013–2025 (n = 977; retrieval snapshot: 9 March 2026). The dashed vertical line at 2020 demarcates the pre-pandemic (2013–2019) and post-pandemic (2020–2025) analytical periods. The grey shaded region indicates the 2020–2021 COVID-19 pandemic period. The 2025 bar is interpreted as a latest-year indexed count and is not used for CAGR estimation.

The first growth phase (2013–2019) fluctuated between 22 and 43 papers annually, reflecting an emerging niche. Output then rose from 43 papers in 2019 to 67 in 2020, 92 in 2021, 98 in 2022, 121 in 2023, and 123 in 2024. The 2025 indexed count suggests continued growth, but it is treated cautiously because it comes from a dynamic OpenAlex snapshot rather than a stable complete-year comparator.

3.2. Geographical and Institutional Distribution (RQ2)

1) Country-Level Productivity

Figure 3 shows that India leads with 149 publications (15.3%), followed by China (136; 13.9%), the United States (73; 7.5%), and the United Kingdom (49; 5.0%). Morocco, Saudi Arabia, Malaysia, Indonesia, and Pakistan also appear among productive contributors, indicating that SA-EdTech research has diffused across Asian, MENA, and Western research systems.

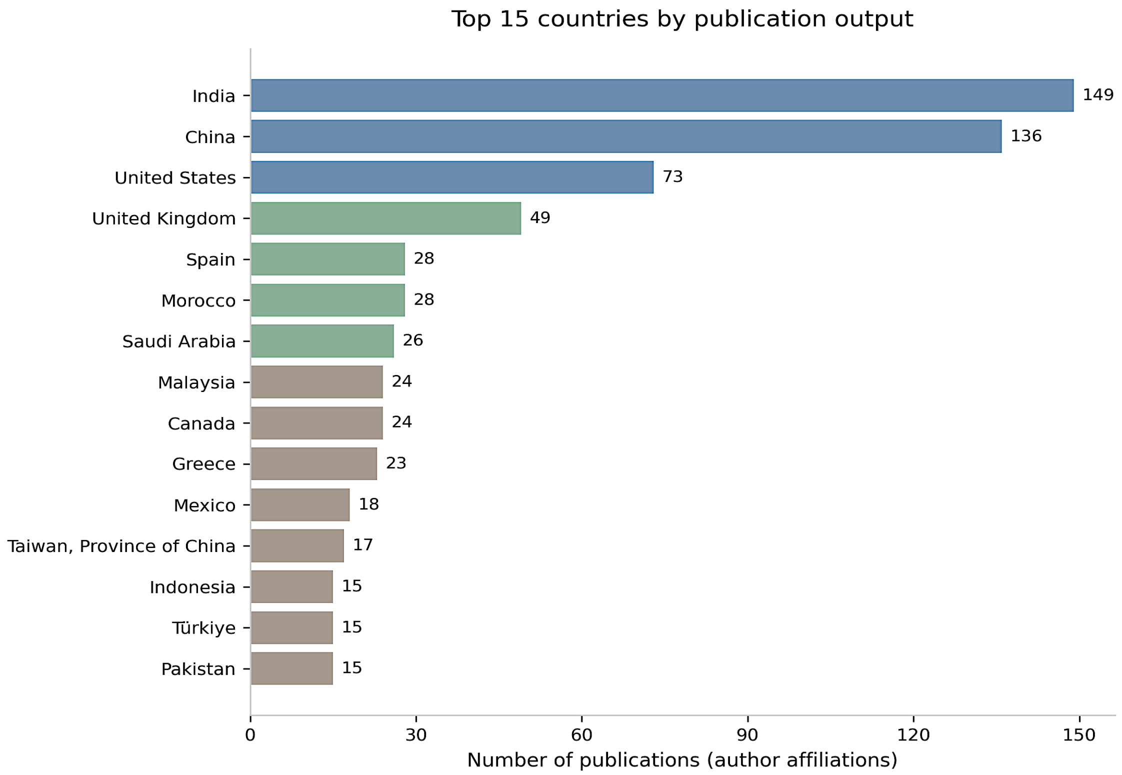

Figure 3. Top 15 countries by number of publications on sentiment analysis in educational technology (2013–2025). Countries are ranked by total paper count. Colours distinguish Asian-Pacific (blue), Middle Eastern and North African (orange), Western (green), and other (grey) affiliations.

2) Institutional Productivity

Figure 4 shows a dispersed institutional landscape. The University of Piraeus, Mohammed V University, Instituto Tecnológico de Culiacán, and National University of Tainan share the top rank with 8 papers, while several Indian institutions also appear prominently. The Open University is the only top institution with a primary distance-learning mission.

