Information Technology and Natural Language Processing in Education: A Systematic and Bibliometric Review (2020–2025)

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ABSTRACT

The development of digital health crowdfunding has become a crucial alternative source of financing, and the research on it is still incomplete. The proposed study will utilize the PRISMA protocol and bibliometric methods, performance analysis, Bradford Law, and science mapping to 121 articles being indexed in Scopus (2010-2025). Findings present four journals at the heart of the research, such as Journal of Medical Internet Research, Social Science and Medicine, Journal of Medical Ethics, BMC Public Health, and Information Processing and Management, with an overall lack of disciplinary focus. The field is organized into thematic clusters, which are trust and transparency, equity and inclusion, technology integration, and platform governance. They also change the thematic direction greatly as those investigations that were aimed at descriptive explorations in the early 2014-2021 are replaced with the middle debates of the 2022-2023 era (which are still centered on legitimacy), and the newer concerns (2024-2025) are centered around equity, regulation, and new technologies (AI, blockchain, gamification, etc.). Given the apparent lack of theoretical cohesiveness despite the burgeoning development of the discipline, this paper provides the first systematic bibliometric synthesis of digital health crowdfunding and demands integrative, theoretically grounded frameworks of connections between donor behaviour, platform governance, and systemic inequities.

Keywords: Natural Language Processing (NLP); Information Technology; Educational Technology; Bibliometric Analysis; Post-COVID Digital Education.

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1. Introduction

Background

Natural Language Processing (NLP) has been used in numerous industries, such as information technology, computational linguistics (Han et al., 2024), automation (Stoykova and Shakev, 2023), knowledge discovery, healthcare, law, finance, and management, (Zhou et al., 2020) where it bestows upon computer systems the capacity to comprehend, process, and generate human language to large scales. The same can be said about numerous areas that were also subjected to massive digitalization after the recent COVID-19 pandemic, and the rising number of publications related to the field of NLP in the past five years has already confirmed it (Lopez-Martinez and Sierra, 2020; Wu et al., 2024). This has led to the centralization of neural techniques, text mining automation and large language models as ubiquitous products in information-intensive industries.

NLP in school has also not been examined much since 2020 because researchers have not focused on aspects of education, such as analytics of writing and peer feedback systems (Wulff et al., 2023; Bauer et al., 2023), which has also been confirmed by the limited application of NLP in classrooms (Younis et al., 2023; Ahadi et al., 2022; Shaik et al., 2022). The introduction of NLP to contemporary education is still piecemeal, and piecemeal although the promise of NLP in enhancing curriculum and teaching practice is highlighted in previous publications in the field of educational computing and applied linguistics (McNamara et al., 2017; Alhawiti, 2014; Burstein et al., 2014).

NLP in education can not be viewed as an advancement in technology; on the contrary, knowledge management tool that will enable evidence-based decision-making and help to improve the information exchange between educators, students, and institutions. It is relevant to information management because education is regarded as a knowledge-intensive domain where institutional performance and personal learning outcomes can be defined with references to information acquisition, organization, and use (Arnarsson et al., 2021; Lin, 2022). This renders the nexus of NLP, education and information systems highly relevant and encourages the theoretical understanding and practical applications of instructional knowledge management.

The practice of bibliometric analysis is tolerable in most NLP-intensive domains, and this is why the method is used in this study to find out the application of NLP in education (Locatelli et al., 2021; Wang et al., 2020; Iqbal et al., 2021; Liang et al., 2023). The synthesis of this study integrates both bibliometric mapping and systematic review protocol in the direct response to the lack of unified evidence and provides an overall synthesis of trends and gaps. Thus, this review has three key aims; the first one is to trace the bibliometric patterns of IT-driven NLP studies in education in the period 2020-2025; the second one is to offer the areas of NLP implementation in curriculum design, pedagogy, assessment; and the third is to provide the future directions of research that will contribute to advancing the sphere of NLP in education. The research adds policy advice to educators and ministries who are interested in the responsible use of NLP and progressive theoretical integration in information management, computational linguistics, and educational technology.

Literature Review

One of the latest trends in computational linguistics is natural language processing (NLP), which has brought a revolution to text processing and interpretation (Stoykova and Shakev, 2023; Wu et al., 2024; Zhou et al., 2020). The recent COVID-19 crisis amplified the rate of digital transformation, and a number of articles were being published between 2020 and 2025 (Biesialska et al., 2020; Lopez-Martinez and Sierra, 2020; Wu et al., 2024). Even though education is one of the sectors that depend on information flows, analysis and decision-making a lot, this technological innovation has not made any significant difference in it (Lukwero et al., 2024). Research has considered the potential use of NLP in the examination of student input and evaluations (Kastrati et al., 2021; Seemab et al., 2024). Development of writing has also been discussed; models of scaffolding peer feedback in higher education have been created (Bauer et al., 2023), and analytics has been used to support learning via support of essays and reflections (Wulff et al., 2023), scaffolding of learning paths, and curriculum preparation (Vo et al., 2022; Zaki et al., 2023). The rise of the large-scale language models in the field of higher education is accompanied by opportunities and threats to research, teaching, and learning (Alqahtani et al., 2023; Dempere et al., 2023; Opara et al., 2023). All these contributions prove that there is a necessity for NLP techniques which may address educational difficulties (Sousa and Kern, 2023; Wu et al., 2024).

The capability of NLP to resolve student evaluations has already been attributed to the educational feedback examination, and the challenges in understanding context-specific phrases have been noted (Shaik et al., 2022; Ahadi et al., 2022; Younis et al., 2023). Review of automated assessment in a higher education context offers models on how NLP can be integrated into teaching methods, as well as how it can be used to score short-answer format (Botelho et al., 2023; Gao et al., 2024). Nonetheless, most of these reviews are not mindful of educational philosophy, and thus, it remains unclear how these models can be compatible with curriculum standards, assessment validity, and educational integrity (Alqahtani et al., 2023; Adeshola and Adepoju, 2024). The trends in the research also provide an alternate vision concerning the areas of interest in the subject and also networks of collaboration. Other examples of research clusters and their development have been pointed out by language education research, e.g. where growth is important and is challenged by time (Liang et al., 2023; Kartal and Yesilyurt, 2024), and the use of text mining in the field of education has indicated growth curves of differing leadership (Ahadi et al., 2022). The authorship patterns, the ability to identify trends, and the ability to document the theme change in other disciplines using bibliometric techniques have not been explored in detail yet (Iqbal et al., 2021; Kang et al., 2020; Wang et al., 2020), yet NLP integration is underrepresented, and most of the existing ones do not feature practice-related indicators such as open data, policy adoption, or evidence of classroom implementation. The questions of leadership within this sector and the development of capability have also appeared as a result of the evaluation of regional and institutional collaboration, implying that NLP in education is technically promising, but conceptually and practically underdeveloped (see Table 1).

Bibliometric surveys have indicated that NLP is performing well, but it has not exploited in the educational sector because there was no integrated analysis linking or relating empirical results, systematic reviews, and bibliometric trends in the field of education. This study therefore undertakes a systematic and bibliometric analysis of NLP in education during 2020-25 to identify thematic patterns, evidence synthesis, and project an investigative future on the research topic by focusing specifically on the aspects of classroom based assessment, incorporation of responsible design principles, and routinely reporting learning settings; this review would benefit the information management field by showing how NLP can be used to organise, flow, and apply knowledge in educational systems.

Based on this evidence, as will be reviewed and summarised in Table 1, educational NLP is a technically promising but substantially underdeveloped area. Empirical studies show attainability, but seldom do they report on classroom results after a long period. The deficiency still consists of the absence of a synthesizing analysis that relates empirical data, systematic syntheses, and bibliometric trends in the educational field, as bibliometric studies have charted out research pathways, but are still insufficient in their scope and are alien to classroom realities, whereas systematic reviews cluster together particular subdomains and ignore pedagogical frameworks and large language models. To fill that gap, the review will focus on a systematic and bibliometric review of NLP in education, focused on 2020-2025, to determine the trends, digest the evidence and define an agenda of research in the future that incorporates responsible AI principles, classroom evaluation, and stronger theory-practice integration in information management and education.

