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Artificial Intelligence and Entrepreneurship Within Academic Ecosystems: A Bibliometric Analysis (2019–2025)

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Abstract:

This article addresses a specific gap in the bibliometric literature on artificial intelligence and higher education. While prior reviews by Kavitha et al. (2024), Flores-Velásquez et al. (2024), and Sahar and Munawaroh (2025) have broadly mapped AI adoption in higher education, none has jointly examined AI's role within university entrepreneurial ecosystems, nor systematically tracked the generative AI inflection point that emerged after 2022 in this sub-field. To address this gap, the study applies a bibliometric protocol grounded in the PRISMA framework to an initial pool of 222 Scopus-indexed documents published between 2019 and 2025, reduced to a final corpus of 165 articles after applying disciplinary, temporal, and document-type exclusion criteria. The corpus was processed with VOSviewer to map publication trends, leading journals, country contributions, and keyword co-occurrence networks. Results reveal a pronounced geographic concentration of research output, with China alone accounting for 37 percent of the corpus and the nine most productive countries jointly contributing nearly four-fifths of all publications. Keyword co-occurrence analysis identifies artificial intelligence, students, and entrepreneurship education as the field's dominant thematic anchors, with artificial intelligence acting as the principal structural connector bridging pedagogical and entrepreneurial sub-themes. These patterns point to pedagogical innovation, entrepreneurial competency-building, and generative AI integration as the field's core research clusters. From a managerial perspective, the findings call on university incubators and technology transfer offices to embed AI literacy and generative AI tools into entrepreneurship curricula and venture-support processes, consistent with the conceptualization of AI as a general-purpose technology. The study's main limitations stem from its exclusive reliance on the Scopus database and its purely quantitative bibliometric design; future research should combine multiple databases and incorporate qualitative approaches to further explore innovation dynamics within university entrepreneurial ecosystems.

Keywords: Artificial Intelligence, Academic Entrepreneurship, University Ecosystems, Bibliometric Analysis, Generative AI.
Classification JEL: I23, L26, O30.
Paper type: Empirical Research

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1. Introduction

In the context of the accelerated digital transformation of higher education, artificial intelligence (AI) has become a major driver of the reconfiguration of university ecosystems. Since 2019, research at the intersection of AI, academic entrepreneurship, and university innovation has expanded rapidly, although the literature remains fragmented, limiting a comprehensive understanding of the field's evolution and emerging research directions.The rise of generative AI tools, and particularly the widespread diffusion of large language models (LLMs) such as ChatGPT from late 2022 onwards has constituted a major inflection point in this field of research. These technologies have transformed teaching, knowledge creation, and university entrepreneurship by lowering technological barriers for student entrepreneurs (Nambisan et al., 2019; Obschonka & Audretsch, 2020). Universities, traditionally perceived as training and research institutions, are now repositioning themselves as full-fledged entrepreneurial ecosystems, integrating incubation structures, technology transfer mechanisms, and open innovation frameworks (Etzkowitz, 2013; Chesbrough, 2003) In this context, bibliometric analysis is a particularly appropriate method for mapping the evolution of a rapidly expanding research field by providing an objective synthesis of publication trends, influential contributors, and conceptual structures (Zupic & Čater, 2015; Donthu et al., 2021).

The present study analyzes a corpus of 165 Scopus-indexed articles published between 2019 and 2025 using VOSviewer. The selected period captures the emergence of AI as a strategic driver of entrepreneurial transformation in higher education while encompassing the disruptive diffusion of generative AI after 2022, making it particularly suitable for examining this emerging research domain. Building on this rationale, the study addresses three research questions. (RQ1) How has scientific production on AI and academic entrepreneurship evolved during 2019-2025, and what bibliometric patterns characterize its recent expansion? (RQ2) Which countries, institutions, and journals dominate this field, and what bibliometric patterns are associated with the observed geographical concentration? (RQ3) What thematic clusters structure the literature, and how do they differ from those identified in broader bibliometric studies on AI in higher education? Unlike previous bibliometric reviews by Kavitha et al. (2024), Flores-Velásquez et al. (2024), and Sahar and Munawaroh (2025), which primarily examine AI adoption in higher education from educational or technological perspectives, the present study focuses specifically on the intersection of artificial intelligence, academic entrepreneurship, and university entrepreneurial ecosystems. It therefore extends the existing literature by highlighting the entrepreneurial dimension of AI through the analysis of incubation, venture creation, entrepreneurial competencies, and innovation support structures. This study contributes to the literature in three ways: first, by providing a dedicated bibliometric mapping of AI and academic entrepreneurship; second, by interpreting bibliometric patterns through established entrepreneurship theories; and third, by deriving implications for university governance and entrepreneurial support ecosystems.