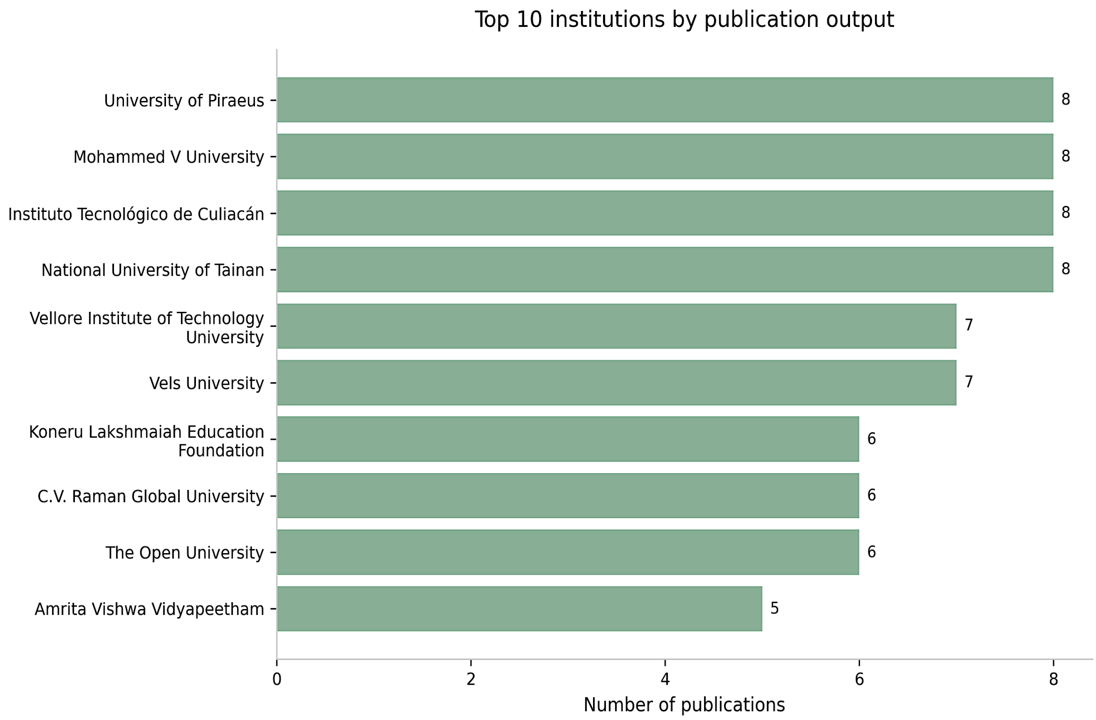

Figure 4. Top 10 institutions by publication count on sentiment analysis in educational technology (2013–2025). Institution names are displayed in full where space permits.

3) Author-Level Productivity

Figure 5 identifies Azhar Imran, Jianqiang Li, and Ahmad Alshammari as the most prolific authors, each with 21 papers. Ramón Zataraín Cabada and María Lucía Barrón Estrada represent emotion-aware tutoring research, while Maria Virvou, Christos Troussas, and Jesús G. Boticario represent European work on affective user modelling and adaptive systems.

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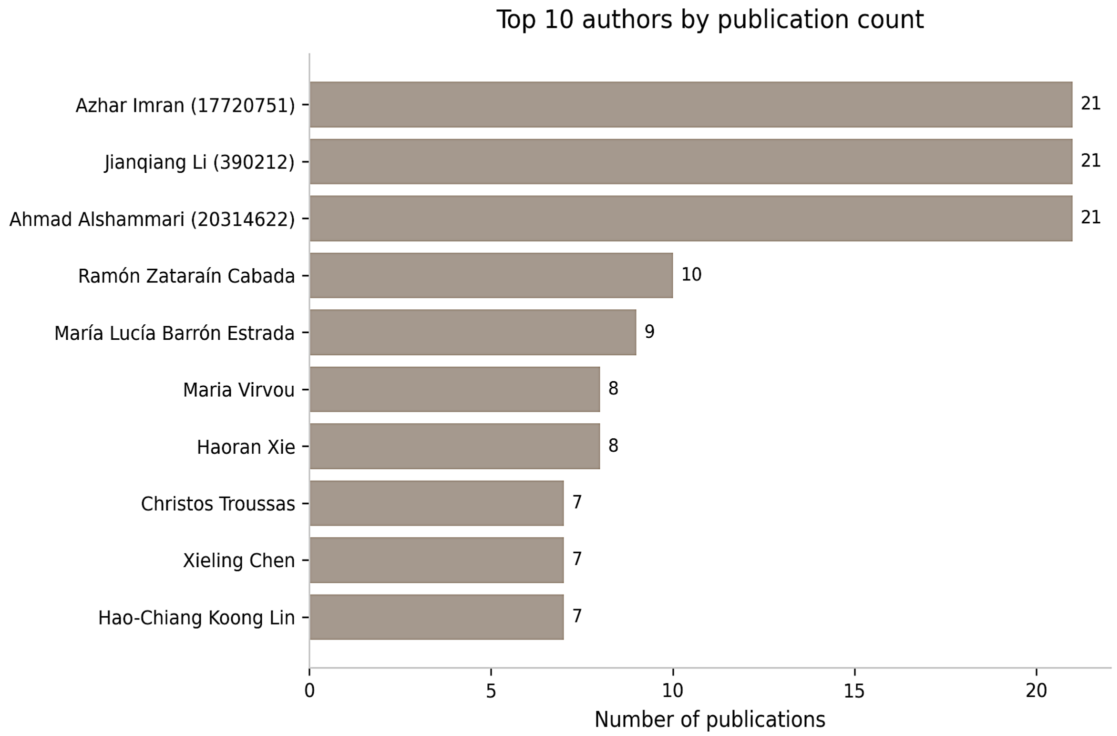

Figure 5. Top 10 most prolific authors by publication count in sentiment analysis in educational technology research (2013–2025). Bar lengths represent total paper count within the OpenAlex corpus.