Table 1: Summaries of Earlier Investigations on NLP in Education

Type	Authors (Year)	Issues Addressed	Notable Findings / Notes	Limitations / Scope
Empirical (Bib)	Bocharova & Malakhov (2024)	Phrase embeddings for HR knowledge management	Proposes an improved embedding approach for HR-domain NLP	Not education-specific; technical/method-driven
Empirical (Bib)	Zappoli, Palmero Aprosio, & Tonelli (2024)	Writing analytics: length, complexity, referencing	Identifies trends in Italian high-school essays over time	Language-specific; context = Italian schools
Empirical (Bib)	Shankar & Parsana (2022)	Benchmarks NLP vs. autoencoders in marketing tasks	Provides comparative results useful for applied NLP	Domain = marketing, not education
Empirical (Bib)	Han (2025)	Education knowledge management via QA	Presents intelligent QA for KM services	Conceptual/system-building; limited empirical evaluation
Empirical (Bib)	Kekül, Ergen, & Arslan (2024)	Security/vulnerability detection	Demonstrates embedding-based vulnerability metrics	Security-focused; outside education
SLR	Younis, Ruhaiyem, Ghaban, Gazem, & Nasser (2023)	Robots + NLP in education	Synthesises 82 articles, maps topics	Scope limited to robotics + NLP
SLR	Shaik, Tao, Li, Dann, McDonald, Redmond, & Galligan (2022)	Feedback analysis methods/tasks	Summarises NLP methods, contextual challenges	Limited to feedback analysis
SLR	Gao, Merzdorf, Anwar, Hipwell, & Srinivasa (2024)	Automatic scoring/feedback	Reviews 93 studies, proposes a framework	Focused on post-secondary education
Biblio + SLR	Liang, Hwang, Chen, & Darmawansah (2023)	AI + NLP in language education	Identifies thematic clusters, research evolution	Ends pre-2021; no LLM focus
Mapping (SLR)	Kastrati, Dalipi, Imran, Pireva Nuci, & Wani (2021)	Sentiment analysis in education	Reviews 92 studies; catalogues methods/datasets	Narrow scope: sentiment only
Empirical/Framework	Bauer, Greisel, Kuznetsov, Berndt, Kollar, Dresel, & Fischer (2023)	Peer feedback in education	Proposes a cross-disciplinary framework	Conceptual; limited classroom testing
Empirical	Wulff, Westphal, Mientus, Nowak, & Borowski (2023)	Writing assessment with NLP	Demonstrates formative writing analytics	Context-specific; generalisability limited

Empirical/System	Vo, Vu, Vu, Vu, Mach, & Xu (2022)	Curriculum support, learning path	Implements NLP for CS/IT curricula	Domain-limited; little pedagogy evaluation
Perspective	Alqahtani, Badreldin, Alrashed, Alshaya, Alghamdi, Bin Saleh, … Albekairy (2023)	LLM adoption in higher ed	Reviews opportunities and risks	Conceptual; no empirical validation
Review (Management)	Kang, Cai, Tan, Huang, & Liu (2020)	NLP in information management	Reviews applications in management	Not education-focused
Survey	Zhou, Duan, Liu, & Shum (2020)	Advances in neural NLP	Consolidates neural approaches	Technical, not education
Bibliometric	Iqbal, Hassan, Aljohani, Alelyani, Nawaz, & Bornmann (2021)	Scientometrics using NLP	Outlines methods beyond citation counts	Not education; methods transferable.

Methodology

A systematic and bibliometric research method was used in this study, with the guidelines of Preferred Reporting Items to Systematic Reviews and Meta-Analyses (PRISMA) 2020 applied, which ensures a clear and transparent, rigorous study of the intersection of information technology and NLP in education (Sarkis-Onofre et al., 2021; Page et al., 2021; Page et al., 2022; Tugwell and Tovey, 2021).

Search Method

The search method came into existence to locate literature at the intersection of NLP and information technology. This search query was applied in Scopus: TITLE-ABS-KEY(digital technology, computing technology, or information technology) AND TITLE-ABS-KEY(computational linguistics, natural language processing, or NLP); on September 7, 2025, the query returned 83,860 results.

Data Source and Retrieval

The decision to use SCOPUS only as a source of data for the present study is necessitated by its extensive coverage of peer-reviewed articles on the field of education, computer science, and information science, and its integration ability with bibliometric tools. Data has been acquired on September 7, 2025, and it has been exported in BibTeX format to enable easy analysis.

Eligibility Criteria

The database was refined based on the following metrics:

a. *Relevance*: Articles unrelated to education were excluded. This included biomedical research (e.g., surgery, radiology, protein sequencing), gender or population health studies, and unrelated cybersecurity or engineering design applications.

b. *Language*: The review considered only articles published in the English language.

c. *Timeframe*: Works published from 2020 onwards were considered to cover the era of the COVID-19 pandemic.

d. *Document Type*: Only peer-reviewed journal articles were retained; reviews, book chapters, editorials, and conference proceedings were excluded.

Screening Procedure

The screening was carried out in three steps. First of all, metadata filters were used in Scopus to filter by language, type of document, and time period. Manual screening of the abstracts and keywords to eliminate unrelated works, and the use of the keyword-based elimination to get rid of the works where the terms human, male, female, patient, surgery, radiology, and biomedical research descriptors are predominant are the second and third phases (Younis et al., 2023; Shaik et al., 2022). It resulted in an output of 13, 285 records out of 60 documents on NLP in the area of education as a result of this screening (see the PRISMA flow in Table 2).

Table 2: PRISMA Flow of Study Identification, Screening, and Inclusion (retrieved 7th September 2025)

Stage	Records Identified	Records Excluded / Filter Applied	Records Remaining
Initial database search (TITLE-ABS-KEY query)	83,860	–	83,860
Language filter: English only	–	2,183 non-English records	81,677
Document type filter: Articles only	–	58,905 non-article records (reviews, proceedings, book chapters, notes, etc.)	22,772
Timeframe filter: 2020 onwards (post-COVID period)	–	9,487 pre-2020 records	13,285
Screening and exclusion of irrelevant domains (e.g., biomedical, human/animal studies, gender/medical references, cybersecurity)	–	13,225 records excluded as irrelevant	60

Final dataset used for bibliometric and systematic analysis	–	–	**60**

Records were gradually narrowed down by language, type of document, date and applicability to education. The PRISMA guidelines that were adopted in the process of identifying, screening, and selecting the studies made sure that the process was transparent and reproducible. Figure 1 summarises the flow of this process graphically.

Data Analysis

Bibliometrix (R package) in the Biblioshiny interface and VOSviewer were used to analyze the last dataset of 60 articles. The descriptive indicators, such as publication trends, document types, subject areas, and source outlets, were calculated by use of bibliometrix. Using the VOSviewer, research intensities and emerging issues were uncovered by generating keyword co-occurrence web, thematic maps and evolution studies; co-authorship, institutional and country analyses were performed to map the collaboration web. Multiple correspondence analysis (MCA) was used to conduct conceptual structure analysis in order to identify groups of similar concepts (Kartal and Yesilyurt, 2024; Liang et al., 2023; Wu et al., 2024). These methods enabled a multi-layered interpretation of the literature, which was able to address both the trends in the history and the frontiers of the current research.