Conceptually, the analysis is grounded in Schumpeter's theory of creative destruction (1942), Knight's theory of uncertainty (1921), and Sarasvathy's effectuation theory (2001, 2008), which provide the theoretical basis for interpreting the observed bibliometric patterns. From a practical perspective, RQ1 informs university decision-makers about the evolution of the field, RQ2 supports incubator managers and innovation support organizations by identifying leading actors and collaboration patterns, and RQ3 assists researchers in identifying emerging themes and future research opportunities. The remainder of this article is organized as follows. Section 2 presents the theoretical and conceptual framework. Section 3 describes the bibliometric methodology. Section 4 presents the findings. Section 5 discusses their theoretical, managerial, and methodological implications. Finally, Section 6 concludes.

2. Theoretical And Conceptual Framework

2.1. Artificial Intelligence as a General-Purpose Technology

AI qualifies as a general-purpose technology (GPT) that horizontally transforms industries, processes, and innovation models (Nambisan et al., 2019). In academic settings, this translates into new modes of knowledge production, automated learning support, and enhanced opportunity identification for student entrepreneurs (Obschonka & Audretsch, 2020; Pedro et al., 2019). Earlier work shows a progression from intelligent tutoring systems toward broader adaptive, data-driven, and student-centered learning environments (Roll & Wylie, 2016; Popenici & Kerr, 2017; Chen, Chen, & Lin, 2020).

2.2. Entrepreneurship Theories in The Age of AI

Schumpeter's creative destruction (1942) provides a lens through which AI-driven disruption can be read: generative AI tools lower entry barriers for university startups, enabling them to prototype, iterate, and compete at previously inaccessible speeds. Knight (1921), revisited by Drucker (1985), reminds us that AI reduces but does not eliminate entrepreneurial uncertainty by improving forecasting and opportunity assessment (Nambisan, 2017). New frameworks are needed to capture both the cognitive and creative dimensions of AI-augmented entrepreneurship (Obschonka et al., 2025). At the same time, important theory and application gaps remain in how AI is adopted and evaluated in educational settings (Chen, Xie, et al., 2020). The repeated co-occurrence of "entrepreneurial intention" in our corpus is consistent with the dominance of the theory of planned behavior (Ajzen, 1991) as a theoretical backbone for empirical studies on AI and student entrepreneurship. Beyond the theory of planned behavior, effectuation theory (Sarasvathy, 2001, 2008) provides a complementary perspective by emphasizing entrepreneurial action under conditions of uncertainty through the mobilization of available resources, stakeholder commitments, and iterative experimentation. In university entrepreneurial ecosystems, AI technologies reinforce this logic by facilitating opportunity recognition, rapid prototyping, and adaptive decision-making. Consequently, effectuation constitutes an appropriate theoretical lens for interpreting the growing convergence between AI and academic entrepreneurship observed in the bibliometric analysis.

2.3. The University Ecosystem as An Entrepreneurial Hub

The concept of ecosystem, originally borrowed from biology (Moore, 1993), has been applied to university settings to capture the interconnected nature of actors, resources, and institutions supporting entrepreneurial activity. Although the ecosystem metaphor has become widely accepted in entrepreneurship research, several scholars argue that university entrepreneurial ecosystems differ from biological ecosystems because their boundaries are dynamic, socially constructed, and interconnected with broader regional and national innovation systems. Consequently, the ecosystem concept should be interpreted as an analytical framework rather than a perfectly bounded organizational structure. This perspective also acknowledges that the ecosystem metaphor simplifies complex institutional interactions and should therefore be interpreted with caution when applied to higher education contexts. The entrepreneurial university model (Etzkowitz, 2013; Isenberg, 2011) frames universities as systemic ecosystems connecting research, incubation, technology transfer, and societal impact. The open innovation paradigm (Chesbrough, 2003) provides a complementary lens through which AI-mediated knowledge flows between universities, firms, and startups can be analyzed. Building on effectuation logic (Sarasvathy, 2001, 2008), student-entrepreneurs in AI-rich environments are increasingly able to co-create value iteratively rather than following predetermined business plans.Taken together, these theoretical perspectives provide a coherent framework for understanding the relationship between artificial intelligence, entrepreneurship, and university

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ecosystems. Taken together, these theoretical perspectives provide a coherent framework for understanding the relationship between artificial intelligence, entrepreneurship, and university ecosystems. Artificial intelligence acts as a transformative technological driver, entrepreneurial theories explain how individuals and organizations respond to emerging opportunities and uncertainties, while the ecosystem perspective highlights the institutional context in which these dynamics unfold. This integrated framework supports the interpretation of publication trends, leading actors, and thematic clusters identified in the bibliometric analysis.

This integrated framework, articulated as a three-stage relationship (technological driver → behavioral and cognitive response → institutional context), constitutes the conceptual model guiding the interpretation of the bibliometric results presented in Section 4.

The theoretical framework also guided the construction of the bibliometric search strategy. Specifically, artificial intelligence represents the technological dimension, entrepreneurship captures entrepreneurial processes and opportunity creation, whereas university defines the ecosystem context in which these interactions occur. Together, these concepts informed the search equation used in the Scopus database and ensured consistency between the theoretical framework and the bibliometric protocol.