3.3. Collaboration Network Analysis (RQ4)

1) Co-Authorship Networks

The full co-authorship graph encompasses 2,996 author nodes and 29,087 edges, indicating a densely connected underlying network. However, when filtered to authors with three or more publications (n = 80 nodes, 62 edges), the network reveals a markedly fragmented structure organised into 40 distinct communities (Figure 6). This fragmentation suggests that most productive authors cluster in small, internally cohesive research groups with limited inter-community bridging—a pattern characteristic of young interdisciplinary fields in which disciplinary silos (computer science, educational technology, cognitive science) have not yet fully coalesced [31].

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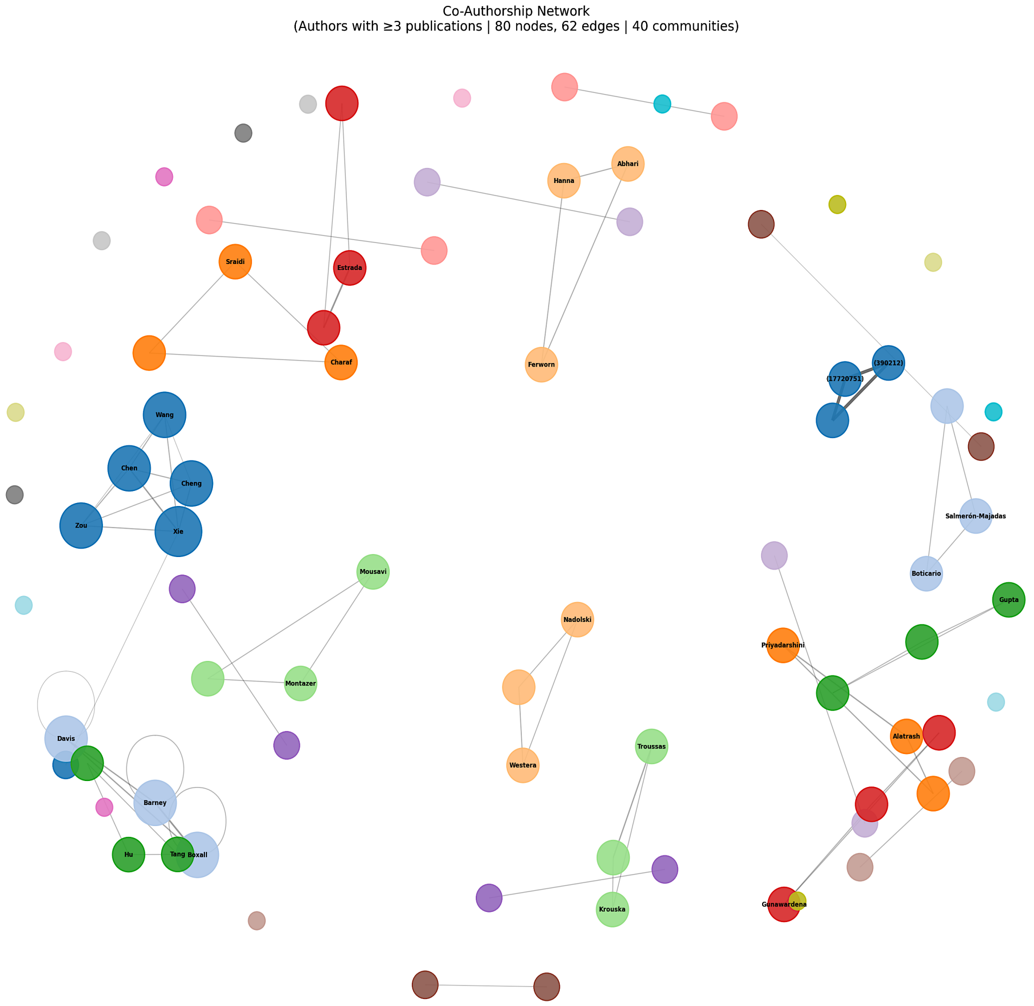

Figure 6. Co-authorship network of prolific authors (those with ≥ 3 publications, n = 80 nodes, 62 edges). Node size is proportional to degree centrality; edge thickness reflects the number of co-authored papers. Colours denote distinct communities identified by the Louvain algorithm (40 communities detected in total; the five largest are labelled).

Degree and betweenness centrality identify Haoran Xie as the most visible bridge author, followed by collaborators including Di Zou, Gary Cheng, Fu Lee Wang, and Xieling Chen. The five largest communities correspond broadly to Chinese language-learning analytics, the Imran–Alshammari–Li productivity cluster, management-science-adjacent work, Spanish adaptive learning research, and a smaller interdisciplinary group.

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2) Country Collaboration Networks

The international collaboration network (Figure 7) comprises 72 country nodes and 157 edges. India–United States represents the strongest bilateral collaboration link (8 joint papers), followed by Malaysia–United Kingdom, Saudi Arabia–Pakistan, China–Hong Kong, and USA–UK (all with 5 joint papers). Saudi Arabia emerges as a notable collaboration hub, co-authoring with the UK (4 papers), China (3 papers), Pakistan (5 papers), and other partners. The network reveals a partial North–South collaboration structure in which several Global South research communities collaborate internationally primarily with English-speaking Western nations rather than with each other.

