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ORIGINAL STUDY

Artificial Intelligence in Higher Education: A Bibliometric and Science-Mapping Analysis from an Institutional and Management Perspective

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ABSTRACT

This article maps the field of artificial intelligence in higher education (HEI-AI) from an institutional and management perspective. We draw on 52,270 peer-reviewed articles and reviews indexed in Web of Science and Scopus between 1959 and 2025. Using the bibliometrix package and its biblioshiny interface in R, we combine descriptive indicators with science-mapping techniques, including co-authorship and co-citation networks, keyword co-occurrence, thematic mapping and thematic evolution. The initial corpus of 94,845 records was cleaned by merging the two databases, removing duplicates and restricting the sample to full-length journal articles and reviews that explicitly address AI in higher education.

The results show a long period of slow growth followed by an exponential expansion after 2023, closely aligned with the diffusion of generative AI tools such as ChatGPT. At the country level, China dominates in publication volume, while the United States leads in citation impact. Countries such as France contribute fewer but highly cited papers and function as additional intellectual hubs. Conceptual and thematic analyses indicate a gradual shift towards more technical and data-driven work, centred on artificial intelligence, teaching and learning in tertiary education, and learning analytics, prediction, classification and performance metrics. Interpreted through neo-institutional theory, these patterns point to legitimacy-oriented AI adoption, coercive and mimetic isomorphism, and the growing influence of bibliometric indicators on organisational fields. The paper argues that HEI-AI should be understood as a strategic management and governance issue rather than only a pedagogical innovation, and it outlines implications for institutional AI strategies, policy design and future research on organisational adaptation in higher education. AI is not just technology; it is a process that redefines the institutional structure.

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Introduction

Artificial intelligence (AI) technologies are increasingly regarded as a meta-paradigmatic force which, fuelled by the extraordinary pace of recent advances in information and communication technologies, is transforming many dimensions of human life (Moradimokhles *et al.*, 2025, p. 30). AI has been described as one of the most profound technological developments humanity has ever produced, with implications that reach into almost every sector and sphere of life (Pichai, 2023). Central to this significant technological evolution are institutions of higher education—intricate organisational entities that serve as both the subjects and the objects of extensive societal transformation.

From the standpoint of management studies, Mintzberg's (Mintzberg, 1979, pp. 366–367) examination of professional bureaucracies conceptualizes universities as entities distinguished by an intricate knowledge repository and a pronounced level of professionalization. In accordance with the tenets of neo-institutional theory, these entities are characterized as organisational constructs that, in their quest for legitimacy, modify their practices in response to external environmental stimuli and integrate prevailing institutional norms. As a result, they function as critical analytical elements in the inquiry of organisational evolution (see DiMaggio & Powell, 1983, pp. 148–151; Meyer & Rowan, 1977, pp. 340–343). Within this framework, the adoption of radical technological innovations such as artificial intelligence by higher education institutions should be understood not simply as a technical adjustment, but as part of a broader process of institutional transformation.

AI technologies have a rapidly expanding influence across the higher education ecosystem. In particular, applications based on machine learning and deep learning are increasingly used in learning analytics, intelligent tutoring systems and administrative decision-support processes (Zawacki-Richter *et al.*, 2019, pp. 1–3; Hwang *et al.*, 2020, pp. 1–3). More recently, the diffusion of generative AI tools such as ChatGPT and DALL·E has made this impact even more visible and has accelerated debates on ethics, governance and policy in higher education (Bond *et al.*, 2024, pp. 2–3).

This technological shift is profoundly reshaping the strategic management practices, organisational cultures and stakeholder relationships of higher education institutions. Prior to the current proliferation of artificial intelligence, academic establishments had already experienced successive phases of technology-enhanced pedagogy, particularly through e-learning and blended-learning initiatives (Caner, 2010; Caner, 2012). The integration of artificial intelligence into higher education therefore calls for a strong management science perspective. Universities are large-scale organisations with multiple stakeholders, complex decision-making processes and high expectations of accountability. Practices such as predicting student success, integrating big data into decision-support mechanisms and embedding generative AI tools into administrative processes affect not only instructional design but also core managerial functions, including strategic planning, resource allocation, performance and quality assurance, risk management and ethical compliance.

Unsurprisingly, artificial intelligence in higher education has attracted growing attention in the scholarly literature. AI applications have gained marked momentum in recent years, particularly in higher education contexts, and have been framed in international reports as 'inseparably' linked to the future of higher education (Zawacki-Richter *et al.*, 2019, p. 1). A number of bibliometric studies corroborate this trend (Hinojo-Lucena *et al.*, 2019; Kavitha *et al.*, 2024; López-Chila *et al.*, 2023; Bond *et al.*, 2024; Crompton & Burke, 2023; Maphosa

& Maphosa, 2023; Ullrich *et al.*, 2022), showing an exponential increase in research on artificial intelligence in higher education (HEI-AI) in recent years.

At the same time, AI has been examined in the literature through a range of adjacent thematic lenses, including blended learning (Ishmuradova *et al.*, 2024), AI-assisted teaching (Medina, 2025), mobile learning (Irwanto *et al.*, 2023a), Massive Open Online Courses (MOOCs) (Irwanto *et al.*, 2023b), e-learning (Maan & Malhotra, 2024; Brika *et al.*, 2022; Gao *et al.*, 2022), learning management systems in higher education (Amofa *et al.*, 2025; Phan *et al.*, 2022) and the broader development of AI in education (Carrión-Barco *et al.*, 2025; Valdiviezo *et al.*, 2024; Doğan & Şahin, 2024; Shaikh & KıranlıGüngör, 2025). Taken together, these studies suggest that AI has become a strategic research and policy domain not only in terms of pedagogical applications, but also for the governance of higher education and, more broadly, for management science. However, the managerial and institutional dimensions of artificial intelligence in higher education remain comparatively under-examined in a systematic way.

Bibliometric analyses offer a powerful toolbox for making sense of such extensive and interdisciplinary bodies of literature, for quantitatively examining scientific production and for mapping the intellectual structure of research fields (Cobo *et al.*, 2011, pp. 1382–1384; Ellegaard & Wallin, 2015, pp. 1809–1811). From a management science perspective, bibliometric studies play a key role in understanding the institutional structure of research fields, the dynamics of scientific communication networks and patterns of knowledge flow; they provide an objective measurement frame for mapping research specialisation and anticipating future directions (Baas *et al.*, 2020, pp. 377–379; Sobral, 2020, pp. 154–155; Zupic & Čater, 2015, pp. 429–431; Martínez *et al.*, 2015, pp. 257–258).

Research positioning, gap and contributions

Existing bibliometric studies on AI in higher education typically analyse a relatively limited number of publications (most often between 300 and 2,000) and tend to rely on a single database (either Scopus or Web of Science). Moreover, a large share of the existing literature is confined to specific subfields, particularly generative artificial intelligence and intelligent tutoring systems. Crucially, most of the current bibliometric work is grounded in an educational-sciences perspective; comprehensive analyses that examine the institutional, organisational and managerial dimensions of AI in higher education from a management science standpoint are still rare.

The aim of this study is to address the gaps identified in the existing literature. Drawing on a combined dataset of 52,270 publications retrieved from the Web of Science and Scopus databases, it aims to map the scientific landscape and intellectual foundations of the HEI-AI field from a management science perspective. Without imposing *ex ante* field delimitations, the analysis identifies which research areas have become prominent in relation to AI in higher education and which thematic clusters structure the field, thereby providing a broad overview relevant to strategic decision-making in universities.

From a management science viewpoint, the study offers three main contributions:

- **Foundations of organisational adaptation:** It identifies the intellectual foundations of organisational-level adaptation to AI technologies in higher education institutions. Within a neo-institutional framework, it makes visible the knowledge bases and conceptual lenses that higher education organisations draw upon in their AI adoption processes.
- **Mapping diffusion mechanisms:** By charting interdisciplinary knowledge flows and collaboration networks, the study examines the diffusion mechanisms of AI in higher

education from a management perspective. The observed patterns provide an empirical basis for discussing the two-stage model of innovation adoption – early, more technical/rational adoption and later, legitimacy-oriented adoption – proposed by Tolbert & Zucker (1983, p. 26), as well as the 'new diffusion thesis' emphasising both economic and social motives for early and late adopters (Özen, 2013, p. 129).
- **Strategic insights:** The broad, non-field-delimited analysis identifies salient thematic and managerial clusters that can inform strategic decision-making by higher education leaders and policy-makers, highlighting where AI-related research is most concentrated and how it is evolving.