3. Empirical Framework and Methodological Approach

3.1. Research Methodology

This study employs bibliometric analysis, a quantitative method widely used in management sciences to map publication dynamics, identify influential authors and journals, and detect emerging thematic clusters (Zupic & Čater, 2015; Donthu et al., 2021; Liu et al., 2024). Bibliometric methods introduce objectivity into the evaluation of scientific literature by mitigating researcher bias through the aggregated judgments of multiple scholars (Zupic & Čater, 2015). Data were collected from the Scopus database because of its broad coverage of scientific publications in management, innovation, entrepreneurship, and higher education. The final dataset consisted primarily of journal articles together with a limited number of conference papers, reflecting the rapid evolution of this emerging research field. Editorials, reviews, notes, conference reviews, books, and other non-research document types were excluded. Comparable bibliometric approaches have recently confirmed the relevance of such mapping exercises at the intersection of AI and higher education (Kavitha et al., 2024; Flores-Velásquez et al., 2024). To ensure the quality and scientific reliability of the dataset, the analysis focused primarily on peer-reviewed publications indexed in Scopus. Although a limited number of conference papers remained in the dataset because of their relevance to this emerging field, this constitutes a potential limitation that is acknowledged in the discussion section.

3.2. Selection Criteria and Analytical Protocol

The final corpus comprised 165 Scopus-indexed documents published between 2019 and 2025. The selected time window was designed to capture the emergence and rapid development of artificial intelligence in university entrepreneurship, particularly following the widespread diffusion of generative AI technologies after 2022. Editorials, reviews, notes, conference reviews, books, and other non-research document types were excluded.

Relevant conference papers were retained because they constitute an important dissemination channel in this rapidly evolving research field. The systematic selection process, structured around identification, screening, and final inclusion phases, is formalized in the PRISMA flow diagram below (Figure 1).

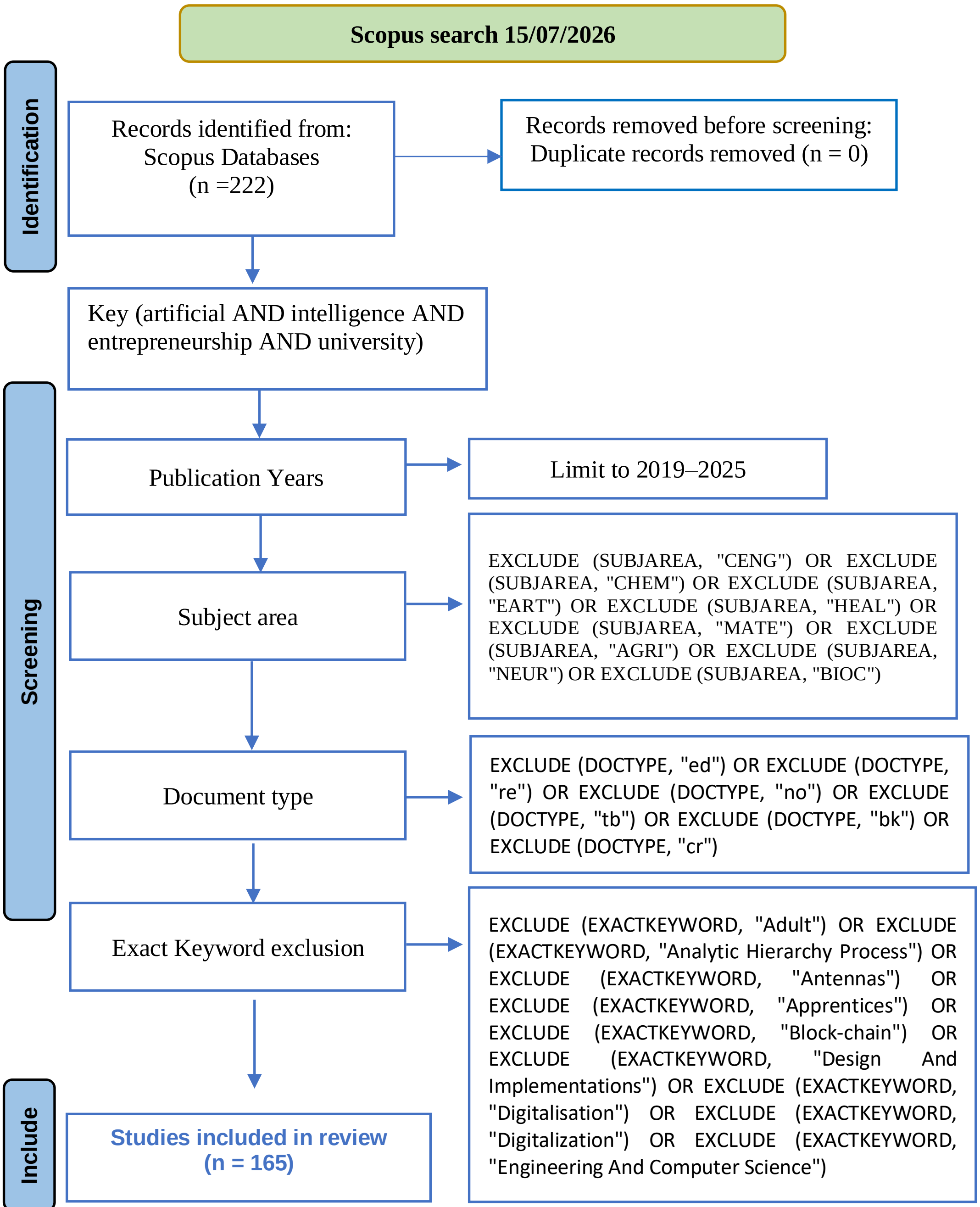
The bibliographic search was conducted in the Scopus database using the following search equation:

TITLE-ABS- KEY(artificial AND intelligence AND entrepreneurship AND university) AND PUBYEAR > 2018 AND PUBYEAR < 2026 AND (EXCLUDE (SUBJAREA , "CENG") OR EXCLUDE (SUBJAREA , "CHEM") OR EXCLUDE (SUBJAREA , "E ART") OR EXCLUDE (SUBJAREA , "HEAL") OR EXCLUDE (SUBJAREA , "MAT E") OR EXCLUDE (SUBJAREA , "AGRI") OR EXCLUDE (SUBJAREA , "NEUR") OR EXCLUDE (SUBJAREA , "BIOC")) AND (EXCLUDE (DOCTYPE , "ed") OR EXCLUDE (DOCTYPE , "re") OR EXCLUDE (DOCTYPE , "no") OR EXCLUDE (D OCTYPE , "tb") OR EXCLUDE (DOCTYPE , "bk") OR EXCLUDE (DOCTYPE , "cr ")) AND (EXCLUDE (EXACTKEYWORD , "Adult") OR EXCLUDE (EXACTKEY WORD , "Analytic Hierarchy Process") OR EXCLUDE (EXACTKEYWORD , "Antennas") OR EXCLUDE (EXACTKEYWORD , "Apprentices") OR EXCLUDE (EXACTKEYWORD , "Block-chain") OR EXCLUDE (EXACTKEYWORD , "Design And Implementations") OR EXCLUDE (EXACTKEYWORD , "Digitalisation") OR EXCLU DE (EXACTKEYWORD , "Digitalization") OR EXCLUDE (EXACTKEYWORD , "En gineering And Computer Science")).

The complete search query, including Boolean operators, publication year restrictions, subject area exclusions, document type filters, and keyword exclusions, is reported in Appendix A to ensure the reproducibility of the study.

As shown in Figure 1, the initial search identified 222 records. Successive filtering stages were then applied by restricting the publication period (2019–2025), excluding non-relevant subject areas (Chemistry, Health Sciences, Agricultural Sciences, Earth and Planetary Sciences, Materials Science, Neuroscience, Biochemistry, and Chemical Engineering), removing non-research document types (editorials, reviews, notes, conference reviews, books), and eliminating irrelevant Exact Keywords unrelated to the research topic. These filtering steps resulted in a final dataset of 165documents. Before exporting the dataset, a semantic cleaning procedure was conducted within Scopus by removing irrelevant Exact Keywords (e.g., Adult, Antennas, Analytic Hierarchy Process, Engineering and Computer Science, and Digitalization). This step reduced semantic noise and improved the thematic consistency of the bibliometric network. The cleaned dataset was exported to VOSviewer (version 1.6.20) for network construction and visualization. Network visualization was performed using the default clustering algorithm and the Association Strength normalization method implemented in VOSviewer (Van Eck & Waltman, 2010). VOSviewer was selected among available bibliometric mapping tools (e.g., bibliometrix; Aria & Cuccurullo, 2017) for its visualization capabilities. Keyword co-occurrence analysis was performed using the co-occurrence option, considering all keywords as the unit of analysis and applying the full counting method (Perianes-Rodriguez et al., 2016). A minimum occurrence threshold of five was adopted, resulting in the selection of 40 keywords out of 1,142. Although Scopus provides broad coverage of scientific publications, relying on a single database may limit the comprehensiveness of the analysis. Future studies could compare these findings with Web of Science or apply alternative occurrence thresholds to assess the robustness of the bibliometric results. No comparative robustness check across alternative databases or occurrence thresholds was conducted within the scope of this study, given resource and time constraints; this represents a deliberate methodological boundary rather than an oversight, and is addressed explicitly as a direction for future research in Section 5.