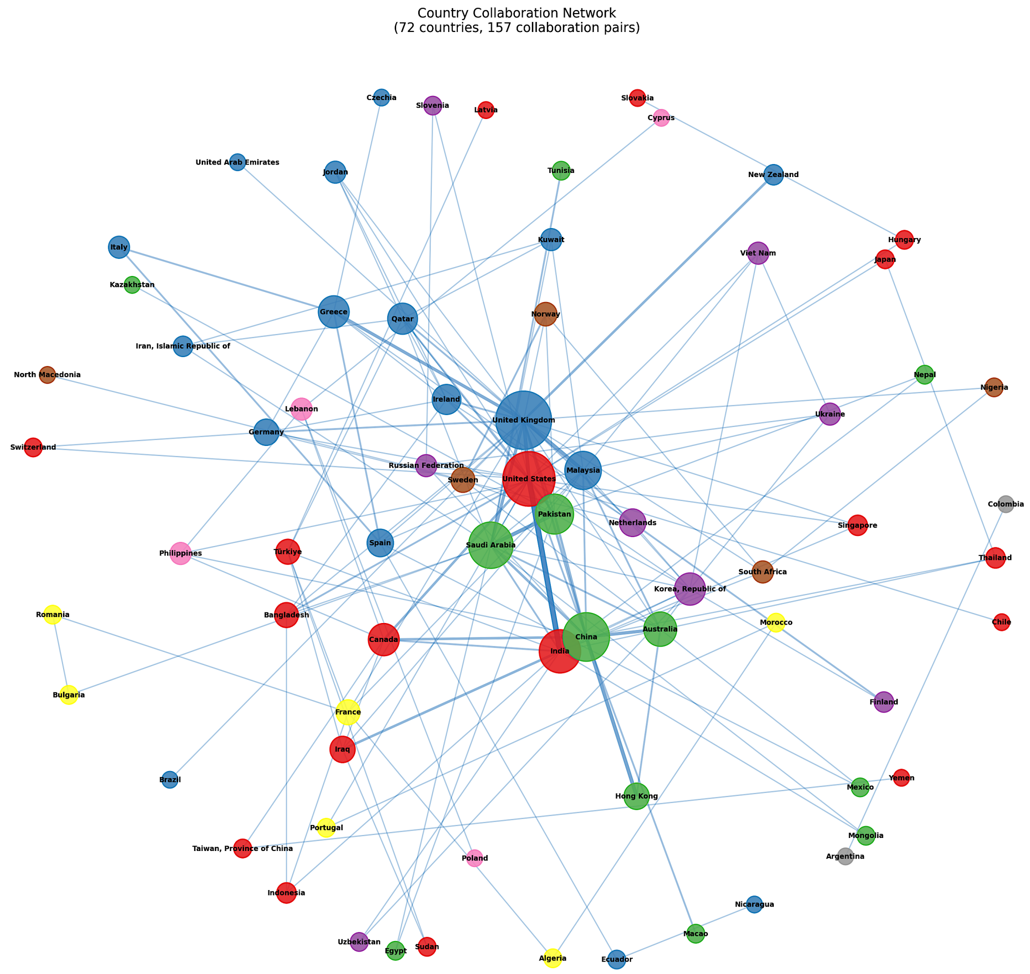

Figure 7. International collaboration network for sentiment analysis in educational technology research (2013–2025). Nodes represent countries; edges represent joint publications. Node size is proportional to total paper count; edge thickness reflects the number of jointly authored papers. The top-10 collaboration pairs are labelled.

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3.4. Thematic Clustering and Topic Evolution (RQ3)

1) Identified Research Clusters

NMF topic modelling applied to 768 abstracts with sufficient text yielded six interpretable thematic clusters (Figure 8). The clusters, their characteristic keywords, and their proportional representation in the corpus are detailed in Table 1.