In summary, the Discussion and Conclusion sections interpret the results using key concepts from management science and organisational theory and discuss implications for future research and policy.

Methodology

This section sets out the aim of the study, explains the data analysis methods, describes the data collection procedures, outlines how the dataset was integrated and prepared, and summarises the bibliometric analyses carried out.

Aim of the study

The primary aim of this study is to identify the main trends in research on artificial intelligence in higher education – including publication volume and growth dynamics, leading journals and authors, country and institution distributions, citation patterns, conceptual themes and thematic evolution – by means of bibliometric analysis, and to offer an overall picture of the field interpreted through a management science perspective.

Data analysis method

A bibliometric analysis technique was employed to quantitatively examine the scientific output on artificial intelligence in higher education and to map the intellectual and structural features of the field.

To this end, data on publications retrieved from the Web of Science (WoS) and Scopus databases were processed and analysed using the R software and the RStudio environment. For bibliometric analyses, the bibliometrix package developed by Aria & Cuccurullo (2017) and its web interface biblioshiny were used. Bibliometrix was preferred because it enables standardised implementation of comprehensive analyses – such as descriptive bibliometrics, collaboration networks, citation and co-citation analyses, and conceptual structure and thematic mapping – on large-scale datasets.

Biblioshiny and Microsoft Excel were used for visualisation; tables, network graphs and thematic maps were produced using these tools.

Data collection process

The data for this research consist of scholarly documents indexed in the WoS and Scopus databases, including various document types that were later filtered for the purposes of the analysis. On 7 September 2025, in both databases a comprehensive Boolean search string was applied, incorporating the following groups of terms:

- **Artificial intelligence and related technologies:** “Artificial Intelligence”, “Machine Learning”, “Deep Learning”, “Generative AI”, “Large Language Models”, “LLM”, “Natural Language Processing”, “NLP”, “Intelligent Tutoring System*”, “Learning Analytics”
- **Higher education context:** “Higher Education”, “University”, “Universities”, “College”, “Academia”, “Academic”

In WoS, the search was carried out in the “Topic” field (title, abstract, author keywords and Keywords Plus); in Scopus, it was applied to the TITLE-ABS-KEY field (article title, abstract and author keywords).

Web of science data

Web of Science is a bibliographic database covering scientific articles published in approximately 22,000 peer-reviewed journals worldwide and providing tools for advanced citation analysis and bibliometric investigation (European University Institute, 2024).

In this study, a search was conducted in the WoS Core Collection using the search string specified above in the Topic field, and 45,876 records were retrieved. The bibliographic records were exported in BibTeX format and, because of their large number, had to be downloaded in 92 separate files. These files were merged and converted in the R environment using the bibliometrix package. During this parsing process, 764 duplicate records were identified and removed from the dataset. As a result, an aggregate of 45,112 distinct publications sourced from the Web of Science (WoS) was readied for subsequent analysis (Web of Sciencea, 2025a; 2025b).

Scopus data

Scopus is one of the largest multidisciplinary bibliographic databases in the world, with robust quality-assurance procedures, and provides various metrics and analytical tools for assessing scientific outputs (Baas *et al.*, 2020, p. 377; Elsevier, 2025).

In this study, the “Documents” option was selected in the Scopus search interface, and the same search string as in WoS was applied to the TITLE-ABS-KEY field. This search yielded 87,008 publications, and the corresponding records were exported in csv format (Scopusa, 2025a; 2025b).

Merging and cleaning of the datasets

In bibliometric research, scholars often rely solely on WoS or solely on Scopus; when both databases are used, they typically either conduct separate analyses or choose one database over the other. However, although WoS and Scopus are the two most widely used and prestigious databases worldwide, the journals and subject areas they cover do not perfectly overlap (Taştan *et al.*, 2023, pp. 1319–1320).

Echchakoui (2020) argues that bibliometric analyses based only on WoS or only on Scopus provide a limited view of the knowledge base and trends in a field and proposes a four-step procedure for combining these two databases to obtain more reliable results. Similarly, Caputo & Kargina (2022) note that most bibliometric studies in management and related fields still rely on a single database, whereas integrating WoS and Scopus data yields a more comprehensive and balanced picture of the field.

In this study, the approach suggested by Echchakoui (2020), the recommendations of Caputo & Kargina (2022) and the procedures adapted by Atabay (2024) and operationalised by Sabır Taştan (2025a; 2025b) were followed. WoS and Scopus datasets were automatically merged in the RStudio environment using the bibliometrix package (Aria & Cuccurullo, 2017). The process can be summarised in three main steps:

1. **Conversion:** BibTeX files exported from WoS and csv files exported from Scopus were converted into data frames using the bibliometrix function *convert2df()*, with “wos”

and “scopus” specified as data sources, respectively. At this stage, duplicate records within the WoS dataset were removed, resulting in 45,112 publications, while the Scopus dataset remained at 87,008 records.

2. **Merging and removal of duplicates:** The two data frames obtained from WoS and Scopus were merged using the *mergeDbSources()* function, and publications that appeared in both databases were automatically removed as duplicates. As a result, 37,275 duplicate publications were eliminated, and a combined raw dataset (HEIAI) comprising 94,845 unique publications was created.
3. **Export and preparation for analysis:** The merged dataset was exported to Excel format, uploaded into the biblioshiny interface, and all bibliometric analyses were conducted on this integrated dataset.

Analysis and final dataset

Following the merging of the WoS and Scopus datasets and the removal of duplicate records, a raw dataset of 94,845 unique publications on artificial intelligence in higher education (HEIAI) was obtained. However, in order to enhance the validity and comparability of the bibliometric analysis, reduce distortions arising from differing citation dynamics across document types, and more accurately map the current research front of the field, the scope of the analysis was restricted to full-length, peer-reviewed journal articles.

As a result, various document classifications including “Conference Paper,” “Book,” “Book Chapter,” “Editorial,” “Meeting Abstract,” “Correction,” “Retracted Publication,” and similar designations were omitted from the subsequent analysis. Only documents classified as “Article” and “Review” were retained. After this filtering, the final cleaned dataset used in the analyses comprised 52,270 publications.

Table 1. Document types in the raw dataset.

Article	46491	Editorial Material	534
Article; Book Chapter	202	Editorial Material; Book Chapter	15
Article; Data Paper	117	Editorial Material; Early Access	15
Article; Early Access	1259	Erratum	729
Article; Early Access; Publication With Expression of Concern	2	Letter	172
Article; Early Access; Retracted Publication	12	Letter; Early Access	2
Article; Proceedings Paper	254	Meeting	1
Article; Publication With Expression of Concern	2	Meeting Abstract	61
Article; Retracted Publication	314	News Item	15
Bibliography	7	Note	233
Biographical-Item	3	Proceedings Paper	9200
Biographical-Item; Book Chapter	1	Report	1
Book	1774	Reprint	2
Book Chapter	3771	Retracted	116
Book Review	25	Retraction	20
Book Review; Early Access	5	Review	4290
Conference Paper	23121	Review; Book Chapter	10
Conference Review	1669	Review; Early Access	113
Correction	20	Review; Publication With Expression of Concern	1
Correction; Early Access	2	Review; Retracted Publication	2
Data Paper	14	Short Survey	48
Editorial	200	Total	94845

Table 1 offers a detailed overview of the allocation of the 94,845 documents within the unprocessed dataset categorized by document type. Table 2 illustrates the principal bibliometric descriptive statistics pertaining to the refined dataset.

Table 2. Descriptive statistics for the publications (filtered dataset).

Indicator	Value	Indicator	Value
Timespan	1959–2025	Keywords Plus (ID)	65,316
Sources (journals, books, etc.)	9,920	Author's Keywords (DE)	88,975
Documents	52,270	Authors	130,340
Annual Growth Rate (%)	7.58	Authors of single-authored documents	2,706
Document Average Age (years)	4.1	Single-authored documents	3,264
Average citations per document	20.32	Co-authors per document	6.4
References (total cited references)	1,339,054	International co-authorships (%)	17.17

All stages of data collection, removal of duplicates, and screening based on eligibility criteria were visualized in accordance with the PRISMA 2020 guidelines to enhance the transparency and reproducibility of the research. The systematic flow from the initial raw data pool to the final dataset of 52,270 articles included in the analysis is presented in Fig. 1.