Figure 1: Flowchart Of the Bibliometric Selection Process (PRISMA)



Source: Own elaboration

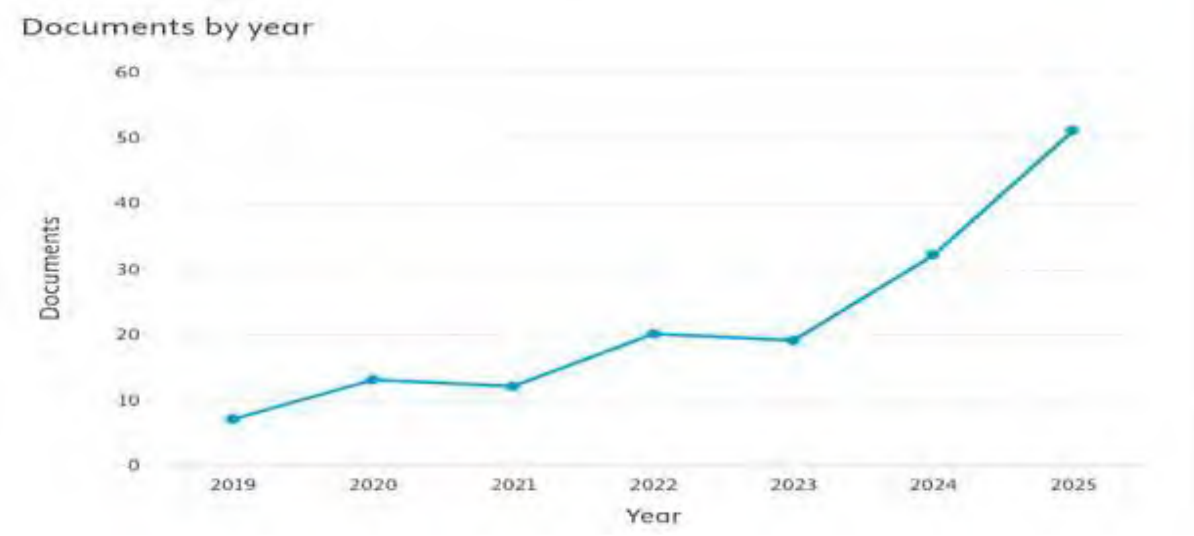
4. Results

4.1. Descriptive Analysis and Temporal Evolution of Scientific Output

The annual evolution of publications from 2019 to 2025 is presented below (see Figure 2).
Figure 2 highlights three phases in the literature's evolution: an emerging phase (2019–2021) with limited output, a structuring phase (2022–2023) marked by growing interest in digital transformation, and an exponential growth phase (2024–2025), during which more than half of the corpus was published. This surge coincided with the widespread diffusion of Large Language Models and generative AI tools, particularly ChatGPT, which stimulated extensive research on their educational implications (Farrokhnia et al., 2023). The tripling of publications between 2023 and 2024 aligns with broader bibliometric evidence highlighting the rapid

expansion of AI in higher education research after 2022 (Flores-Velásquez et al., 2024; Kavitha et al., 2024; Sahar & Munawaroh, 2025).

Figure 2: Chronological Evolution of Published Documents by Year (2019–2025)



Source: Scopus

4.2. Analysis Of Publishing Outlets and Leading Journals

Identifying the most active journals helps locate the main scientific arenas of research and guide future scholars toward influential publication venues. Previous reviews show that AI in higher education mainly focuses on pedagogical use, institutional adoption, and generative AI (Zawacki-Richter et al., 2019; Crompton & Burke, 2023; Ouyang et al., 2022) (see Table 1).
Table 1 reveals a dual publishing structure balancing volume and impact. *Lecture Notes in Networks and Systems* leads in both dimensions, accounting for the largest share of the corpus (6 documents, 177 citations), reflecting Springer Nature's strong presence in AI-related engineering education proceedings. By contrast, management-oriented outlets display disproportionately higher scientific impact relative to their volume: the *International Journal of Management Education* (CiteScore 14.9) and the *Journal of Intelligent & Fuzzy Systems* (CiteScore 3.8) each contribute only three documents to the corpus yet account for 41 and 99 citations respectively, driven by highly cited articles on AI-powered education and AI-driven entrepreneurial performance among university students. Conference proceedings dominate numerically: EDUCON, ECIE, LACCEI, and ASEE together contribute a substantial share of the corpus, though citation levels vary: while ECIE and LACCEI documents have not yet been cited, EDUCON and ASEE show modest early citation activity (10 and 1 citations respectively), consistent with the exponential growth phase identified in Figure 2. This pattern suggests that entrepreneurship and management journals, although fewer in number, exert disproportionate scientific influence on the field, while engineering and computer science venues drive its numerical expansion. Generative AI has emerged as a recurring research theme across both types, and specialized outlets such as ECIE continue to support the development of emerging entrepreneurship-related topics, as exemplified by Bozhikin et al.'s (2023) study on geopolitical risks and entrepreneurial intentions, and by Zulfiqar et al.'s (2025) study on AI-powered education and entrepreneurial spirit among university students.