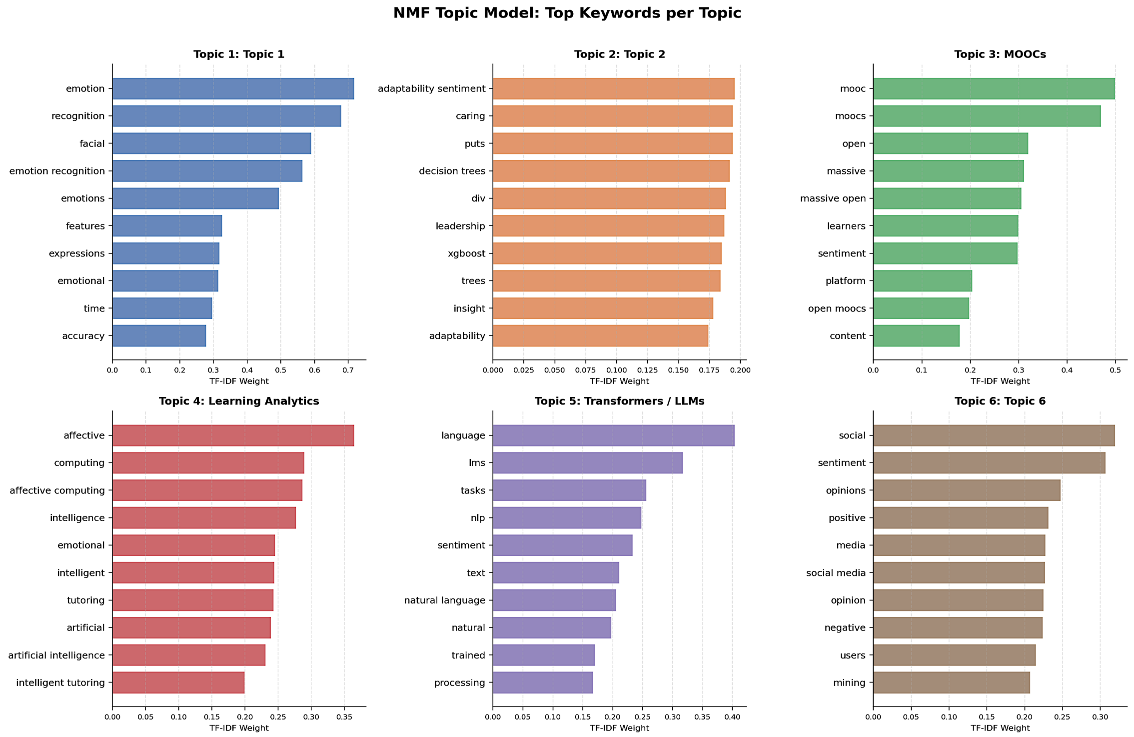

Figure 8. Top-15 keywords for each of the six NMF-identified topics, weighted by TF-IDF loading scores. Bar length reflects keyword weight within the topic; colours distinguish the six themes.

Table 1. Summary of six NMF-identified thematic clusters: label, key terms, paper count, corpus share, and exemplary high-cited works.

Cluster Label	Top Keywords	Papers	%	Example High-Cited Work
Emotion Recognition	emotion, recognition, facial, expression, real-time	147	19.1	Savchenko (2022), TAFFC
ML Classifier Ensembles	adaptability, decision trees,	22	2.9	—

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Cluster Label	Top Keywords	Papers	%	Example High-Cited Work
	XGBoost, random forest, leadership			
MOOCs & E-learning	MOOC, massive open, learners, forum, platform	132	17.2	Onan (2021), CAE; Wen et al. (2014)
Learning Analytics	affective computing, intelligent tutoring, personalised, analytics	204	26.6	Chen et al. (2023); D'Mello et al.
Transformers / LLMs	language, NLP, BERT, pre-trained, tasks, sentiment	102	13.3	AutoPrompt (Shin 2020)
Social Media Sentiment	social media, opinions, Twitter, positive/negative, mining	161	21.0	Adeshola & Sani (2023); Yadollahi (2017)

The Learning Analytics cluster is the largest (26.6%; 204 papers), followed by Social Media Sentiment (21.0%; 161), Emotion Recognition (19.1%; 147), MOOCs & E-learning (17.2%; 132), Transformers / LLMs (13.3%; 102), and ML Classifier Ensembles (2.9%; 22). Together, these clusters show that the field spans educational analytics, online discourse, computer vision, MOOC evaluation, and newer transformer-based classification.

2) Citation Impact by Cluster

Table 2 presents citation metrics disaggregated by thematic cluster, and Figure 9 visualises the same pattern by comparing average and total citation counts. The MOOCs cluster generates the highest average citations per paper (17.3), followed closely by Transformers/LLMs (16.7) and Social Media Sentiment (15.2). This pattern reflects both the prominence of individual highly-cited anchor papers within these clusters—including Onan's (2021) deep learning MOOC evaluation study (368 citations), Wen et al.'s (2014) MOOC forum sentiment study (280 citations), and the AutoPrompt paper (Shin et al., 2020;

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1,124 citations)—and the broader visibility of MOOC and transformer-related research in mainstream ML and education venues.

Table 2. Citation impact metrics by thematic cluster.

Cluster	Papers	Avg. Citations	Median Citations	Total Citations
MOOCs & E-learning	132	17.3	3.0	2,287
Transformers / LLMs	102	16.7	1.0	1,708
Social Media Sentiment	161	15.2	2.0	2,455
Learning Analytics	204	10.4	1.0	2,113
Emotion Recognition	147	10.3	2.0	1,516
ML Classifier Ensembles	22	0.0	0.0	1

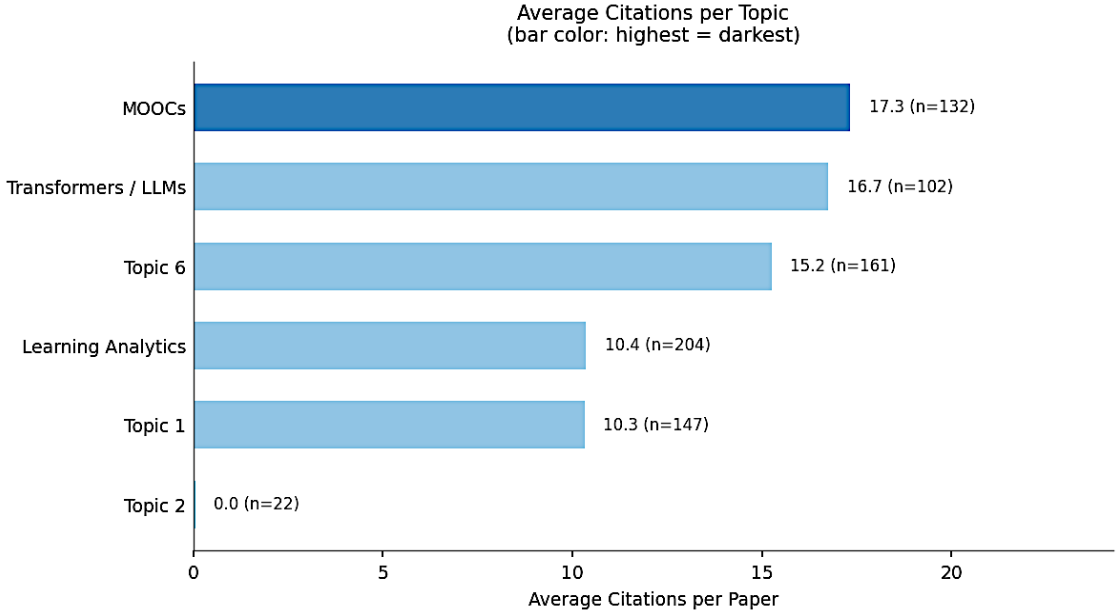

Figure 9. Average and total citation counts per thematic cluster, sorted by average citations. The dashed horizontal line indicates the overall corpus average (μ = 12.6 citations per paper).