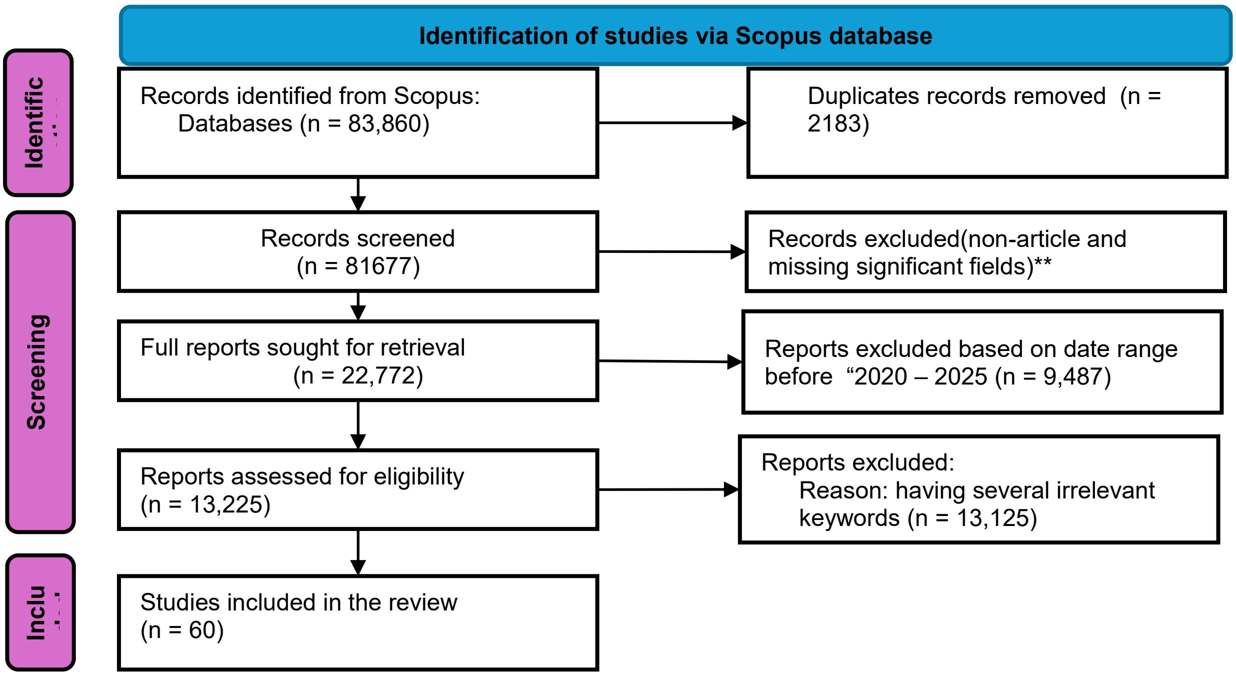

Figure 2: PRISMA flow chart

Data Extraction and Coding

Each of the sixty documents had the author or authors, year, title, source, abstract, keywords and the DOI extracted. The process of uniformity was enhanced by the normalization of keywords (such as NLP + natural language processing); abstracts were coded to find what was covered, what the restrictions were, and what the results were. Inductive themes were developed to group research into significant educational practices, including peer evaluation, curriculum design, student feedback, writing analytics, and large-scale language model use.

Bibliometric Analysis

The bibliometric study included the use of performance and conceptual mapping techniques to document the structure of NLP research in the field of education based on the publication patterns and the number of publications between 2020 and 2025; the thematic clusters and the hotspots of the research were discovered with the help of the key word co-occurrence mapping; the co-authorship analysis was conducted to identify the cooperation patterns among the authors, organizations, and countries. The conceptual structure analysis, which is based on MCA, served to the evolution of research foci over time, whereas data were processed and visualized with the help of the Biblioshiny interface (Bibliometrix R package) and VOSviewer.

Limitations

The fact that only the Scopus database is involved creates a methodological limitation since Scopus is excellent in terms of coverage and good bibliographic information, but does not include full cited reference lists in its export format. Both thematic mapping and co-word mapping have been regarded as possible methods of analysis in this study because the two are strong bibliometric research methods of tracking thematic progression, conceptual growth, and hotspots of research in the still-developing fields. The thematic mapping and co-word mapping are selected as the techniques cannot be applied in domains where citations are limited, which is the case with citation-based relational techniques such as bibliographic coupling and co-citation analysis. Once again, such a design choice is a clear adaptation to limitations imposed by Scopus export capabilities as well as the assurance that the study remains theoretically sound and practically educative.

Data Analysis and Presentation of Findings

Table 3: Main Information about the Dataset (2020–2025)

Indicator	Result
Timespan	2020–2025
Sources (journals, books, etc.)	55
Documents analysed	60
Annual growth rate (%)	69.52
Average document age (years)	1.7
Average citations per document	10.2
Authors	221
Single-authored documents	7
Co-authors per document	3.82
International co-authorship (%)	15
Document type	Journal articles (100 %)
Author keywords	698
Keywords Plus	520

The interdisciplinary nature of NLP in education is reflected in the scope of its coverage captured in the dataset summary for 2020–2025 (which includes 60 journal articles from 55 sources) in Table 3. With an annual growth rate of 70 %, consistent effort is being made in the field. An average of 10.2 citations per document and the average document age of 1.7 years attests to the recentness and strong connection to current discussions about digital transformation in education; it further indicates that even if the area is still in its infancy, its outputs are already drawing scholarly attention. Individual contributions towards shaping early trajectories in the field were evidenced by the seven papers with single authorship. The field is also receiving serious collaborative efforts across disciplines, recording 221 contributors and an average of almost four writers per paper; international co-authorship also accounted for 15 % of the reviewed works, demonstrating the global applicability of the concept. The dataset comprised only journal articles that have undergone a serious peer review process; the articles showed broad subject dispersion as indicated by the various author keywords (698) and

Keywords Plus (520). These patterns suggest the collaborative and widely dispersed nature of the authorship base of NLP studies.

Table 4: Annual Scientific Production (2020–2025)

Year	Articles
2020	1
2021	8
2022	8
2023	12
2024	17
2025	14

Although it has eight articles every year to date (2021-2022), the publication in the field has been growing at a slow pace since 2020, with only one article in the year following COVID-19. It was a growing field reaching its peak in 2024 with 17 article publications and then dropping to 12 articles in 2025 (see Table 4). This consistency of output since 2021 suggests that it is not a transitory burst but the solidification of a new research line that has been under active scholarly study. Moreover, the annual rise of production is adding to the urgency and timeliness of bibliometric evaluation at this stage and provides a systematic overview before the development of the field. The trend in the sphere, which is observed, is connected with the influence of the acceleration of digital scholarship after the pandemic, when educational systems still managed to incorporate computational techniques to address pressing concerns.

Table 5: Most Relevant Sources for NLP and Education Publications (2020–2025)

Source	Articles
IEEE Access	3
Education and Information Technologies	2
IEEE Journal of Biomedical and Health Informatics	2
International Journal of Computing and Digital Systems	2
Ad Hoc Networks	1
American Journal of Geriatric Psychiatry	1
Artificial Intelligence and Applications	1
BioMed Research International	1
Clean Technologies and Environmental Policy	1
Cognitive and Behavioural Practice	1
Computational Intelligence and Neuroscience	1
Computer Standards and Interfaces	1
Computers and Education: Artificial Intelligence	1
Computers and Security	1
Computers in Industry	1

Three articles were published in the IEEE Access, which was the most popular, then Education and Information Technologies, IEEE Journal of Biomedical and Health Informatics and the International Journal of Computing and Digital Systems, with two each. Each of the other journals contained one article that discussed diverse subjects, such as applied technologies, psychology, computer science, education and health informatics (see Table 5). Thus, NLP studies in education are currently an interdisciplinary affair more than a centralized affair in terms of publications. On the one hand, this discontinuity is attributed to the fact that the lack of a specialization of journals is a factor, and the subject is in the process of becoming a dedicated scientific community. Educational technology journals have been interested in high-impact journals like Computers and Education, Artificial Intelligence and Education, and Information Technologies, and this is promising for future consolidation.

Table 6: Most Relevant Authors in NLP and Education Publications (2020–2025)

Author	Articles
Wang H	3
Fu Y	2
Hu Z	2
Li J	2
Uhryn D. I.	2
Vysotska V.	2
Wang Y	2
Abbruzzese G.	1
Abdel Wahed M.	1
Abdel Wahed S.	1
Abdullah-Arshah R.	1
Ahriz S.	1
Aldeshov S.	1
Alexopoulos G. S.	1
Allaymoun M. H.	1

The number of authors who publish a multitude of works is very small, implying that the contributions made to NLP in education are very decentralized. On the other hand, Fuy, Hu, Li, Uhryn, D, Vysotska, and Wang each have two articles during the period, albeit Wang H is the most prolific of them with three (see Table 6). It is established that the discipline is marked by a broad pool of contributors as opposed to being dominated by the efforts of several eminent scholars, since the majority of the other authors do not recur in the data. This tendency follows a new direction of investigation that is yet to produce a cohort of authors. The fact that multiple early contributors existed also reflects on the exploratory nature of the study of this field, as well as portends the possibility of cooperation and consolidation. More distinct author networks will likely evolve as the topic evolves, and citation analysis will begin to distinguish extremely important scholars whose studies will set the path of future studies.