Table 1: The 10 Academic Journals with The Most Published Papers Between (2019–2025)

Journal	TP	TC	Cite Score	Most cited article	Times cited	Publisher
Lecture Notes in Networks and Systems	6	177	1.2	Technological Revolution in the 21st Century: Digital Society vs. Artificial Intelligence	159	Springer Nature
IEEE Global Engineering Education Conference (EDUCON)	4	10	2.8	India industry-university collaboration - A novel approach combining technology, innovation, and entrepreneurship	8	IEEE
International Journal of Management Education	3	41	14.9	AI-powered education: Driving entrepreneurial spirit among university students	25	Elsevier
Journal of Intelligent & Fuzzy Systems	3	99	3.8	Artificial intelligence learning and entrepreneurial performance among university students: evidence from malaysian higher educational institutions	48	SAGE
Lecture Notes on Data Engineering and Communications Technologies	3	0	1.3	Research on Innovation and Entrepreneurship Education in Universities Based on Artificial Intelligence Technology	0	Springer Nature
Proceedings of the European Conference on Innovation and Entrepreneurship (ECIE)	3	0	1.0	Charting the Future of Entrepreneurial Orientation: A Systematic Review and Science Mapping of Generative AI's Emerging Impact	0	Academic Conferences and Publishing International Limited
Proceedings of the LACCEI International Multi-Conference for Engineering Education and Technology	3	0	0.3	Between Productivity and Ethics: Adoption of Artificial Intelligence by University Students in Educational and Entrepreneurial Processes | Entre la productividad y la ética:Apropiación de inteligencia artificial por estudiantes universitarios en procesos formativos y emprendedores	0	Latin American and Caribbean Consortium of Engineering Institutions
ASEE Annual Conference and Exposition Conference Proceedings	2	1	0.8	The Water Working Group at West Texas A&M University: A creative means for interdisciplinary research catalyzation and faculty development	1	American Society for Engineering Education
Applied Mathematics and Nonlinear Sciences	2	4	2.9	Research on the Teacher Team Construction of Innovation and Entrepreneurship Education in Higher Vocational Colleges and Universities under the Background of “Double Creation” Upgrading	3	Walter de Gruyter
Communications in Computer and Information Science	2	0	1.1	Explainable Artificial Intelligence Approach to Predict Student Entrepreneurial Competency	0	Springer Nature

TP = total publications and TC = total citations within the reviewed corpus (not the journal's overall output); Cite Score is Scopus's standard journal-level indicator, independent of the corpus.

Source: Own elaboration, based on Scopus data.

4.3. Analysis Of Geographic Contributions and Leading Institutions

Assessing the geographic distribution of publications and institutional affiliations helps map the main global research centers on AI and university entrepreneurship, while also revealing disparities in regional research output. The country co-authorship network and the ranking of the most productive countries and institutions are presented in Figure 3 and Table 2.

Figure 3: International Cooperation and Country Co-Authorship Network Under VOSviewer

Source: VOSviewer Visualization

Table 2: Ranking Of Leading Countries and Institutions by Publication Volume

Country	Educational Institutions	TP
China	College of Mechanical Engineering, Ningbo University of Technology, Ningbo, China	61
Indonesia	Bina Nusantara University	12
India	PES University, Center for Innovation and Entrepreneurship, Bengaluru, India	10
Mexico	School of Engineering and Sciences, Mexico	10
Viet Nam	National Economics University, Viet Nam	9
Russian Federation	Plekhanov Russian University of Economics	8
Brazil	Industrial Engineering Program, Federal University of Bahia, Brazil	7
Malaysia	School of Economics Finance and Banking, University Utara Malaysia, Changlun, Malaysia	7
United States	Department of Chemical and Biomedical Engineering, College of Engineering, University of South Florida - USF, United States	7

Note: TP reflects Scopus's country-level document count within the reviewed corpus (based on all co-authors' affiliations, not only the first author); the institution listed corresponds to the author affiliated with that country, which may not be the first author of the document.

Source: Own elaboration

A joint analysis of Figure 3 and Table 2 reveals three main patterns in global scientific production. First, China and other Asian countries dominate the field: out of a corpus of 165 documents, China alone accounts for 61 publications (37%), followed at a considerable distance by Indonesia (12), India (10), and Viet Nam (9), reflecting strong investment in digital university ecosystems, particularly in engineering-oriented institutions such as Ningbo University of Technology. Second, the United States and several European or Eurasian countries play a bridging role, each contributing a comparable share: the Russian Federation (8 documents) and the United States (7 documents) illustrate a more dispersed, moderate level of engagement rather than a dominant research hub. Third, Latin American countries such as Mexico (10) and Brazil (7) show an active and interconnected research presence focused on technology transfer and entrepreneurship in emerging economies, while Malaysia (7) confirms a comparable level of engagement in Southeast Asia. Together, these nine countries account for 131 of the 165 documents in the corpus (79%), indicating a strong geographic concentration of research activity in a limited number of countries. Overall, this distribution indicates that