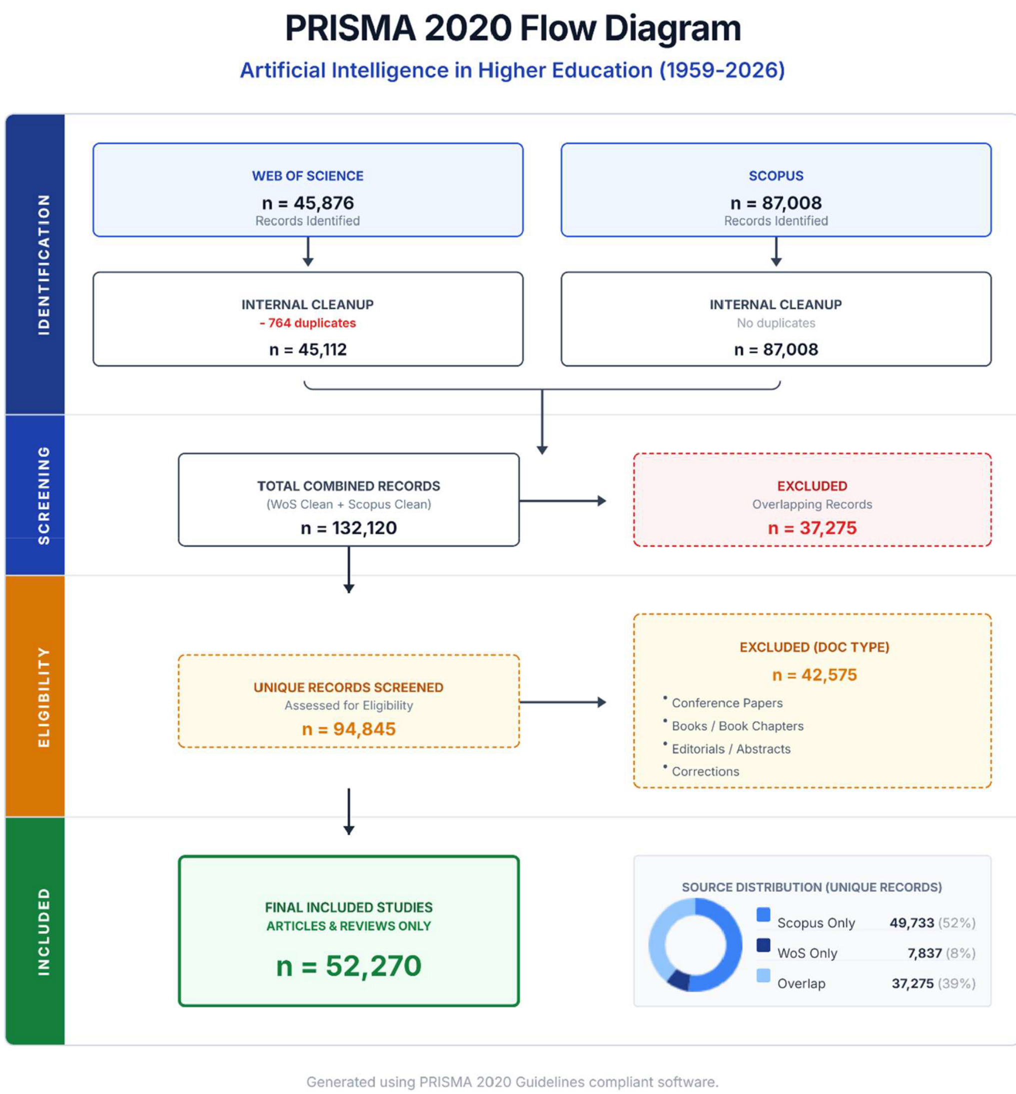

Fig. 1. Prisma 2020 flow diagram.
Source: Author's elaboration prisma 2020 by Page *et al.* (2021).

Data quality assessment conducted via the Biblioshiny interface confirmed that the filtered final dataset of 52,270 documents is of high analytical quality. In particular, the proportion of missing values in the AB (Abstract) and CR (Cited References) fields – which are critical for co-citation and conceptual structure analyses – was limited to only 0.08% and 1.63%, respectively, owing to manual cleaning of the raw data. These low levels of missingness indicate a robust empirical basis for co-citation and thematic analyses.

The quality-control output also showed that the WC (Web of Science subject categories) field, which is specific to WoS, is missing for 34.54% of the records in the merged dataset. This absence does not reflect a data-loss error but is a natural consequence of unique publications imported from Scopus, which does not use the WoS subject-classification scheme. Conducting analyses on the basis of the WC field would therefore systematically exclude more than one-third of the dataset and introduce substantial bias into the results. For this reason, the conceptual-structure and thematic analyses in this study rely instead on the DE (Author Keywords) and ID (Keywords Plus) fields, which are populated in both databases and exhibit a much lower missing-data rate of 12.67%, thus providing a more reliable foundation.

According to the indicators in Table 2, the oldest publication in the filtered dataset dates from 1959, while the most recent works are predominantly from 2025 and early-access publications dated 2026. On average, the publications are 4.1 years old; the annual growth rate of the field is 7.58%, and each document has received 20.32 citations. The dataset covers 9,920 distinct sources (mainly journals and books) and includes 1,339,054 cited references. In total, it contains 88,975 different author keywords and 65,316 Keywords Plus terms. The dataset under consideration contains a total of 130,340 authors, of which 2,706 documents are single-authored, with an average of 6.4 authors per document. The fraction of scholarly articles generated via international collaborative authorship constitutes 17.17%.

Findings

This section presents the descriptive bibliometric indicators, the conceptual structure (thematic mapping), the intellectual structure (citation analysis) and the key findings from a management science perspective.

Descriptive analysis

Annual scientific production

The first and most striking finding of the analysis concerns the distribution of scientific production in the “Higher Education and Artificial Intelligence” (HEI-AI) field over time (Fig. 2).

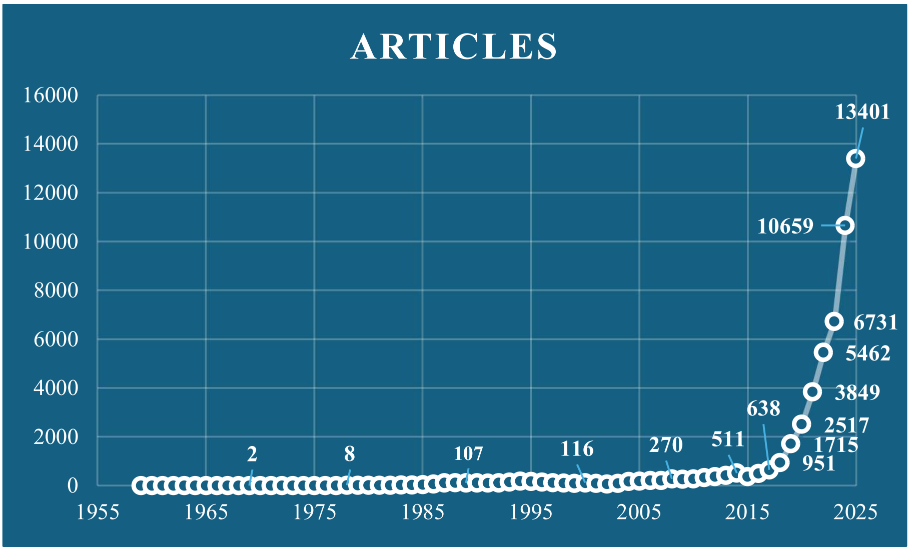

Fig. 2. Number of publications per year.

The graph points to three distinct phases in the development of the field:

1. **Stagnation and early phase (approximately 1991–2017):** During this period, the topic remained largely confined to niche areas such as "intelligent tutoring systems". Annual publication numbers were very low, and HEI-AI appeared mainly in small-scale and experimental studies.
2. **Initial growth (2018–2023):** From 2018 onwards, interest in the field rises steadily, driven in particular by the spread of machine-learning and learning-analytics applications. The growing number of publications shows that AI begins to move from isolated experiments to more systematic use in both teaching and administrative processes in higher education.
3. **Explosion phase (2024–2025):** The sharpest change occurs from late 2023. Between 2024 and 2025, the number of publications increases dramatically and surpasses the cumulative output of all previous years. This jump is closely linked to the public release and rapid diffusion of generative AI tools such as ChatGPT in late 2022.

Taken together, this pattern underlines why the present study is timely. The abrupt expansion of HEI-AI research in the last two years makes it crucial to map the field's conceptual structure (which themes are gaining prominence) and its intellectual foundations through a comprehensive bibliometric analysis.

Most relevant sources

Table 3 shows the main academic outlets in which HEI-AI publications are concentrated. The findings reveal that the field has a markedly interdisciplinary character and cannot be confined to a single discipline.