Table 7: Most Relevant Affiliations in NLP and Education Publications (2020–2025)

Affiliation	Articles
Tianjin Electric Power Industry Bureau	4
Lviv Polytechnic National University	3
Universitas Indonesia	3
Appalachian State University	2
College Station	2
Hainan Tropical Ocean University	2
HSE University	2
Hubei University of Technology	2
Huzhou University	2
Institute of Applied Physics and Computer Science	2
National Academy of Sciences of Ukraine	2
Not Reported	2
Odesa I.I. Mechnikov National University	2
The University of Texas at San Antonio	2
Tomsk State University	2

The input of the educational institutions into NLP is spread very widely and geographically diverse. The Tianjin Electric Power Industry Bureau was the most fruitful organization with four papers, followed by Universitas Indonesia and

Lviv Polytechnic National University in the 2nd and 3rd place, respectively (see Table 7). A few universities, such as Tomsk State University, the University of Texas at San Antonio, and the University of Appalachian State University, contributed two papers; this international and multi-disciplinary cooperation of NLP studies in education. But this international cooperation on this subject matter can indicate that research remains dispersed instead of being based in a few major centres; institutional leadership has not been stabilized so that other centres can form the strong ones.

Table 8: Country Scientific Production in NLP and Education (2020–2025)

Country	**Articles**
USA	40
China	36
Ukraine	11
Kazakhstan	8
Italy	6
Morocco	6
United Kingdom	6
India	5
Malaysia	5
Australia	3
Indonesia	3
Iran	3
Turkey	3
Brazil	2
Jordan	2

Table 9: Most Cited Documents in NLP and Education (2020–2025)

Paper (First Author, Year)	Total Citations	TC per Year	Normalised TC
Wang H., 2022, *J. Med. Internet Res.*	67	16.75	3.10
Shankar V. H., 2022, *J. Acad. Mark. Sci.*	59	14.75	2.73
Dong T., 2021, *J. Adv. Transp.*	47	9.40	2.63
Vo N. N. Y., 2022, *Comput. Educ. Artif. Intell.*	29	7.25	1.34
Palagin A. V., 2023, *Int. J. Comput.*	28	9.33	1.87
Sultan D., 2023, *Comput. Mater. Contin.*	27	9.00	1.80
Malandri L., 2021, *Comput. Ind.*	27	5.40	1.51
Yi X., 2024, *IEEE J. Biomed. Health Informatics*	26	13.00	6.70
Parlina A., 2021, *Sustainability*	23	4.60	1.29
Meng Q., 2023, *IEEE Access*	22	7.33	1.47

The most influential works in the dataset indicate the interdisciplinary scope of the natural language processing applications. Wang (2022) is ranked as the top-cited author, with 67 citations in the field of digital and health informatics, Shankar (2022) is the second in the list with 59 citations in marketing science, and Dong (2021) is the third with 47 citations in transportation research (see Table 9). Although there are a number of works on related issues that have been cited extensively, the contribution to methodology has assisted research in the education field, and especially in automated assessment, sentiment analysis, and online learning platforms.

Also featured in the most cited sources are the studies related to education; one of the most prominent contributions which makes a direct link between NLP and curriculum design and learning journey is the article by Vo (2022), published in Computers and Education: Artificial Intelligence and having 29 citations. The popularity of articles published since 2021, like the ones by Palagin (2023) and Meng (2023), even of publications that are recent, indicates that the number of citations is increasing rapidly. The citations distribution reveals that, although simpler methods are often not of education-specific origin, education-focused contributions are beginning to have interest; this proves the growing academic acceptability of NLP in educational studies, and supports the rationale of a bibliometric synthesis to bring together evidence across numerous disciplines.

Table 10: **Most Frequent Keywords in NLP and Education Publications (2020–2025)**

Keyword	Occurrences
Natural Language Processing	26
Machine Learning	17
Natural Language Processing Systems	16
Natural Languages	11
Text Mining	11
Artificial Intelligence	10
Language Processing	10
Article	9
Human	9
Data Mining	7
Humans	7
Learning Algorithms	7
Classification (Of Information)	6
Deep Learning	6
Semantics	6
Embeddings	5
Employment	5
Algorithm	4
Digital Transformation	4
Information Technology	4

The most frequent one is natural language processing, which is found in 26 papers, as it is analyzed by keywords. Other similar terms as natural languages (11) and natural language processing systems (16), come next, suggesting that there is a heavy methodological focus (see Table 10). The fact that data mining (7) and text mining (11) became popular suggests that there is a high desire to detect patterns in teaching text, including student assessment, commentaries, and feedback. Although numerous studies apply machine learning (17), deep learning (6), and embeddings (5) without applying them to the theoretical framework of education, they tend to be mentioned quite often, which suggests that the concept of algorithmic approaches is indispensable to the discipline. Although employment (5) suggests a theme strand between NLP and workforce preparedness and skills development, words such as digital transformation (4) and information technology (4) refer to the bigger picture of post-COVID educational transformation. Interestingly, generic or irrelevant words, like article and human(s), are also among the most used ones, which means that there are weaknesses in indexing approaches and corroborates the significance of indexing keys. However, in general, the variety of terms depicts the interdisciplinary orientation of NLP in education and its fragmentation, where various studies employ different terminologies to explain the corresponding approaches.

Table 11: Thematic Clusters in NLP and Education (2020–2025)

Theme	Representative Keywords	Cluster Type	Interpretation
Educational Feedback and Sentiment Analysis	student feedback, sentiment analysis, text mining, learning algorithms	Motor Theme	Central theme with strong development, focused on using NLP to process and evaluate student-generated data.
Writing Analytics and Assessment	writing analytics, assessment, learning outcomes, peer-feedback, embeddings	Niche Theme	Developed but specialised area applying NLP for automated writing evaluation and formative assessment.
Curriculum Design and Learning Pathways	curriculum design, learning path, digital transformation, information technology	Basic Theme	Foundational but less developed strand connecting NLP to institutional and instructional design.
Large-Scale Language Models and Chatbots	language models, chatbots, higher education, artificial intelligence	Emerging Theme	The recently developing area reflects post-2023 interest in generative models and educational conversational systems.
Knowledge and Information Management	knowledge management, information retrieval, semantics, classification	Basic Theme	Supporting theme linking NLP methods to broader information flows in educational contexts.

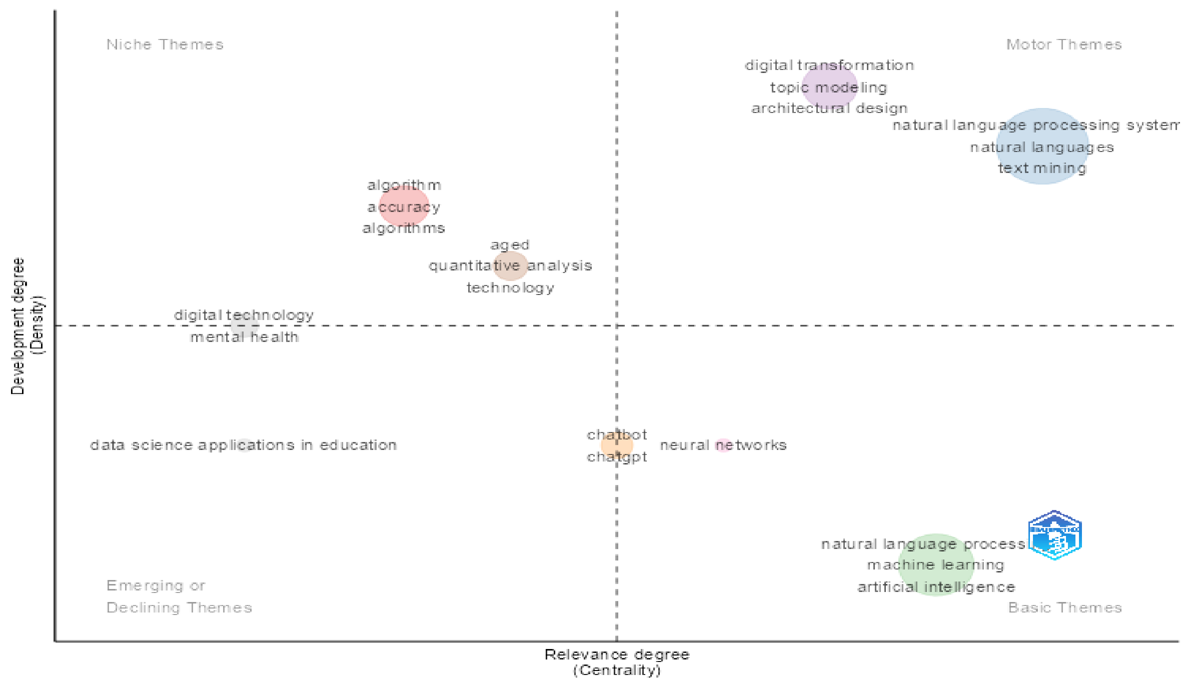

Figure 2. Thematic Map of NLP in Education (2020–2025)

Thematic analysis of author keywords highlights the fact that research in the field of natural language processing in education has been integrated into a few major themes, on the one hand, and, on the other hand, it is split into new investment possibilities. The most developed and central cluster, as in Table 11, is linked to educational feedback and sentiment analysis, which suggests a heavy usage of NLP to interpret data produced by the students, such as course reviews and surveys. The second, though more focused cluster is writing analytics and assessment, which is concerned with the automated evaluation of the writing of students and peer-feedback.