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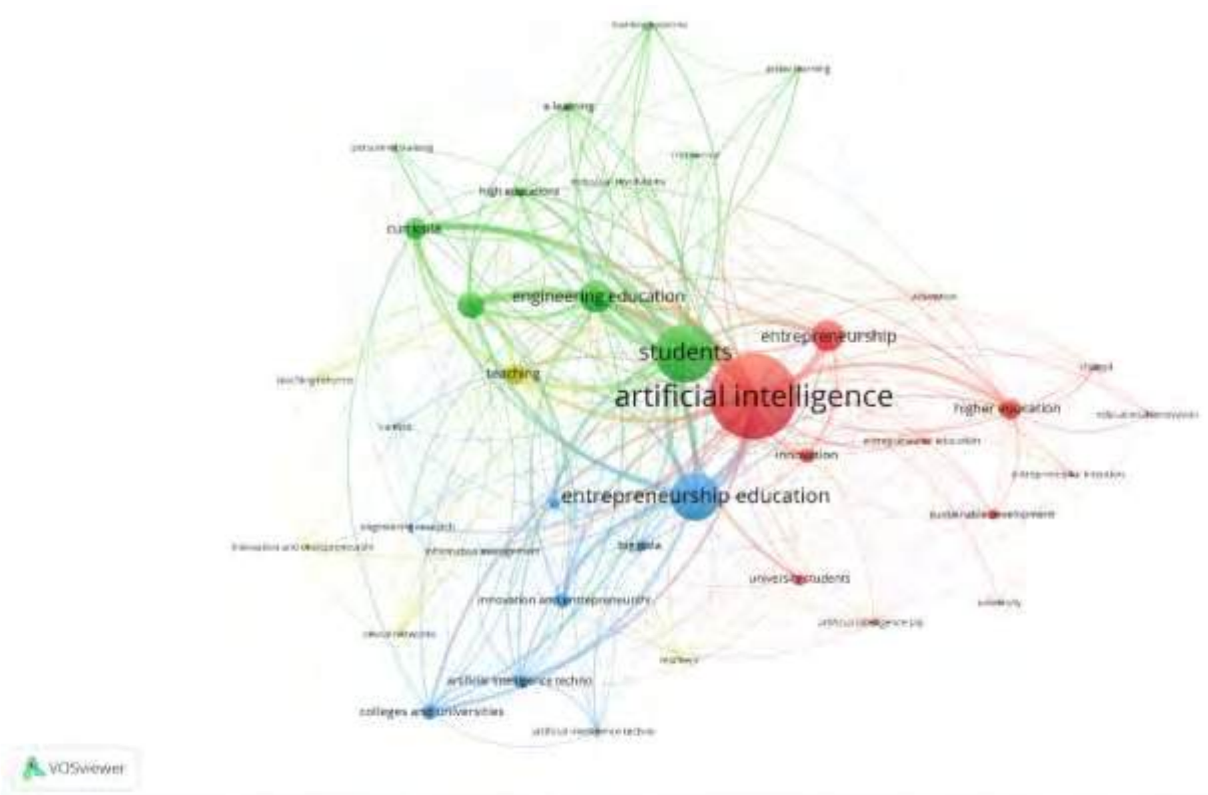
integrating AI into university ecosystems has become a global competitiveness issue, particularly driven by Asian emerging economies.

4.4. Keyword Co-Occurrence and Thematic Structure Analysis

In bibliometrics, keyword co-occurrence analysis is a fundamental step to map the conceptual structure, major thematic trends, and intellectual organization of a research field. Beyond occurrence frequency and total link strength, cluster-level density and degree centrality were examined to provide a more formalized characterization of the semantic network's structure.
The quantitative data for dominant keywords extracted from VOSviewer, along with the mapping of the full lexical network, are presented in Table 3 and Figure 4.

Figure 4: Visualization Of the Keyword Co-Occurrence Network in VOSviewer



Source: Visualisation VOSviewer

Table 3: Occurrence Indicators, Total Link Strength, and Degree Centrality of Key Concepts under VOSviewer

Keyword	Cluster	Occurrences	Total Link Strength	Degree (Links)
Artificial Intelligence	1	91	313	39
Students	2	61	267	39
Entrepreneurship Education	3	50	192	35
Engineering Education	2	33	184	34
Teaching	4	21	117	29
Education Computing	2	27	153	31
Curricula	2	22	118	24
Entrepreneurship	1	32	89	28
Colleges and Universities	3	15	71	20
Artificial Intelligence Technologies	3	13	67	22
College Students	3	11	53	24
Innovation and Entrepreneurship Education	3	14	61	22
Innovation	1	15	45	20

Note: Degree centrality (Links) indicates the number of direct connections of each keyword within the network, complementing occurrence and link strength as a proxy for its structural role.