Table 3. Most relevant sources.

Sources	Number of articles
IEEE Access	900
Scientific Reports	508
Applied Sciences–Basel	424
Education and Information Technologies	400
PLOS ONE	370
Sustainability	324
Bioinformatics	317
Applied Mathematics and Nonlinear Sciences	315
Sensors	299
Education Sciences	247

At the top of the list, IEEE Access – a broad-scope engineering and computer science journal with 900 articles – indicates that a substantial part of the research focuses on technical infrastructure, algorithmic development and engineering applications. Similarly, journals such as Sensors (299 articles) reinforce this strong technical dimension.

By contrast, the presence of Education and Information Technologies (400 articles) in fourth place and Education Sciences (247) in tenth place signals a robust line of research centred on pedagogical applications, student experience and educational impact.

Multidisciplinary mega-journals such as Scientific Reports (508) and PLOS ONE (370) ranking among the top five demonstrate that HEI-AI transcends traditional disciplinary boundaries and attracts researchers from a wide range of scientific fields. Moreover, the presence of domain-specific journals such as Sustainability (324) and Bioinformatics (317) within the top 10 indicates that the application of AI in higher education is also examined in diverse contexts, including sustainability and health sciences education.

Overall, the table indicates that the HEI-AI field is not a narrow pedagogical niche discussed only by educators; rather, it constitutes a broad intersection of engineering, data science and educational research.

Most relevant authors

Analysis of the most productive authors (Fig. 3) provides strong clues about the geographical distribution of research in the HEI-AI field.

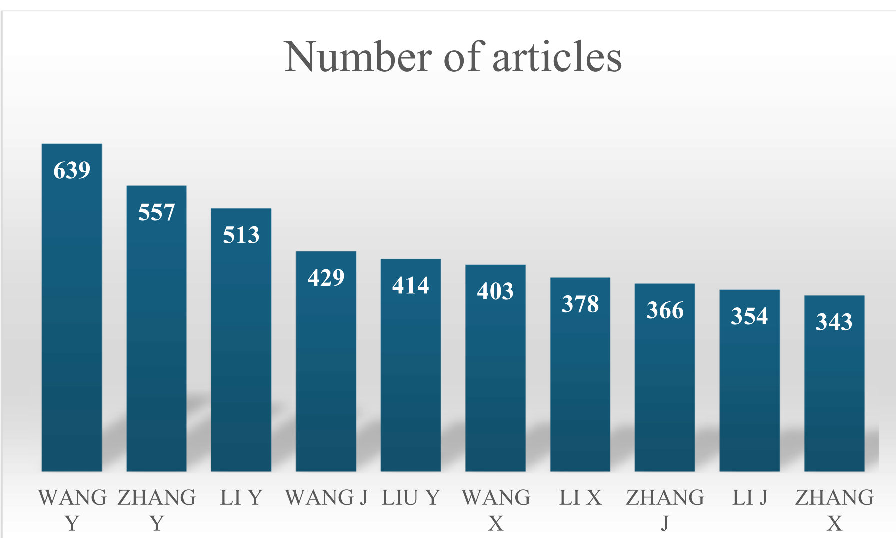

Fig. 3. Most relevant authors.

The fact that all of the top 10 authors (e.g. WANG, ZHANG, LI, LIU) have East Asian surnames indicates that Asian countries – particularly China – play a leading role in scientific production in this area.

The presence in the list of several authors sharing the same surname, such as WANG Y (639 articles) and WANG J (429 articles), suggests that research output is clustered around specific research groups or "schools of thought". This finding assumes added significance when viewed in conjunction with the "most productive countries" analysis presented in the subsequent subsection.

Most relevant countries

Table 4 shows how scholarly contributions in higher education and artificial intelligence are distributed across countries.

Table 4. Most relevant countries.

Country	Articles	Articles %	SCP*	MCP*	MCP %
China	12,208	23.4	10,608	1,600	13.1
USA	7,261	13.9	6,120	1,141	15.7
India	2,356	4.5	2,094	262	11.1
United Kingdom	1,915	3.7	1,378	537	28.0
Spain	1,476	2.8	1,189	287	19.4
Korea	1,361	2.6	1,123	238	17.5
Germany	1,252	2.4	935	317	25.3
Australia	1,187	2.3	883	304	25.6
Saudi Arabia	1,032	2.0	728	304	29.5
Canada	944	1.8	688	256	27.1

* SCP: intra-country, MCP: inter-country.

China ranks first, with 12,208 peer-reviewed publications, and thus emerges as the most productive country in the field. This discovery provides substantial evidence for the significant prevalence of East Asian surnames identified within the compendium of the most prolific authors.

The United States ranks second with 7,261 publications. Notwithstanding its relatively reduced output, the United States persists as a leading intellectual center within this particular field.

The next countries in terms of publication output are India (2,356 publications), the United Kingdom (1,915), and Spain (1,476). Together, these countries form one of the main hubs of global academic debate on HEI-AI. The rest of the top group includes Korea, Germany, Australia, Saudi Arabia, and Canada, which are key contributors from both Europe and Asia.

Most cited countries

The productivity table (Table 4) shows which countries publish the largest number of papers, whereas Fig. 4 highlights the countries whose work receives the highest number of citations in the international literature.

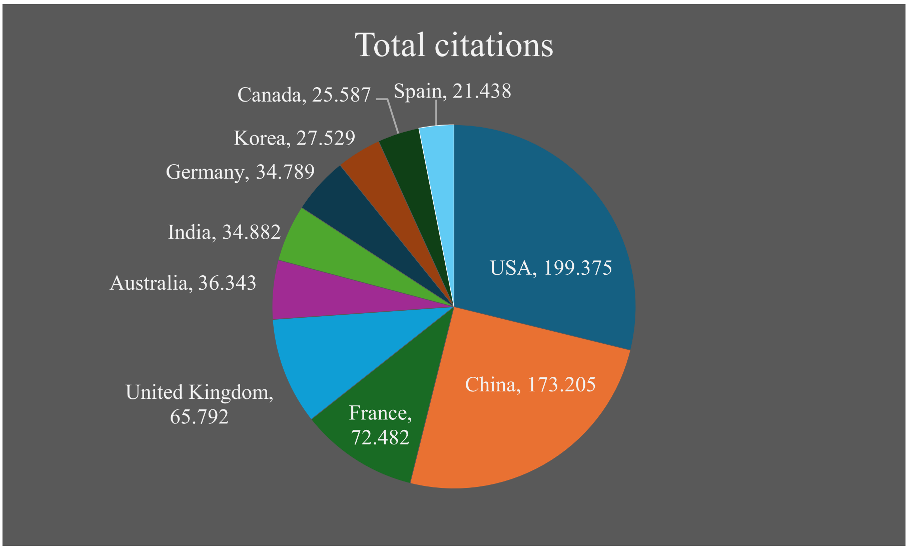

Fig. 4. Most cited countries – Top 10.

Reading Table 4 and Fig. 4 together reveals important nuances in the leadership structure of the field:

1. **Shift in leadership (USA–China):** While China is the clear leader in terms of total publications (12,208), citation counts indicate that the USA, with 199,375 citations, takes the lead in impact; China follows with 173,205 citations. This shows that the United States continues to play a strong role in producing the intellectual foundations and highly cited works of the field, even with a smaller number of publications.
2. **France's substantial influence:** Although France does not appear among the top 10 countries in terms of publication volume, it ranks third in total citations (72,482). This pattern suggests that France produces fewer papers overall, but these tend to be highly cited and play a central role in shaping the theoretical debates in the field.
3. **Stable intellectual hubs:** The United Kingdom holds fourth place for both publication output and total citations, indicating a stable position as an intellectual hub. Australia, Germany and Korea likewise maintain strong standings on both metrics.
4. **Variations in the ranking:** India ranks third in publication volume but drops to sixth place when citation counts are considered, suggesting that its overall impact is more modest than its level of output alone might imply. Similarly, Spain holds a fifth-place standing in terms of production yet experiences a decline to the tenth position with respect to citations.

The findings, when considered as a whole, suggest that the HEI-AI field manifests a bipolar structure. China dominates in terms of publication volume, whereas the United States holds the strongest position in intellectual influence and citation impact.

Most cited documents

Table 5 lists the ten most frequently cited publications in the HEI-AI literature.

The most striking element in this list is the article by Pedregosa *et al.* (2011), which introduces the machine-learning library scikit-learn and has received 63,247 citations—far more than any other item. Its very high citation count reflects the routine use of this open-source package across many scientific domains, including HEI-AI, and suggests that a large share of HEI-AI research is built on shared, standardised tools. The other

Table 5. Most cited documents – Top 10.