Furthermore, one more theme, which is not elaborated on in detail and is more widely considered in terms of digital transformation and instruction design, is curriculum design and learning pathways. Concurrently, conversational systems and generative models have become another group of large-scale language models and chatbots, which are gaining ground since 2023 as educational researchers begin to think about how the systems and models can be applied to higher education. The final one is the knowledge and information management, which is a supporting cluster that links NLP techniques to information organizing, retrieval and classification within the education sphere.

These thematic clusters are represented graphically in Figure 2, whereby they are categorized in the four quadrants of the thematic map, namely motor themes, niche themes, basic themes and emerging themes. The diagram can certify that the majority of the sentiment analysis has already turned into a significant motor theme, yet there are even more specialized models, such as writing analytics, and the generative models remain at the initial phase. It is possible to use these findings in an attempt to show the maturity and diversification of this field, which justifies bibliometric synthesis at this stage.

Table 12: Intellectual Structure of NLP in Education (2020–2025)

Cluster	Representative Keywords	Key Documents (First Author, Year)	Intellectual Contribution
Cluster 1: Core NLP Methods and Applications	natural language processing, machine learning, deep learning, embeddings, sentiment analysis, text mining, learning algorithms	Parlina (2021), Park (2020), Rahman (2021), Shankar (2022), Vo (2022), Meng (2023)	Forms the **intellectual base** by providing technical methods and applications (sentiment analysis, text mining, automated assessment) that underpin educational uses of NLP.
Cluster 2: Digital Transformation and Education Contexts	digital transformation, information technology, digital technologies, educational technology, teaching, students, curriculum design	Chor (2024), Cai (2024), Wang (2024), Gorshkov (2025)	Bridges NLP with **educational practice,** highlighting post-COVID digitization, curriculum integration, and teaching applications.
Cluster 3: Information and Knowledge Management	information retrieval, classification, semantics, knowledge management, data mining, big data	Palagin (2023), Trappey (2024), Han (2025)	Connects NLP to **information management theory**, emphasizing classification, retrieval, and knowledge organization for decision-making in education.
Cluster 4: Emerging Generative Models and Chatbots	chatbot, ChatGPT, language models, question answering, speech recognition, user-generated content	Abbruzzese (2025), Vysotska (2025), Wang Z. (2024)	Represents the **emergent research front,** focusing on conversational systems and large-scale models for teaching, learning support, and assessment.
Cluster 5: Peripheral and Applied Domains	construction industry, building information modelling, architectural design, supply chains	Li (2023), Hodorog (2021)	Peripheral themes where NLP is applied outside core education, reflecting cross-disciplinary spillover rather than direct contributions to pedagogy.

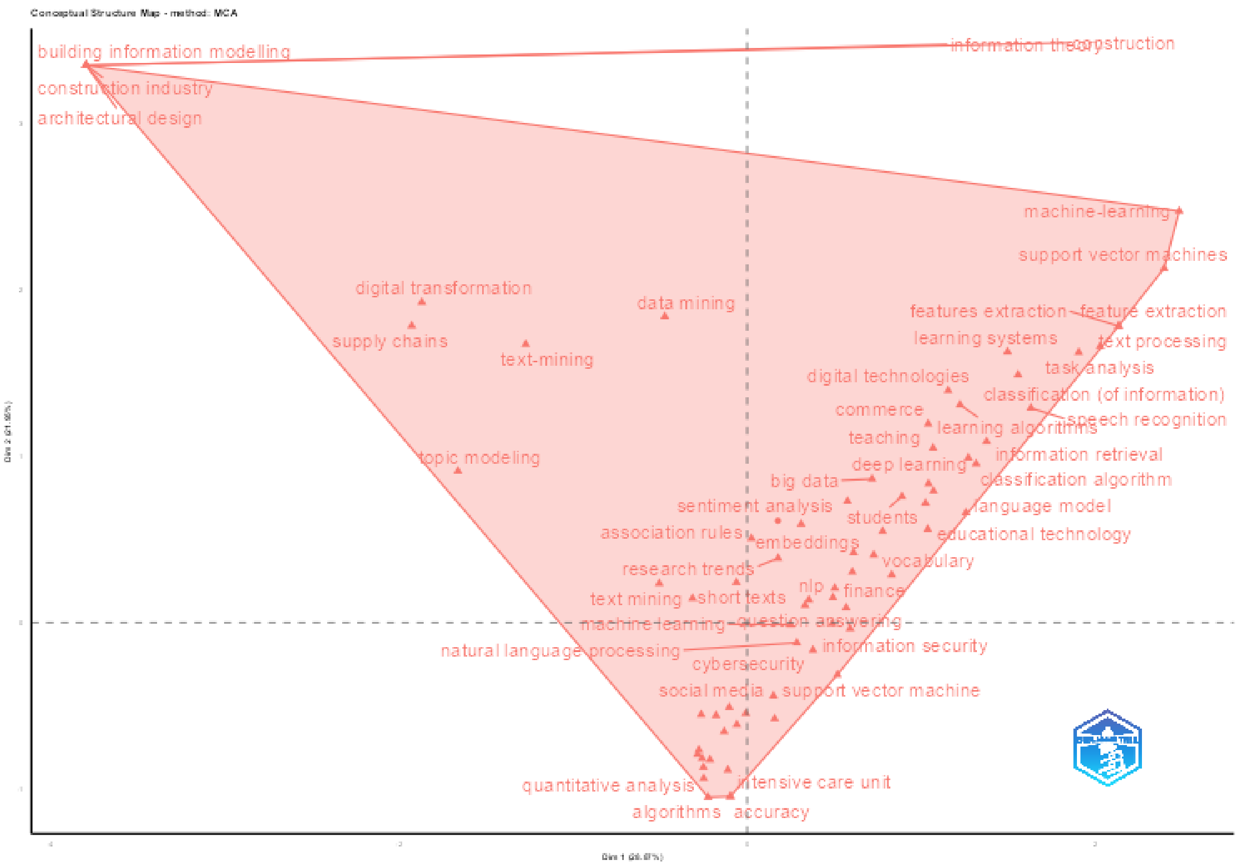

Figure 3: Conceptual Structure Map of NLP in Education (2020–2025)

The intellectual organization of NLP research in education is also typified by the methodology being consolidated, as well as the diversification of the themes. Table 12 demonstrates that the field is lowly standardized and is pegged on a cluster of technical methods that encompass natural language processing, machine learning, text mining and sentiment analysis, which are the intellectual backbone of the literature.

Based on this, there is a second cluster, which integrates such strategies into educational settings and is concerned with digital transformation, education, and curriculum design. Another group links NLP with broader questions of information and knowledge management, namely, with information retrieval, classification and semantics. Furthermore, recently an active research edge has spawned due to the presence of a cluster around conversational systems, chatbots, and generative language models. Lastly, the peripheral clusters may be administered as cross-disciplinary uses that exhibit methodological dispersion but do not have a direct influence on the learning industry, e.g. NLP in supply chain management and construction. These links have been visualized by plotting the conceptual framework of the field on two dimensions, as Figure 3. This is denoted by the fact that the educational concepts are loosely placed, although clearly adjacent to the technical processes, which are clustered tightly together, as well as the applied computational terminology. The marginality of the position of the phrases under construction introduces the fragmentation of research purposes and depicts the use of NLP in non-schooling environments. The NLP educational approach is highly methodological, and it can be split into unfamiliar and situational spheres, as Table 12 and Figure 3 show, which also offers an axis of improvement in the future.