3) Temporal Evolution of Thematic Clusters

Figure 10 traces the normalised thematic weight of each cluster across annual cohorts from 2013 to 2025. Several salient trends emerge that directly address RQ3; however,

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patterns involving the 2025 endpoint should be interpreted as latest-snapshot evidence rather than as final annual evidence.

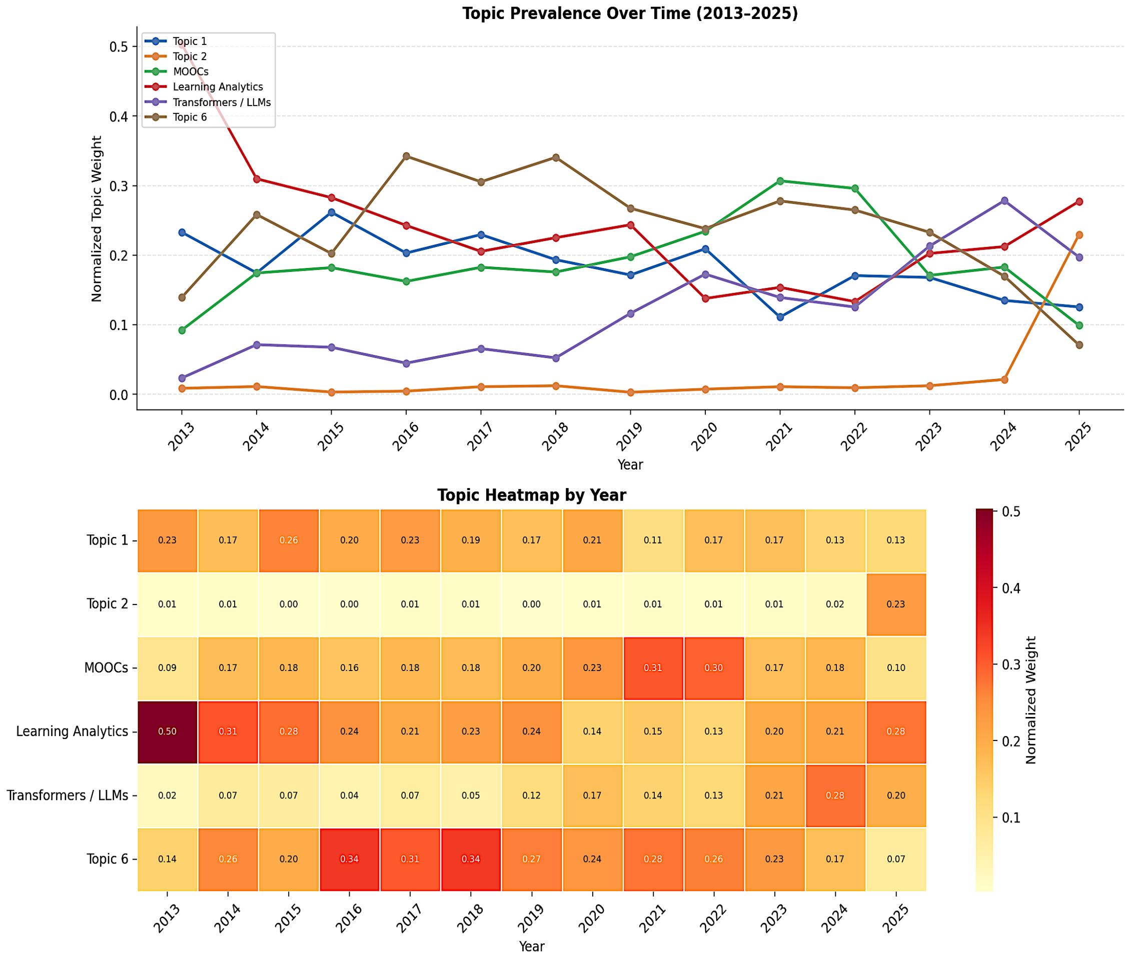

Figure 10. Temporal evolution of six thematic clusters in sentiment analysis in educational technology research, 2013–2025. Values represent normalised mean topic weight per year. The vertical dashed line at 2020 separates the pre-pandemic and post-pandemic periods. Shaded bands indicate ±1 standard error of the mean.

Learning Analytics was dominant in the early years, reflecting the foundational role of affective computing and intelligent tutoring systems. Its relative weight declined after 2018 as SA diffused into MOOCs, social media, transformer-based NLP, and other application areas; this does not imply falling absolute output, but a broader diversification of the field.