Paper	Total citations
Pedregosa *et al.*, 2011, J Mach Learn Res	63,247
Wooldridge & Jennings, 1995, Knowl Eng Rev	4,848
Geem *et al.*, 2001, Simulation	4,589
Saeys *et al.*, 2007, Bioinformatics	4,273
Sarker, 2021, SN Comput Sci	3,853
Searle, 1980, Behav Brain Sci	3,809
Schapire, 1990, Mach Learn	3,797
Clark, 2013, Behav Brain Sci	3,701
Cooper & Herskovits, 1992, Mach Learn	3,374
Katoh & Toh, 2008, Brief Bioinform	3,238

highly cited works point to the main methodological and theoretical pillars of the field. Foundational contributions by Schapire (1990) and Cooper & Herskovits (1992) underpin key machine-learning algorithms, while Saeys *et al.* (2007) anchors a strong line of work on feature selection. The prominence of these methodological references indicates that HEI-AI scholars are especially interested in identifying which student-related variables (for example, socio-demographic characteristics, patterns of engagement or grades) best predict academic performance.

The dissemination of scholarly works such as Searle (1980) and Clark (2013) in prestigious publications like Behavioral and Brain Sciences signifies that the discipline is also informed by cognitive and philosophical underpinnings. More recent survey/review articles such as Sarker (2021) show that the broader AI and data science literature has become a key reference point for HEI-AI researchers.

Spanning the period from 1980 to 2021, the list indicates that the HEI-AI field did not emerge solely from the recent “big data” and generative AI wave; rather, its roots extend back to the fundamental machine learning and knowledge engineering literature of the 1980s and 1990s.

Most relevant affiliations

Fig. 5 displays the most productive institutions and shows that publication output is geographically concentrated in two main regions.

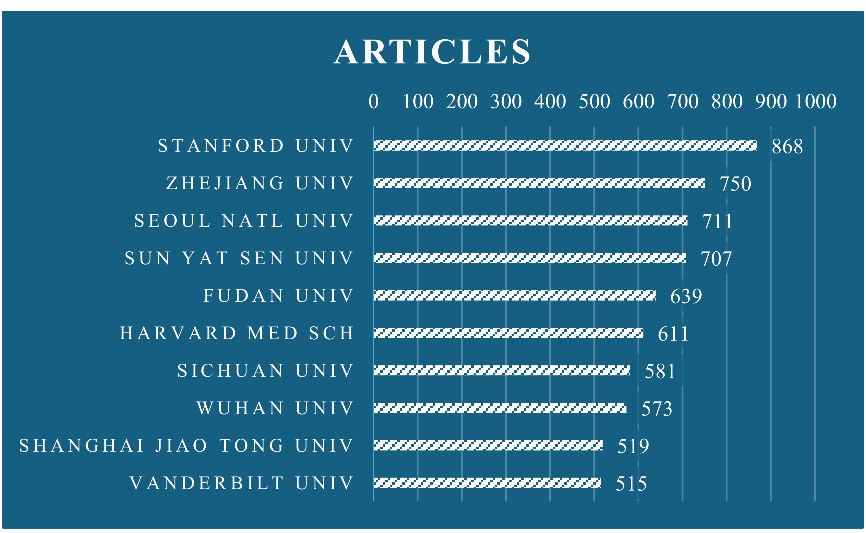

Fig. 5. Most relevant affiliations.

The analysis indicates that roughly 60% of the top 10 institutions are Chinese universities, notably Zhejiang University, Sun Yat-sen University, Fudan University, Sichuan University, Wuhan University, and Shanghai Jiao Tong University. This clearly reflects China's substantial strategic investment and academic production capacity in AI-related research.

Through Stanford, Harvard and Vanderbilt, the USA has a strong presence both at the top of the list (Stanford) and in specific domains such as medicine (Harvard Medical School). The inclusion of Seoul National University in the list shows that South Korea is also an important global actor in this high-technology research area. Conversely, the absence of European universities from the top ten is a noteworthy finding.

Stanford University, with 868 publications, outpaces its closest competitor Zhejiang University (750 publications) by more than 100 publications and thus stands as the most productive institution in the field. The relatively small differences in publication counts among the Chinese universities and other institutions in the top 10 suggest intense competition. The fact that "Harvard Med Sch" appears not as a general university label but specifically as the medical school (611 publications) indicates that the intersection of AI and higher education has become a particular focal area in medical education.

Conceptual structure (thematic mapping)

This subsection examines the themes around which the 52,270 publications cluster, identifying which topics constitute motor, emerging or niche themes and which areas may represent potential research gaps.

Thematic map

The thematic map shows the conceptual structure clusters in the HEI-AI field. Topics are assessed along two dimensions:

- **Centrality (X-axis):** the degree of importance and connectedness of a theme to the field as a whole (importance increases towards the right);
- **Density (Y-axis):** the degree to which a theme is internally developed and mature (development increases upwards).

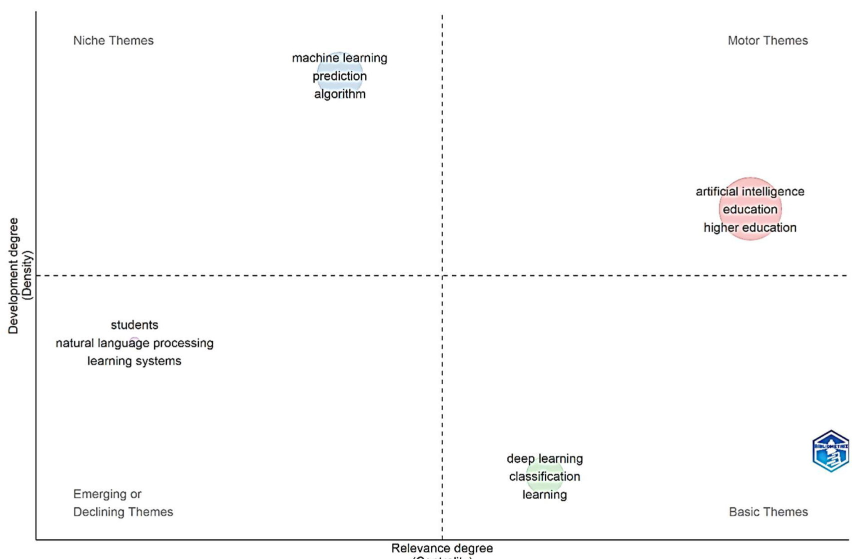

Fig. 6. Thematic map.

The map shows that the field is organised into four main clusters (Fig. 6):

- **Motor themes (upper right):** The clusters “artificial intelligence”, “education” and “higher education” form the motor themes of the field with high centrality and high density, representing the core of intellectual development. Taken together, these thematic elements indicate that artificial intelligence has wide-ranging implications, extending from teaching and learning practices to the governance arrangements of higher education institutions.
- **Niche themes (upper left):** The clusters “machine learning”, “prediction” and “algorithm” are highly developed but have relatively lower centrality and thus represent specialised fronts that are methodologically mature yet less connected to the overall network. These technical method-oriented themes have not yet been fully integrated into the broader educational context.
- **Emerging or declining themes (lower left):** The clusters designated “students,” “natural language processing,” and “learning systems” are classified as emerging or declining, as indicated by their low centrality and density. This analytical observation indicates that these thematic elements may signify domains that have recently surfaced within the academic literature yet have not yet formed substantial focal points, or subjects that were more salient in previous epochs but have recently diminished in prominence.
- **Basic themes (lower right):** The clusters “deep learning”, “classification” and “learning” constitute basic themes with high centrality but relatively low density. Taken together, these themes outline the main conceptual structure of the field and provide both the theoretical and methodological starting point for much of the current research. In particular, deep learning approaches have become a central point of reference at the intersection of artificial intelligence and education.

Overall, the thematic map indicates that the relationship between AI and higher education constitutes the motor theme of the field; machine learning and algorithmic studies form methodological niches; and deep learning plays a core role in sustaining this structure. Emerging themes, in turn, hold the potential to offer new research opportunities in the near future.

Co-occurrence network of keywords

The co-occurrence network of keywords shows that the field is organised around several interconnected main clusters (Fig. 7).