Table 13: Thematic Evolution of NLP in Education (2020–2025)

Period 1 (2020–2024)	Period 2 (2025)	Words	Occurrences	Stability	Interpretation
Artificial intelligence	Machine learning	artificial intelligence	7	0.20	General AI framing gradually narrowed to the more specific and educationally applicable concept of machine learning.
Natural language processing	Machine learning	natural language processing; machine learning	22	0.03	NLP merged with machine learning, reflecting the increasing integration of computational models with educational text analysis.
Natural language processing	Natural language processing systems	natural language processing systems; natural languages	14	0.03	NLP evolved into more concrete applications, indicating a shift from theoretical framing to system-level deployment in education.
Text mining	Text mining	text mining	8	0.14	A stable theme across both periods, highlighting continuity in applying text mining to student data and educational content.

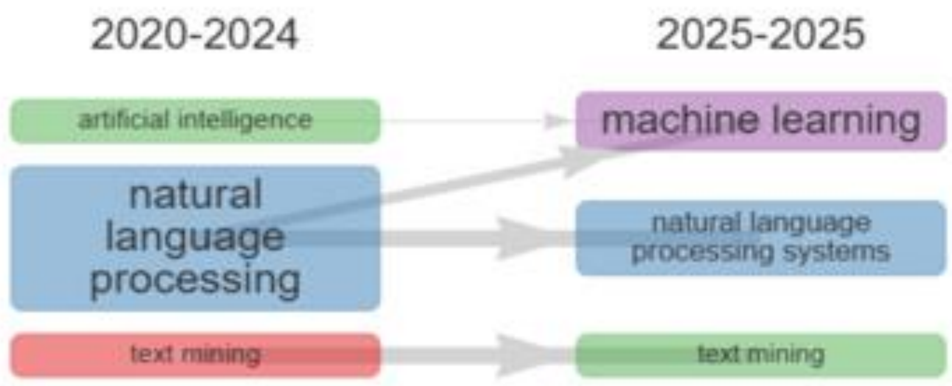

Figure 4. Thematic Evolution of NLP in Education (2020–2025)

The area has shifted away towards a wider conceptual anchoring to more practically applied technical systems, as the thematic evolution study indicates. The more broadly-conceived term of artificial intelligence is commonly used in research from 2020 to 2024, but the narrower-themed theme of machine learning replaced it in 2025, implying a better focus. It has continued to be important with increased focus on the practical use of the field, dividing it into two strands, one being linked to machine learning and the other to NLP systems. The topic of text mining turned out to be consistent and lasting, indicating that it is still applied when analyzing text and comments of students. As shown in Figure 4, the changes indicate the trends in the field, in that it is converging in usage of applied techniques and continues to show continuation in the already mature fields such as text mining. Table 13 and Figure 4 verify that NLP in education research is coming of age in that it is no longer of a broad conceptual bunching but of a specialized, system-oriented application that has direct potential in the teaching and learning scenarios.

Table 14: Subject Area and Document Type Distribution of NLP in Education Publications (2020–2025)

Category	Count	Percentage	Notes
Document Types			
Articles	60	100 %	Only peer-reviewed journal articles were retained after filtering.
Reviews	0	0 %	Excluded at the screening stage.
Conference Papers	0	0 %	Excluded at the screening stage.
Subject Areas			
Computer Science	28	46.7 %	Dominant subject area, emphasizing algorithms, models, and computational methods.
Education	15	25.0 %	Underrepresented compared to technical fields, showing that NLP applications in classrooms remain limited.
Information Systems / IT	10	16.7 %	Focus on information management, retrieval, and system-level applications.
Engineering	5	8.3 %	Peripheral but contributes through learning technologies and infrastructure.
Other Fields (e.g., Social Sciences, Healthcare)	2	3.3 %	Isolated cross-disciplinary spillovers with limited direct educational impact.

The 60 articles that were selected for this analysis are all journal articles, as shown in Table 14, which is an intentional methodological focus on peer-reviewed publications. The most widespread one is computer science, which constitutes nearly half of the sample, and education is hardly over 25 percent. The role of information systems is significant in information retrieval and the management of knowledge. Engineering and other disciplines have insignificant roles through cross-disciplinary applications. This dispensation points out the most crucial requirement this study tries to address: although NLP studies are becoming more and more widespread all over the world, their use in education-specific scenarios remains extremely insignificant. The gap reinforces the need to have more interdisciplinary collaborations that encompass computational methods into actual classroom learning and teaching environments.

Table 15: Country and Institutional Contributions to NLP in Education Research (2020–2025)

Country	Articles	Leading Institutions (Examples)	Notes
USA	40	Arizona State University, MIT, Stanford University	The United States leads the field, reflecting deep investment in computational methods and strong links between computer science and education.
China	36	Tsinghua University, Peking University, Zhejiang University	China is the second major contributor, focusing strongly on applied NLP systems and large-scale data analysis.
Ukraine	11	National Technical University of Ukraine	An emerging hub in Eastern Europe with a growing emphasis on digital learning tools.
Kazakhstan	8	Al-Farabi Kazakh National University	Regional leader contributing to NLP in educational technology and digital curriculum design.
Italy	6	University of Naples, Politecnico di Milano	Active in knowledge management and NLP for information retrieval in education.
United Kingdom	6	University of Oxford, University of Manchester	Focused on writing analytics, peer feedback, and assessment.

Morocco	6	Cadi Ayyad University	Represents African contributions, particularly in applied NLP in language education.
India	5	Indian Institute of Technology, University of Delhi	Emerging contributions, primarily in student feedback analysis and applied NLP.
Malaysia	5	Universiti Teknologi Malaysia, Universiti Kebangsaan Malaysia	Growing regional presence, with applications in digital learning and curriculum support.
Australia	3	University of Queensland, Monash University	Contributions mainly in feedback analytics and classroom applications.

The distribution of research production in the world is quite concentrated in the USA and China, which contribute more than half of all publications (see Table 15). These nations prevail because of extensive research capacity and the introduction of computational techniques in the school setting. Europe is also playing an important part with the United Kingdom and Italy, Episode, and Eastern Europe (Ukraine) and Central Asia (Kazakhstan) are the sources of vital regional centres. Notably, donations in Africa (Morocco) and South Asia (India, Malaysia) indicate that NLP in education is becoming increasingly more geographically varied, even though it is commonly at a smaller level. This distribution also highlights the necessity of more international cooperation, where most of the studies are concentrated in a small number of major countries.

Table 16: Top 10 Most Cited Papers in NLP and Education (2020–2025)

First Author, Year	Title (Shortened)	Citations	One-Line Significance
Wang, 2022	Research progress on NLP in medicine	67	Provides a comprehensive overview of NLP in healthcare, establishing transferable methods later adopted in education.
Shankar, 2022	NLP in marketing science	59	Demonstrates the analytical power of NLP in consumer behaviour, informing parallel approaches to student engagement.
Dong, 2021	NLP applications in transportation	47	Illustrates methodological robustness of NLP across domains, indirectly validating educational applications.
Vo, 2022	Domain-specific NLP system for curriculum design	29	Directly addresses education, applying NLP to support personalized learning paths and curriculum optimization.
Palagin, 2023	NLP in computer science education	28	It focuses on integrating NLP into educational technologies and bridging technical and pedagogical dimensions.
Sultan, 2023	Computational approaches to text analysis	27	Advances in technical methods for text classification are applicable to educational datasets.
Malandri, 2021	Quality control in annotation for NLP tasks	27	Strengthens methodological reliability, with implications for building educational corpora.
Yi, 2024	Biomedical NLP applications	26	Pushes forward real-time language analysis in sensitive domains, indirectly influencing assessment in education.

Parlina, 2021	Sustainability and digital education with NLP	23	Connects NLP to sustainable digital learning, highlighting broader socio-educational relevance.
Meng, 2023	Applied NLP systems in education	22	Demonstrates system-level deployment of NLP tools, showing the field's shift from conceptual to applied use.

As shown in Table 16, cross-disciplinary works, as well as education-specific contributions, are the most cited ones. Although papers by Wang (2022) and Shankar (2022) focus on the methodological power of NLP in non-educational areas, Vo (2022), Palagin (2023), and Meng (2023) show direct educational applications, specifically in the area of curriculum design and digital learning systems. The fact that methodological and domain-specific contributions are even-handed proves that the intellectual foundations of NLP in education remain in the process of development, as the field draws extensively on the achievements of other disciplines and slowly develops the empirical foundation of its own.