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The MOOCs & E-learning cluster rose during the pandemic-era online-learning shift, increasing from 0.198 in 2019 to 0.307 in 2021 before moderating. This suggests that online course forums, reviews, and platform discourse became especially salient data sources during and after emergency remote learning. The Transformers / LLMs cluster is the fastest-rising theme, moving from marginal representation before 2018 to more than 20% of normalised weight by 2023. This pattern mirrors the broader NLP shift initiated by BERT [8] and amplified by later generative models.nThe Emotion Recognition cluster declined relatively from its early strength in 2013–2015 to below 0.13 by 2024–2025, while Social Media Sentiment remained consistently represented. These shifts indicate thematic diversification rather than disappearance of earlier SA-EdTech approaches.

Table 3. Comparative cluster weights in pre-pandemic (2013–2019) and post-pandemic (2020–2025) periods, with trend direction.

Cluster	Pre-Pandemic Weight	Post-Pandemic Weight	Change	Trend
Learning Analytics	0.316	0.203	-0.113	Falling
Social Media Sentiment	0.265	0.219	-0.046	Falling
Emotion Recognition	0.210	0.155	-0.055	Falling
ML Classifier Ensembles	0.007	0.052	+0.049	Rising
MOOCs & E-learning	0.167	0.220	+0.052	Rising
Transformers / LLMs	0.066	0.205	+0.136	Rising

3.5. Keyword Burst Analysis and Emerging Themes (RQ3, RQ5)

Comparison of keyword frequencies between 2013–2019 and 2023–2025 reveals systematic shifts in the field's terminological frontiers. The top burst keywords—those with the largest relative frequency increase—are reported below, while regional topic distributions are presented separately in Figure 11. Artificial intelligence has the highest burst score (+0.042), followed by natural language processing (+0.019), machine learning (+0.015), mathematics education (+0.014), and adaptability

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(+0.011). The term transformer appears only in the recent period, consistent with the growth of the Transformers / LLMs cluster.

3.6. Geographic Gap Analysis (RQ5)

1) Thematic Asymmetry Between Western and Asian Research Communities

Figure 11 reveals a striking thematic divergence between Western-affiliated (USA, UK, Australia) and Asian-affiliated (China, India, Indonesia) research communities. The most pronounced gap concerns the Learning Analytics cluster, which accounts for 42.8% of Western-affiliated publications but only 13.8% of Asian-affiliated publications—a difference of 29 percentage points. Conversely, the Social Media Sentiment cluster is substantially more prevalent in Asian-affiliated research (30.7%) compared to Western-affiliated research (10.8%), a gap of 20 percentage points. The Emotion Recognition cluster is also more prominent in Asian-affiliated contexts (19.8% versus 11.4%).

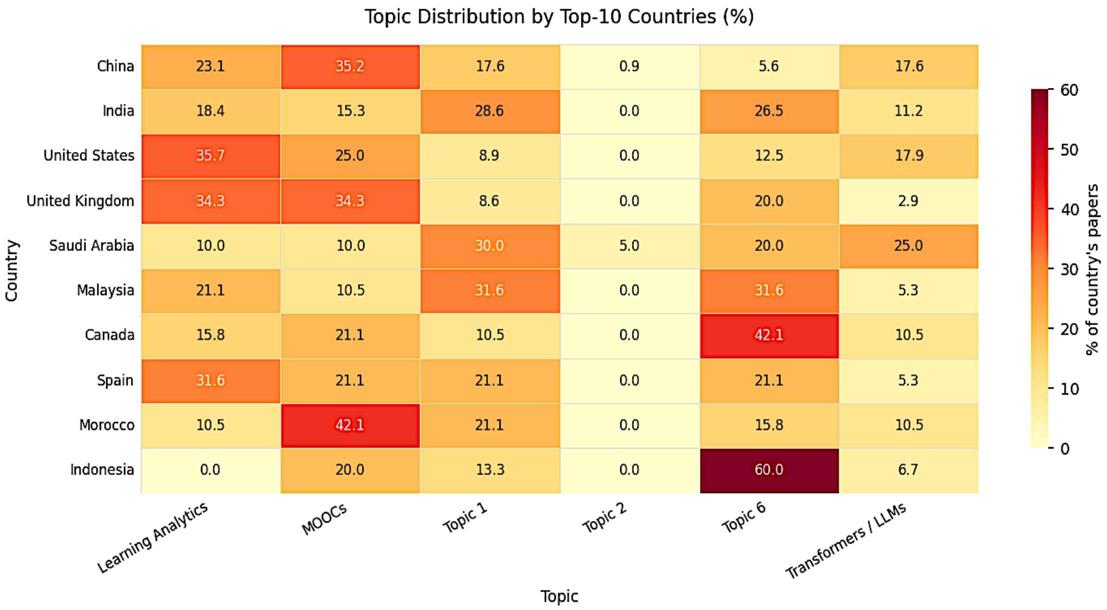

Figure 11. Thematic cluster distribution by regional affiliation. Western countries (USA, UK, Australia) are compared with Asian countries (China, India, Indonesia). Bar lengths represent the percentage of each region's publications assigned to each cluster. Numbers on bars indicate absolute paper counts.

These differences may reflect distinct infrastructure and research priorities. Western institutions' stronger learning analytics orientation is consistent with more mature LMS data ecosystems, whereas Asian institutions' stronger social media orientation may reflect greater accessibility of public platform data and different educational communication practices.

2) Platform-Specific Research Gaps

Platform mention analysis shows that generic terms dominate: LMS appears in 68 papers and MOOC in 126, whereas named platforms appear only 53 times in total, including Coursera (23), edX (9), Moodle (8), Canvas (5), Blackboard (3), Khan Academy (3), Google Classroom (2), and Duolingo (0). This 0.27 specific-to-generic ratio indicates a need for more platform-specific SA research.