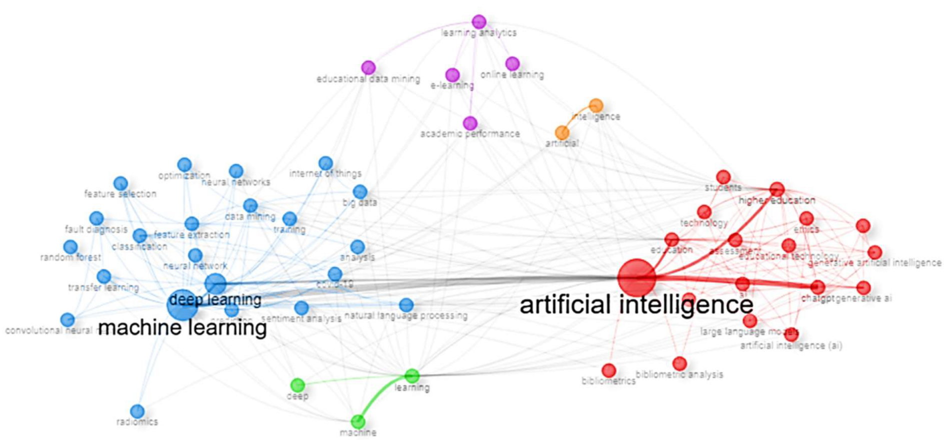

Fig. 7. Keyword co-occurrence network.

At the nucleus of the network resides the notion of “artificial intelligence,” which holds a preeminent status. It has the highest centrality and, through strong links with terms such as “higher education”, “students”, “assessment”, “educational technology”, “ethics”, “generative artificial intelligence” and “large language models”, forms the conceptual backbone of the field. The incorporation of ChatGPT and other generative AI tools into this core architecture reflects the most recent developments in the field.

The blue cluster on the left side of the network, comprising terms such as “machine learning”, “deep learning”, “neural networks”, “data mining”, “feature extraction”, “classification” and “optimization”, represents the technical and methodological dimension of AI. The large node sizes for “machine learning” and “deep learning” indicate high frequency and strong internal coherence.

The purple and orange subclusters at the top of the map bring together themes such as “learning analytics”, “online learning”, “educational data mining”, “academic performance” and “e-learning”, forming a bridge between technical methods and pedagogical applications.

The small but clearly visible green cluster in the lower right (“learning–machine–deep”) functions as a conceptual bridge linking core learning processes with technical methods.

Overall, the network structure shows that AI-related research occupies a central position in the educational context; that machine learning and deep learning provide a strong technical backbone for this literature; and that the learning analytics–educational technologies strand plays a connecting role between these two main clusters.

Thematic evolution

The thematic evolution diagram illustrates the conceptual transformation of the HEI-AI field from the period 1959–2023 to the period 2024–2026 (Fig. 8).

Fig. 8. Temporal thematic evolution of the field.

In the first period, the dominant themes are "learning", "artificial intelligence", "machine learning" and "controlled study". In the second period, these themes evolve into more focused and methodologically deeper subfields.

The shift of "learning" towards the "machine learning" axis in the second period indicates that general discussions about learning have gradually given way to data-driven, algorithmic approaches. Similarly, "artificial intelligence" remains a central axis in both periods but becomes more tightly connected to specific application areas and technical subthemes in the second period.

As the first phase unfolds, *machine learning* emerges as a central theme and gradually gains prominence. Over time, this concept evolves and becomes closely intertwined with *deep learning* in the subsequent period. It is noteworthy that the systematic integration of "controlled study" into the "deep learning" paradigm indicates a gradual replacement of conventional controlled experimental designs with data-intensive, model-based methodologies.

Overall, the thematic evolution points to (i) a shift from general concepts to methodological depth; (ii) the continuity of AI as a central theme across periods; and (iii) the increasing technicalisation of the research agenda along the machine learning → deep learning trajectory.

Intellectual structure (citation analysis)

This section examines, through co-citation analysis, the foundational works and methodological tools on which the field rests.

Co-citation network

The analysis of the co-citation network was performed to elucidate the intellectual architecture and conceptual aggregation within the domain of Higher Education Institutions and Artificial Intelligence. The analysis yielded a distinct four-cluster structure (Fig. 9).

Each cluster signifies a segment of the extant literature that draws on a particular paradigm and knowledge base. A diverse array of centrality metrics was utilized to assess the positional significance and connective functions of references within the network, encompassing betweenness, closeness, and PageRank.

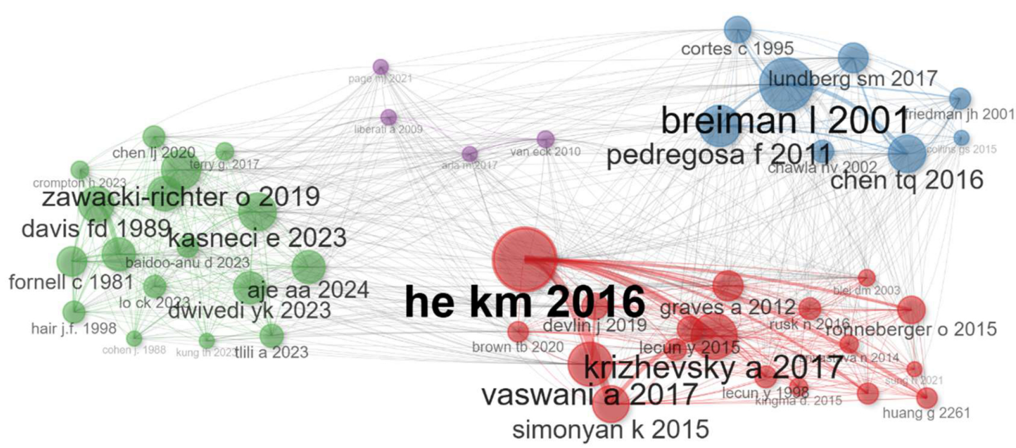

Fig. 9. Intellectual foundations (co-citation map).

- **Cluster 1 – Deep learning and large language models (LLMs):** This cluster includes foundational works in deep learning such as Graves (2012), He *et al.* (2016), Goodfellow *et al.* (2016), Kingma & Ba (2015), Krizhevsky *et al.* (2017), LeCun *et al.*, 1998, Lecun *et al.*, 2015), Ronneberger *et al.* (2015), Simonyan & Zisserman (2014) and Srivastava *et al.* (2014). Vaswani *et al.* (2017) ("Attention Is All You Need"), Devlin *et al.* (2019) (BERT) and Brown *et al.* (2020) (GPT-3) also fall within this cluster, indicating that transformer-based studies have not yet formed a fully independent epistemic community but remain integrated with the deep-learning core. Vaswani *et al.* (2017) and Brown *et al.* (2020) stand out as key bridge publications with high betweenness values, while He *et al.* (2016) occupies a structural centre due to its high PageRank.
- **Cluster 2 – Classical machine learning and explainability:** This cluster centres on classic machine-learning contributions such as Breiman (2001) on random forests, Cortes *et al.* (1995) on support vector machines, Friedman (2001) on boosting, and Chawla *et al.* (2002) on SMOTE, together with more recent tools including Pedregosa *et al.* (2011) on scikit-learn and Chen & Guestrin (2016) on XGBoost. Lundberg & Lee (2017) SHAP approach further provides a widely used framework for addressing model explainability within this cluster. High betweenness values indicate that these publications act as methodological bridges across different disciplines.
- **Cluster 3 – Applications in education and the social sciences:** This cluster encompasses research contributions such as Zawacki-Richter *et al.* (2019), Kasneci *et al.* (2023), Baidoo-anu & Ansah (2023), Dwivedi *et al.* (2023), and Crompton & Burke (2023), which investigate themes pertaining to artificial intelligence in educational technologies, learning analytics, and the implementation of ChatGPT alongside large language models within educational contexts. Furthermore, this cluster brings together key references on technology adoption and social science methodology, including Davis (1989), Venkatesh *et al.* (2003), Fornell & Larcker (1981), Cohen (1988), and Hair *et al.* (1998). This combination indicates a strong epistemic link between pedagogical content and technology acceptance models in AI-in-education research.
- **Cluster 4 – Bibliometric methods and tools:** The core of this cluster is formed by van Eck & Waltman (2010) (VOSviewer), Aria & Cuccurullo (2017) (bibliometrix) and the PRISMA guidelines (Liberati *et al.*, 2009; Page *et al.*, 2021). As these publications are widely used in bibliometric and systematic review studies, they form strong links with all other clusters. In particular, the paper by van Eck & Waltman (2010) occupies a key bridging position in the bibliometric network, as reflected in its very high betweenness centrality.