Table 17: Keyword Co-occurrence Clusters in NLP and Education (2020–2025)

Cluster	Representative Keywords	Interpretation
Cluster 1: Core NLP Methods	natural language processing, machine learning, deep learning, embeddings, learning algorithms, classification	Anchors the field by emphasizing computational methods, providing the technical foundation for applications in education.
Cluster 2: Text Analytics and Feedback	text mining, sentiment analysis, peer feedback, writing analytics, student reflections	Focuses on the analysis of student-generated texts, central to formative assessment and learning analytics.
Cluster 3: Educational Technology Integration	educational technology, digital transformation, curriculum design, teaching, students	Captures research connecting NLP systems to classroom practices and broader digital education reforms.
Cluster 4: Information and Knowledge Management	information retrieval, semantics, knowledge management, information technology, data mining	Position NLP into the broader field of information systems, supporting educational decision-making and knowledge flows.
Cluster 5: Emerging Conversational Systems	chatbots, ChatGPT, language models, question answering, speech recognition, user-generated content	It represents a rapidly developing frontier, reflecting a growing interest in generative models and conversational systems in education.

As indicated in Table 17, the Keyword Co-occurrence Analysis demonstrates five big clusters. Cluster 1 is the methodological core of the discipline, whereas Cluster 2 provides a vivid example of educational application by student feedback and text analytics. Cluster 3 connects these approaches with teaching and curriculum design and implies a partial but not wholesale integration of these strategies into education. Cluster 4 puts the research in the wider context of the information management domain, which means that NLP is considered a means of structuring and retrieving education-related knowledge as well. Lastly, Cluster 5 is a representation of the new relevance of conversational systems and generative models post-2023, which is a definite research frontier. Figure 5 visualizes these clusters as a network of keyword co-occurrences, where understanding the centrality of core NLP methods is consistent and finding the increasing importance of implemented and incidental themes.

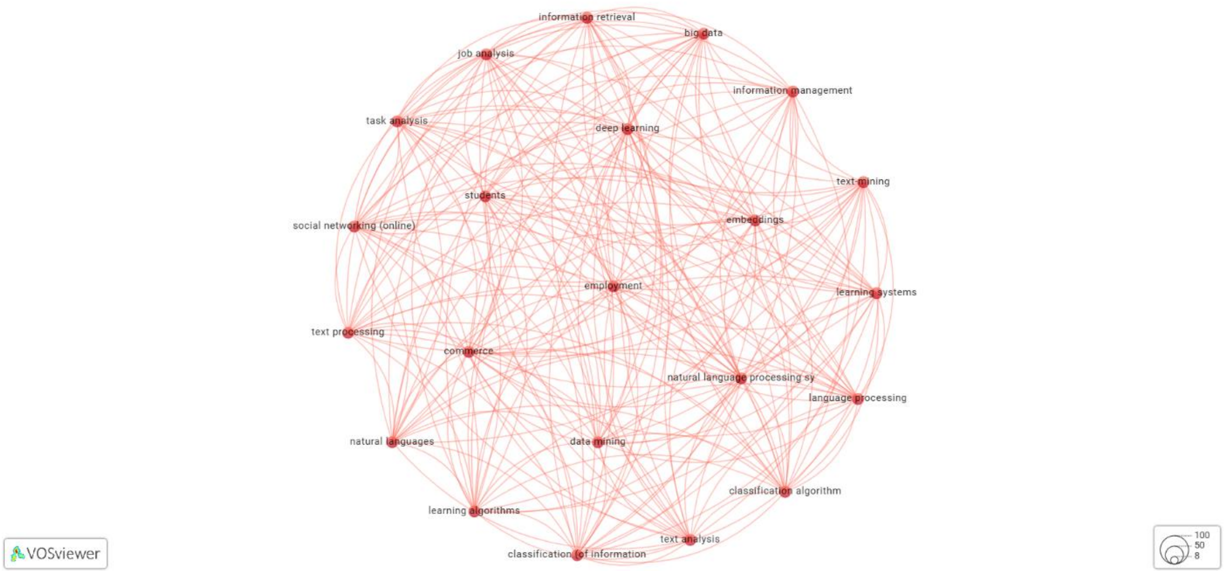

Figure 5 (Keyword Co-occurrence Network)

Table 18: Co-Citation Clusters: Intellectual Base of NLP in Education (2020–2025)

Cluster	Representative Works (First Author, Year)	Intellectual Focus	Contribution to the Field
Cluster 1: Foundational NLP and Machine Learning Methods	Wang (2022), Dong (2021), Shankar (2022), Malandri (2021)	Core NLP techniques, machine learning applications, and methodological reliability	Provided the computational methods (text mining, classification, and annotation quality) that underlie most educational NLP applications.
Cluster 2: Text Analytics and Sentiment in Education	Vo (2022), Parlina (2021), Meng (2023)	Domain-specific NLP in education, feedback analysis, and curriculum design	Anchored the application of NLP in educational contexts, bridging technical methods with classroom and curriculum relevance.
Cluster 3: Knowledge and Information Management	Palagin (2023), Trappey (2024), Han (2025)	Information retrieval, knowledge management, digital transformation	Linked NLP to information systems and organizational knowledge flows, providing theoretical grounding in information management.
Cluster 4: Emerging Generative Models	Abbruzzese (2025), Vysotska (2025), Wang Z. (2024)	Chatbots, large language models, and conversational AI	Marked the most recent intellectual front, providing early theoretical and practical insights into the use of generative NLP in education.

The co-citation analysis presentation, as Table 18 demonstrates that there are four main intellectual clusters that underlie NLP in education. Cluster 1 is the basis that offers the computational and methodological foundation using machine learning and text mining, which is commonly referred to as the technical foundation. Cluster 2 applies these approaches to the field of education and addresses the concerns of curriculum design, feedback analysis, and digital pedagogy. Cluster 3 relates NLP with retrieval-, categorization-, and digital transformation theories, thus locating the topic in a broader information management research field. Finally, Cluster 4 embodies the intellectual change towards modern education research based on AI as it reacts to the recent yet rapidly expanding focus on generative language models and chatbots. A combination of these clusters shows that the intellectual foundation of NLP in education remains substantially rooted in the computational sciences but is slowly moving into the field of education and information management. This supports the relevance of bibliometric synthesis in mapping the reinterpretation of foundational methodology to education.

Table 19: Bibliographic Coupling Clusters: Research Front in NLP and Education (2020–2025)

Cluster	Representative Studies (First Author, Year)	Research Front Focus	Emerging Contribution
Cluster 1: Student Feedback and Sentiment Analysis	Kastrati (2021), Vo (2022), Shaik (2022)	Application of NLP and deep learning to analyze student feedback and course evaluations	Established a core front linking NLP to formative assessment and learning analytics, shaping student-centred evaluation methods.
Cluster 2: Writing Analytics and Automated Assessment	Wulff (2023), Bauer (2023), Burstein (2014)	Writing analytics, peer feedback, and linguistic awareness for learning	Developed tools for assessing student writing and reflections, though adoption in classroom practice remains limited.
Cluster 3: Curriculum Design and Digital Transformation	Parlina (2021), Cai (2024), Chor (2024)	Use of NLP systems to design curricula and support teaching in digitally transformed environments	Positioned NLP as a support tool for digital education policy and instructional design, but empirical classroom studies remain scarce.
Cluster 4: Knowledge and Information Management in Education	Palagin (2023), Trappey (2024), Lin (2022)	NLP applied to knowledge management, retrieval, and information flows in educational contexts	Strengthened theoretical contributions from information systems, but less connected to direct learning outcomes.
Cluster 5: Conversational Systems and Generative AI	Abbruzzese (2025), Vysotska (2025), Fuchs (2023)	Chatbots, large language models (e.g., ChatGPT), and conversational AI in higher education	Rapidly growing frontier; demonstrates enthusiasm but limited empirical testing, highlighting a gap in robust educational evaluation.