3.7. Discussion

The bibliometric trajectory indicates that SA-EdTech research expanded around the period in which COVID-19 accelerated online learning. The evidence does not prove a causal pandemic effect, but the timing is consistent with larger online-learning datasets and greater interest in learner experience quality. A complementary systematic review is needed to assess whether publication growth was matched by stronger study design and methodological rigour.

The fastest-growing thematic cluster—Transformers / LLMs—reflects the broader NLP shift from feature-engineered classifiers to pre-trained language models [8], [33]. For education, multilingual transformer models such as mBERT and XLM-R may reduce labelled-data requirements and support cross-lingual SA [34], although generative LLMs also introduce new validation and interpretability challenges.

The 29-percentage-point gap in Learning Analytics prevalence between Western and Asian-affiliated publications is practically significant because learning analytics positions sentiment signals as inputs to intervention systems rather than only descriptive outputs. The gap may reflect differences in LMS infrastructure, data governance, institutional access to clickstream data, and reliance on social media as an educational communication channel [32].

This gap has implications for global equity and transferability. The bibliometric evidence cannot directly measure model transfer performance, but it suggests that SA systems trained mainly on English-medium Western learner data may be less aligned with Chinese, Hindi, Bahasa Indonesia, Arabic, or code-mixed educational contexts. Multilingual and culturally situated SA models therefore remain a priority [35].

The 40 detected co-authorship communities in a filtered 80-node network reveal substantial fragmentation. This may produce duplicated annotation schemes, inconsistent evaluation metrics, and missed transfer-learning opportunities across sub-themes. Shared benchmark corpora, cross-institutional annotation projects, and open-source toolkits would help connect these communities.

Drawing on all five analytical dimensions, this study identifies six priorities for future SA-EdTech research.

1) Gap 1: Multilingual and low-resource language SA. Future work should develop annotated corpora for Mandarin-, Hindi-, Arabic-, and Bahasa Indonesia-medium educational platforms and test cross-lingual transfer [34].
2) Gap 2: Platform-specific SA. Studies should move beyond generic LMS/MOOC labels and examine platform-specific discourse, assessment structures, interaction norms, and data affordances.
3) Gap 3: SA-integrated adaptive learning. More research is needed on closed-loop systems where sentiment signals trigger timely pedagogical responses rather than merely describing learner attitudes.
4) Gap 4: Longitudinal SA designs. Tracking learner sentiment across full courses or academic years would produce more actionable evidence than single-time-point analyses.
5) Gap 5: Benchmark standardisation. Domain-specific EdTech SA datasets and evaluation protocols, analogous to SemEval shared tasks [17], are needed for cross-study comparison.
6) Gap 6: Explainability. As transformer models become common, interpretable SA methods using attention visualisation, LIME, SHAP, or related techniques should be prioritised for educator uptake.

This study has five limitations. First, OpenAlex may underrepresent works outside well-indexed journals and proceedings. Second, country attribution based on affiliations can obscure diaspora and multi-country contributions. Third, NMF results depend on preprocessing and the selected k, although the six-topic solution was interpretable.

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Fourth, 2025 is treated only as a latest-year OpenAlex snapshot from 9 March 2026. Fifth, OpenAlex citation counts may diverge from Scopus or Web of Science [15].

4. CONCLUSION

This study maps sentiment analysis in educational technology through an open OpenAlex-based bibliometric framework covering 977 publications from 2013 to 2025. The strongest defensible trend is sustained growth through 2013–2024, while 2025 is interpreted as latest-year indexed evidence. Six clusters capture the field's structure: Learning Analytics remains the largest, MOOCs and e-learning expanded in the pandemic-era period, and Transformers / LLMs is the fastest-rising cluster. Collaboration remains fragmented across 40 communities, India and China lead in productivity, and Western-affiliated publications show a stronger learning analytics concentration. The main future needs are platform-specific, multilingual, and adaptive-intervention-oriented SA studies, supported by broader database comparison and full-text systematic validation.

DATA AVAILABILITY STATEMENT

The complete analytical pipeline—including API retrieval scripts, preprocessing code, NMF modelling parameters, and network analysis code—is available in the supplementary materials accompanying this paper. All source data were retrieved from the OpenAlex API (https://openalex.org), which is freely accessible without registration. The preprocessed corpus (cleaned_works.csv, n = 977) and topic-assigned dataset (works_with_topics.csv) are available from the corresponding author upon reasonable request.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

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APPENDIX A

Exact OpenAlex Query Template

```
Unencoded filter template used for paired SA-EdTech retrieval:
title_and_abstract.search:("sentiment analysis" OR opinion mining OR affective computing OR emotion recognition OR subjectivity analysis OR polarity classification) AND title_and_abstract.search:(education OR "educational technology" OR EdTech OR e-learning OR learning management system OR LMS OR MOOC OR online learning OR learning analytics)
```

Representative request URL used for one retrieval pass:

```
https://api.openalex.org/works?filter=from_publication_date:2013-01-01,to_publication_date:2025-12-31,has_abstract:true,language:en&search=sentiment%20analysis%20education&per-page=200&cursor=*
```

The paired-query logic was executed iteratively and then deduplicated by OpenAlex work identifier before performance analysis, network mapping, and NMF topic modelling.

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