This four-cluster structure shows that the HEI-AI field rests on four intellectual pillars:

(i) deep learning and LLMs,
(ii) classical machine learning and explainability,
(iii) applications in education and the social sciences and
(iv) bibliometric methods.

Word cloud

The implementation of a word cloud analysis serves to visualize the most frequently occurring concepts in the extant literature, thereby elucidating the predominant foci of the field (Fig. 10).

Fig. 10. Word cloud.

The prominence of “artificial intelligence”, “machine learning” and “deep learning” in the word cloud indicates that the methodological core of the field is still grounded in machine-learning and deep-learning approaches. The visibility of terms such as “ChatGPT”, “students”, “education”, “higher education”, “learning systems” and “learning analytics” shows that AI applications in educational contexts are rapidly becoming a central area of research.

Terms such as “classification”, “algorithm”, “prediction”, “controlled study” and “performance” point to a strong emphasis on experimental designs, model comparisons and performance evaluation. Meanwhile, concepts such as “natural language processing”, “risk” and “diagnosis” indicate that AI applications extend beyond the higher education context into domains such as health, data analytics and decision-support systems.

Overall, the word cloud suggests that the literature is concentrated along two main axes:

1. **Technical axis:** This axis brings together core methodological topics such as artificial intelligence, machine learning, deep learning, algorithms and classification techniques.
2. **Application axis:** This axis captures how these tools are used in practice, particularly in education, student engagement, higher education learning systems, and applications involving ChatGPT and other natural language processing (NLP) tools.

This structure is consistent with the findings from the thematic map and the co-occurrence network.

Key findings from a management science perspective

The findings derived from the dataset of 52,270 publications indicate that the HEI-AI field is a critical intersection not only for pedagogy but also for strategic management and organisational transformation:

- **Exponential growth and strategic urgency:** The exponential increase in publication counts in 2024–2025 following the public release of generative AI tools points to an urgent need for strategic adaptation and governance in higher education institutions.
- **Interdisciplinary intersections and organisational silos:** The co-occurrence of technically oriented journals (e.g., IEEE Access) and education-focused outlets (e.g., Education and Information Technologies) among the most relevant sources indicates that AI integration represents a multifaceted management challenge, necessitating the dissolution of technical, pedagogical, and managerial silos within academic institutions.

- **Bipolar structure in global leadership:** While China (12,208 publications) leads in terms of publication volume, the USA (199,375 citations) is ahead in citation impact, indicating a dual structure in which one pole reflects a mass-production strategy and the other a central role in shaping intellectual directions and theoretical frameworks.
- **Methodological concentration in the conceptual structure:** Joint interpretation of the thematic map and co-citation analysis shows that the field is organised around two main poles: deep learning and large language models on the one hand, and technology acceptance models and educational applications on the other. This pattern shows how technical tools and social-science perspectives inform one another in universities that conduct research on artificial intelligence.
- **Technicalisation of the research agenda:** A central finding of this study is that the research agenda has become increasingly technical in focus. The thematic evolution results indicate a transition from general concepts such as "learning" to methodological themes such as "machine learning" and "deep learning." The integration of the "controlled study" framework into "deep learning" methodologies over an extended period indicates a gradual supplanting of traditional experimental designs with data-centric, model-oriented approaches. This pattern highlights the growing strategic importance of data governance, model-development capacity and ethical safeguards in higher education institutions.

The Discussion section examines these findings in greater depth through the lenses of neo-institutional theory and strategic management, with particular attention to adoption processes, legitimacy, diffusion and isomorphism.

Discussion

This study examined the institutional and strategic transformation of the higher education and artificial intelligence (HEI-AI) field from a management science perspective, using a comprehensive dataset compiled from the Web of Science and Scopus databases for the period 1959–2025. The bibliometric findings show not just a marked rise in the number of publications, but also a clear shift in the field's core concepts, underlying assumptions and institutional logics. In this section, the findings are discussed in relation to neo-institutional theory and diffusion literature, debates on technicalisation and datafication, global power balances and bibliometric hegemony, as well as managerial and policy implications.

Neo-institutional theory and diffusion dynamics: adopting AI for legitimacy

The annual scientific production graph suggests a three-stage diffusion pattern in the HEI-AI field: a long stagnation/early phase (1991–2017), accelerated initial growth after 2018 and an explosive, exponential increase in 2024–2025. From a neo-institutional perspective, this pattern closely resembles the classic model whereby innovations are initially adopted by a limited group of early adopters for predominantly technical/rational reasons and subsequently diffused across a broader organisational population under legitimacy pressures (Tolbert & Zucker, 1983, p. 26; DiMaggio & Powell, 1983, p. 148).

In the early period, AI applications were concentrated primarily in engineering, computer science and information systems, and in niche areas such as "intelligent tutoring systems", while remaining relatively experimental and limited within higher education. This phase may be interpreted as a "pre-institutionalisation" stage, in which the innovation is adopted largely on rational grounds such as efficiency gains, problem solving or research curiosity.

The sharp increase after 2023, driven by the spread of tools such as ChatGPT, marks a second diffusion phase in which legitimacy considerations come to the fore. In this phase, universities bring AI onto their agendas not only because its pedagogical effectiveness has been empirically demonstrated, but also due to concerns about not appearing "left behind", remaining competitive globally and conforming to environmental expectations. Özen (2013, p. 129) emphasises that, in the "new diffusion thesis", all organisations – both early and late adopters – act on a combination of economic and social motives, contrary to the assumptions of the traditional diffusion thesis. Drawing on Kennedy & Fiss (2009), he notes that early adopters seek economic and social gains such as improved efficiency and enhanced legitimacy, whereas later adopters adopt new practices to avoid economic and social losses, such as falling behind in competition or losing legitimacy (Özen, 2013, p. 129). The accelerated growth of the HEI-AI domain aligns with this perspective. Many organisations appear to be adopting AI less to position themselves as innovation leaders and more to avoid the risk of being left behind.

However, diffusion does not automatically result in a single, uniform pattern of isomorphism. Boxenbaum & Jonsson (2017, pp. 18, 37) show that organisations can reinterpret and transform the same template in line with their local institutional and cultural contexts and existing institutional logics. The thematic and co-occurrence networks in the present study support this view: some universities frame AI mainly around "predicting student success" and "risk management"; others focus on "learning analytics and quality assurance"; and yet others foreground debates on "ethics, privacy and academic integrity". This diversity indicates that, alongside institutional isomorphism, strong translation and localisation dynamics are also at work in the HEI-AI field.

Technicalisation and datafication: thematic evolution and conceptual shift

The thematic map shows that the conceptual structure of the field is organised into four main clusters. The motor themes are structured around the clusters "artificial intelligence", "education" and "higher education", representing the core of the field. The fact that these motor themes cluster together in the co-occurrence network with concepts such as "students", "assessment", "learning analytics", "educational data mining" and "academic performance" indicates that AI research extends far beyond classroom pedagogy; it now spans the measurement of learning outcomes, performance monitoring and data-driven decision-support systems related to quality assurance and institutional governance.

On the map, the clusters built around "machine learning", "prediction" and "algorithm" appear in the upper-left quadrant as niche themes, indicating technically specialised lines of inquiry. Their high density suggests that technical methods in the literature have reached an advanced degree of maturity, whereas their relatively lower centrality indicates that these studies occupy a more limited position within the overall network of the field. In other words, although machine learning and algorithmic studies constitute a strong methodological core, they have not yet become a dominant "grand narrative" that fully defines the HEI-AI literature.

The prominence of terms such as "classification", "prediction", "performance" and "controlled study" in the word cloud and co-occurrence analyses suggests that the use of AI in higher education is increasingly embedded in a logic of decision support, forecasting and performance evaluation. While this pattern points to a high level of methodological sophistication, it also raises the risk that the human, ethical and contextual dimensions of learning may become secondary to data-driven optimisation.

From a neo-institutional perspective, this situation brings into focus the risk of "ceremonial adoption" discussed by Meyer & Rowan (1977, p. 340): although AI is widely adopted to gain institutional legitimacy and reinforce the image of being a "modern/innovative university", some practices may have limited impact on actual organisational routines, creating gaps between formal structures and enacted practices. It is therefore essential to discuss technical and data-driven AI applications not only in terms of performance and efficiency indicators, but also in terms of how they transform teaching–learning relationships, institutional identity and academic values.