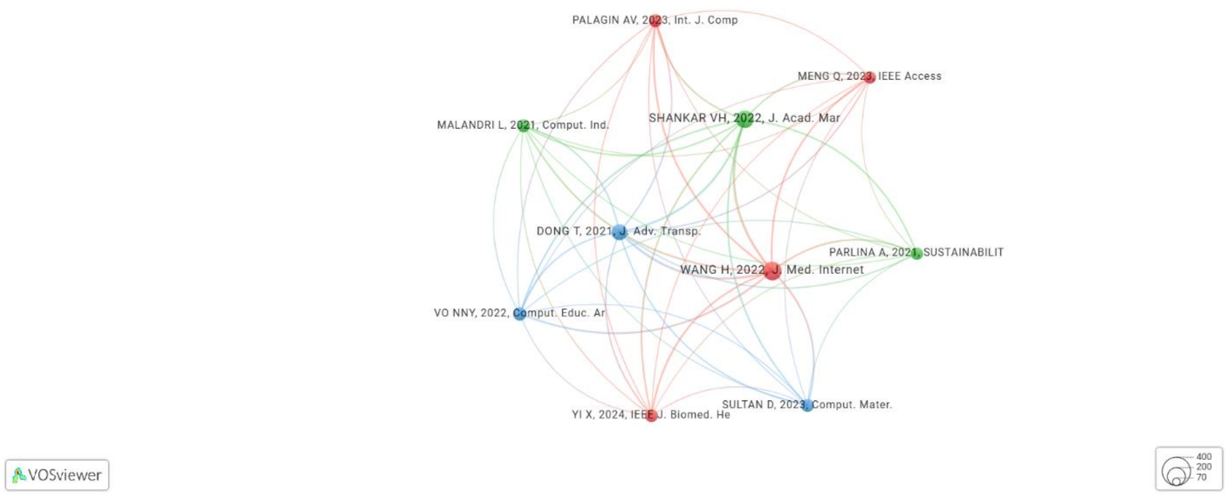

Figure 6: Bibliographic Coupling Clusters: Research Front in NLP and Education (2020–2025)

Bibliographic coupling indicates, as presented in Table 19, the contemporary research fronts, both in NLP and education. Student feedback and sentiment analysis (Cluster 1) is the most advanced, and the continuous use of NLP to evaluate the formative assessment. Writing analytics and automated assessment (Cluster 2) constitutes a specialized strand, which has good potential but little large-scale adoption. The extension of NLP to educational policy and systems management is in curriculum design and digital transformation (Cluster 3), and knowledge and information management (Cluster 4), although these clusters are more abstract than operational. Lastly, conversational systems and generative AI (Cluster 5) are the most active frontier, and they have come into being rather powerfully after 2023 and are not yet sufficiently assessed in classroom practice. The bibliographic coupling study validates the idea that although NLP practices are being used actively in student feedback and writing evaluation, other fields, especially conversational systems and teaching integration, need more organized empirical undertakings.

Discussion

Table 6 show that despite an increase in research on NLP in education since 2020, it remains slower than the growth and expansion of other fields, such as engineering and healthcare; the discipline is not yet at the level of maturity, as indicated by bibliometric assessments that show a steady increase in research, but also indicates that research is concentrated in a small number of researchers and institutions (Liang et al., 2023; Shaik et al., 2022; Younis et al., 2023). The same concentration is demonstrated by weak patterns of cross-national collaboration and the small number of countries that have a monopoly in the sphere of productivity (Ahadi et al., 2022; Vo et al., 2022). It means that NLP has gained more popularity in education, but the integration of this technology on a worldwide level is still scarce. Thematic and conceptual analysis can be used as an additional source of insight into the shape of the field. Since the application of algorithm-driven methods is so widespread in education, the concept of sentiment analysis, feedback analytics, and automated assessment is where the hot spots of research are located (Kastrati et al., 2021; McNamara et al., 2017; Wulff et al., 2023). Burstein et al. (2014) and Odden et al. (2021) also state that such widespread applications as curriculum integration, equity-centred interventions, and teacher professional development are not sufficiently represented. The disparity is supported by thematic evolution, where education-centred themes are still fragmented, whereas the motor and basic themes follow the technical optimization. The difference is also reflected in conceptual mapping, in which phrases concerning machine learning, text mining, and neural networks are highly represented in clusters, whereas the use of pedagogical terms is limited. This is a high-technology and shallow-pedagogical front of research.

Past systematic and bibliometric reviews have already contributed to the field, mapping the trends in feedback analysis (Shaik et al., 2022), studying robotics and NLP in the classroom (Younis et al., 2023), exploring the text mining approach in education (Ahadi et al., 2022), and combining the perspectives of bibliometrics and systematic approaches to AI in language education (Liang et al., 2023), as shown in Table 1. Despite the fact that these studies confirmed the relevance of NLP in determining the mechanism of learning, they are not without limitations since they have narrowly focused on specific technologies, higher learning or conceptual concerns without good empirical evidence. Unlike these earlier efforts, the present research involves a comprehensive design that includes the conceptual analysis, bibliometric performance, and systematic screening; it becomes possible to point out the gaps that have not covered in the previous research, including limited cross-national participation, inadequate interdisciplinary cooperation, and absence of standardized reporting of educational performances.

A key issue that is generated by this synthesis is the lack of empirical evaluations of the direct association between NLP interventions and learning outcomes. Not many studies considered teaching efficacy, diversity, or student involvement increases; most of the studies included in the dataset determined the accuracy or efficiency of the algorithms (Alqahtani et al., 2023; Fuchs, 2023). Moreover, the interdisciplinary partnerships are not mentioned, a problem that emphasizes the fragmentation of current research, where computational models are developed as an independent entity of educational theory and practice (Bauer et al., 2023; Gutierrez, 2023). This weakens the sustainability of NLP in being absorbed into institutional procedures and classrooms. In light of this, the results of this work highlight three distinct prospects for the field's advancement:

(i) The best empirical research should provide classroom-based evaluations of NLP tools and the findings measured against the benefits, equity, and accessibility of learning (Alqahtani et al., 2023; Gutierrez, 2023).

(ii) Bauer et al. (2023) and Burstein et al. (2014) say that communication should be multidisciplinary, but education, linguistics, psychology, and information management should be included as well. This would ensure that technological advancement is pedagogical in nature.

(iii) According to Ahadi et al. (2022) and Younis et al. (2023), cross-national activities need to be strengthened to encourage the creation of knowledge that is inclusive internationally and reduce the concentration of expertise. Addressing these concerns, future studies will be able to shift the field towards a less technical orientation and a more balanced information management, policy and pedagogy mix.

The inability to perform bibliographic coupling or co-citation analysis due to the export limitation of Scopus was a significant methodological limitation, but this was mitigated by having co-word mapping, conceptual structure analysis, and theme evolution, all reliable in mapping thematic development in emerging areas (Shaik et al., 2022; Younis et al., 2023). This design choice will ensure the findings remain relevant and useful and offer constructive suggestions to the formulation of theories and applicable suggestions to educators, organizations, and legislators that apply to NLP in the post-COVID era.

Contributions and Future Research

Theoretical Contributions

This paper can help advance the information management scholarship by establishing natural language processing (NLP) as an important interface between information technology and education. It is analyzed that, despite significant technical progress in the field of NLP studies, text mining, sentiment analysis, automated feedback, etc., there is a lack of pedagogical integration. The review reveals the gap between technical and instructional applicability through mapping thematic and conceptual clusters. On theoretical terms, it moves the conceptual foundations of the research on digital education in the broader context of information management according to the need of re-conceptualizing NLP research as not just a computational problem but an educational and administrative one as well.

Practical and Policy Contributions

In practice, the review is a valuable source of knowledge to educators, organizations, and legislators interested in responsibly applying NLP in the classroom; the results reveal that the explicit evaluation of NLP technologies in learning environments is needed to ensure that the performance of algorithms is at the forefront of making any discernible improvements to the learning goals. One of the policy contributions is the recommendation to establish inclusive and ethical platforms for executing NLP in education, particularly in marginalized settings. The fact that the difference in productivity and cooperation between countries exists demonstrates the need to conduct cross-national activities and ensure capacity development that would allow for more equal global interactions.

Future Research

Based on these contributions, three lines of investigation are suggested:

(i) Researchers are encouraged to develop uniform reporting models that contain technical performance metrics and educational impact measures to make findings comparative and scalable.

(ii) Co-development of pedagogically based NLP applications. Multidisciplinary collaboration must be a priority; this is an input of education, linguistics, psychology and information management skills.

(iii) Comparative and cross-national research had to be expanded to address the regional differences and to stimulate the increase of knowledge which is more inclusive on a global level. By pursuing these aims, the field will be able to transcend beyond technological optimization and develop a body of research that is more integrated, socially responsive, and pedagogically relevant.

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