Global power balances and bibliometric hegemony

Country- and institution-level analyses reveal a distinct geopolitical differentiation in the HEI-AI field. China's clear leadership in publication volume (e.g. 12,208 publications) is consistent with evidence that AI has been placed at the centre of a long-term national industrial and competitiveness strategy and that universities operate under strong state-led institutional pressures in line with this strategy (Packer & Huang, 2025; Su & Wu, 2025). In line with DiMaggio & Powell (1983) concept of coercive isomorphism, this suggests that universities' engagement in AI is linked not only – and in some cases not primarily – to performance concerns, but also to legitimacy and policy objectives. By contrast, the continuing citation advantage of the United States indicates that Western academic norms, quality standards and entrenched core–periphery relationships remain highly influential. The fact that France ranks among the top three most cited countries (72,482 citations) despite not being in the top 10 in terms of output reflects a different strategy of producing "fewer but highly impactful" publications that substantially shape theoretical debates in the field.

This bipolar structure echoes debates on the hegemony of global rankings and bibliometric indicators (e.g. Belenkuyu & Karadag, 2022). The creation of ranking indexes and citation-based indicators establishes a symbolic field of power that favors certain countries and institutions. As a result, higher education institutions feel compelled to adopt similar approaches to allocating resources, managing institutional reputation and positioning themselves in an increasingly competitive landscape. In the HEI-AI field, countries with high publication volumes gain advantageous positions in global citation networks, whereas those producing fewer but highly cited works become intellectual centres – all of which are components of a broader hegemonic structure.

The distribution of journals reinforces this pattern. The prominence of technical or multidisciplinary outlets such as IEEE Access, Sensors, Scientific Reports and PLOS ONE among the most prolific sources indicates that evaluation criteria are heavily oriented towards technical outputs and quantitative metrics. By contrast, education-focused journals such as Education and Information Technologies represent a smaller portion of the output and carry the pedagogical dimension of the field. This can be read as evidence that the HEI-AI field is increasingly shaped by an epistemology grounded in technical and engineering logics.

Moreover, the co-citation analyses show that the intellectual foundations of the field rest, on the one hand, on core algorithmic studies (e.g. deep-learning architectures, standardised machine learning libraries) and, on the other, on technology adoption models and theories of education and learning. The high citation rates of standardised open-source software frameworks, such as scikit-learn (Pedregosa *et al.*, 2011), point to a shared technical infrastructure that speeds up the spread of new tools and encourages technical isomorphism across organisations.

Positioning of the study in the literature and discussion of contributions

In methodological and theoretical terms, this study diverges from the existing literature in several important respects. First, by combining both Web of Science and Scopus and by carefully filtering out different document types, it offers a broader and more standardised research front than many previous bibliometric studies. While HEI-AI-focused works such as Hinojo-Lucena *et al.* (2019), Maphosa & Maphosa (2023), López-Chila *et al.* (2023) and Valdiviezo *et al.* (2024) typically rely on narrower datasets and single databases, the present study provides a more comprehensive mapping of the historical development, thematic structure and intellectual precursors of the field.

Secondly, the investigation is anchored not solely in an educational sciences framework but also in the domain of management science and a neo-institutionalist theoretical perspective. The framework proposed by Çiftçi et al. (2016) for mapping national scientific fields and the bibliometric methodology outlined by Zupic & Čater (2015) for management and organisation research are broadly aligned with the methodological background of this study. However, the analysis presented here makes an original contribution by conceptualising the HEI-AI field as an "organisational field" explored through themes such as legitimacy, isomorphism, diffusion and institutional logics, rather than solely through thematic clusters.

Managerial and policy implications

The results present numerous significant ramifications for the management and policy formulation processes within the realm of higher education. First, the role of AI in higher education increasingly goes beyond a conventional "IT infrastructure" issue and is becoming an integral part of the institution's strategic resource base. The concentration of a substantial share of publications in technical and engineering-oriented journals suggests a pressing need for interdisciplinary AI governance mechanisms in universities that can bridge technical capacity and pedagogical vision.

Second, the fact that themes such as ethics, privacy, academic integrity and fairness in assessment do not yet form clusters as dominant as the technical themes in the co-occurrence networks indicates that regulatory frameworks and institutional policies are lagging behind the pace of AI diffusion. As a result, policymakers need to move beyond purely restrictive approaches and instead develop flexible institutional frameworks for AI, roll out broad-based AI literacy programmes, and put in place clear and workable ethical guidelines.

Third, the research front appears to be approaching saturation in technical and quantitative studies. The next step clearly requires qualitative, critical and mixed-methods research that examines the impact of AI on organisational culture, academic identity, leadership styles, academic labour regimes and global inequalities. This study provides a starting map of the field's historical and conceptual coordinates for such future research.

Limitations and potential avenues for future research

This study is based on one of the most extensive datasets currently available in this domain. However, it is still constrained by several limitations. First, the analysis is restricted to the Web of Science and Scopus databases; studies indexed in national databases or broader platforms such as Google Scholar – particularly those published in languages other than English – are not included. This may cause the AI experiences and contributions of universities in the Global South to appear more muted than they actually are.

Second, the exponential increase in publications in 2024–2025 makes it difficult to assess their citation performance reliably at this stage; owing to citation delay, it will take time to identify which recent works will become highly cited foundational studies.

Third, bibliometric techniques are well suited to tracing overall trends, network patterns and thematic clusters, but they do not directly evaluate the quality of the arguments, the richness of the teaching insights or the ethical sensitivity of specific publications. Future research that combines bibliometric analysis with qualitative content analysis, case studies and critical discourse analysis could thus deepen the quantitative findings presented here and offer a richer understanding of HEI-AI as an evolving organisational field.

Conclusion

Drawing on 52,270 publications indexed in the Web of Science and Scopus databases between 1959 and 2025, this study has provided a comprehensive management science mapping of the historical development, intellectual foundations and thematic structure of the artificial intelligence in higher education (HEI-AI) field. The findings show that AI has evolved beyond a short-lived "technology wave" to become a lasting institutional reality that is reshaping how universities process information, make decisions and produce organisational legitimacy.

The annual publication curve reveals a three-stage diffusion pattern in HEI-AI: a long preparatory phase, followed by acceleration, and finally an exponential surge between 2023 and 2025. This pattern is consistent with a two-stage adoption dynamic in which early phases are driven predominantly by technical and rational considerations, while later phases are increasingly shaped by legitimacy pressures and concerns about "not falling behind". The thematic and conceptual analyses indicate that the field is becoming progressively more technical and datafied, with learning analytics, prediction, classification and performance assessment logics moving to the centre of pedagogical and institutional decision-making. This configuration points to a dual situation in which methodological maturity is clearly increasing, yet the human, ethical and contextual dimensions of learning risk being overshadowed.

At the country, institutional, and journal levels, findings demonstrate a close intertwining of HEI-AI with global power relations and bibliometric hegemony. China's dominance in publication volume and the United States' leading position in citation impact, when read alongside the prominence of technical and multidisciplinary journals, suggest that the epistemological framing of the field is largely shaped by engineering and data-science logics. From this perspective, AI in higher education is no longer merely an issue of IT infrastructure, but has become a strategic resource, a competitive instrument and a key component of institutional image management.

These findings possess profound implications for leaders in higher education and those engaged in policy formulation. Universities need AI strategies that integrate technical capacity with pedagogical vision, ethical principles and institutional values; this requires transparent, flexible and inclusive institutional policies on AI use, as well as AI literacy programmes targeting academic and administrative staff and students. At national and international levels, policy-making processes should move beyond purely restrictive approaches and develop regulatory frameworks that are guidance-oriented and equity-focused. By providing a detailed scientific map of the field, this study also offers an analytical starting point for future qualitative and mixed-method research on HEI-AI in relation to organisational culture, academic identity, leadership and global inequalities.

In sum, AI represents far more than a technical innovation in higher education. This shift reflects a wider institutional change. It raises basic questions about how universities work, what they treat as sources of legitimacy, and how the global academic field is being reorganised. The universities of the future will be shaped by those institutions that are able to govern this algorithmic transformation not merely as a technological investment, but as an integral element of building a human-centred, just and sustainable academic order.

AI is not just technology; it is a process that redefines the institutional structure.

Responsible Use Statement for Artificial Intelligence Tools: During the preparation of this work, the authors used OpenAI's ChatGPT (GPT-5 model) to improve the linguistic clarity and scholarly tone of the manuscript. After using GPT-5, the authors reviewed and edited the content as needed and take full responsibility for the final manuscript. All research design, data analysis, and substantive interpretations remain the original work of the authors.

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Conflict of interest

The authors declare no conflict of interest.

Data availability

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Author contribution

All authors contributed equally to this work. All authors read and approved the final manuscript.

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