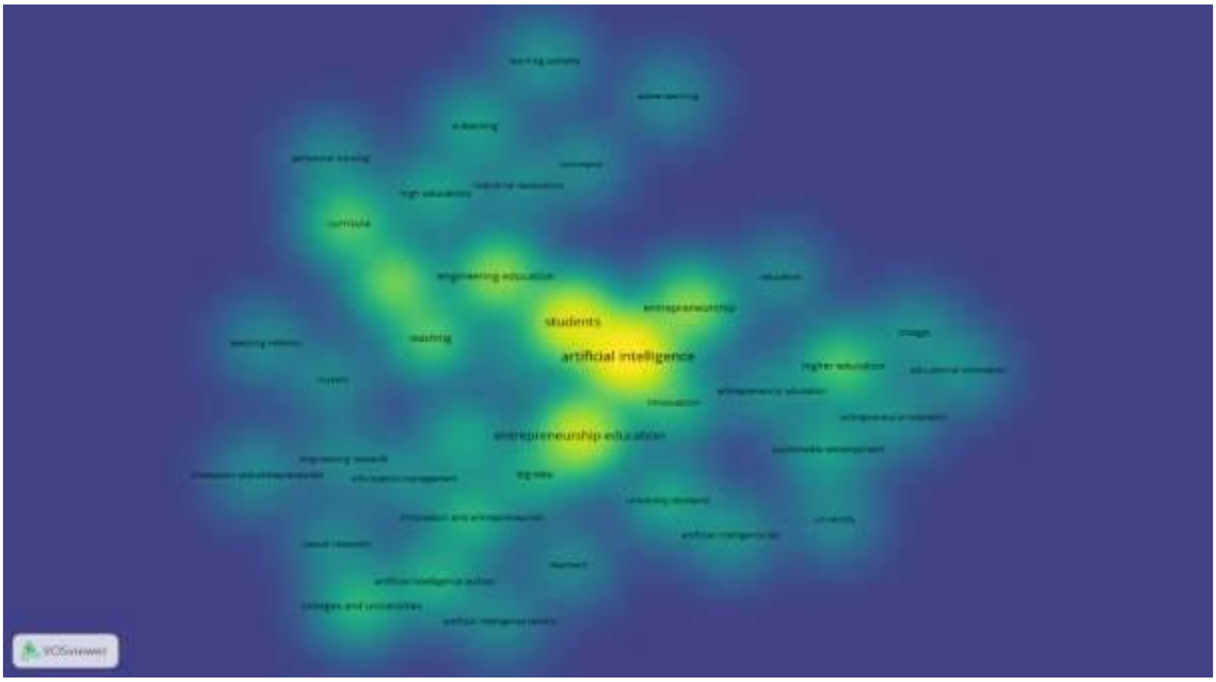
Source: VOSviewer

Table 4: Cluster-Level Density Indicators

Cluster	Number of keywords	Total occurrences	Total link strength	Average TLS per keyword (density proxy)
Cluster 1 (AI & Learner Core)	13	221	659	50.7
Cluster 2 (Pedagogical Innovation)	12	194	1018	84.8
Cluster 3 (Entrepreneurship Ecosystem)	10	134	596	59.6
Cluster 4 (Teaching Practices)	5	41	209	41.8

Source: Own elaboration, based on VOSviewer export

Figure 5: Density Visualization of the Keyword Co-Occurrence Network in VOSviewer



Source: Visualisation VOSviewer

A thorough examination of Tables 3 and 4, together with the clusters in Figure 4, maps the conceptual structure of the literature around four interconnected thematic clusters rather than a purely descriptive list of keywords. Cluster 2 (Pedagogical Innovation), comprising terms such as "engineering education," "curricula," "education computing," and "students," displays the highest internal density (average TLS per keyword of 84.8), indicating a tightly interconnected pedagogical vocabulary reflecting a coherent research tradition on curriculum redesign and digital teaching methods. Cluster 1 (AI and the Learner Core), centered on "artificial intelligence" (91 occurrences, TLS 313) and "entrepreneurship" (32 occurrences, TLS 89), shows comparatively lower internal density (50.7) despite the highest individual link-strength values, suggesting that "artificial intelligence" functions less as a self-contained thematic core and more as a structural connector bridging multiple clusters, a role confirmed by its high degree centrality (39 direct connections, tied for the highest in the network alongside "students"). Cluster 3 (Entrepreneurship Ecosystem), anchored by "entrepreneurship education" (50 occurrences, TLS 192, 35 connections), occupies an intermediate position, combining moderate density (59.6) with strong connective capacity, positioning it as a secondary bridge between the pedagogical and AI-centered clusters. Cluster 4 (Teaching Practices) remains the smallest and least dense (41.8), suggesting a more peripheral and still-emerging thematic area. This degree-centrality-based reading indicates that "artificial intelligence," "students," and "entrepreneurship education" act as the principal hubs of the semantic network, connecting otherwise distinct pedagogical, technological, and entrepreneurial sub-themes, a pattern consistent with recent work on AI literacy and student acceptance of generative AI tools (Ng et al., 2021; Khosravi et al., 2022; Strzelecki, 2024; Yilmaz et al., 2023). While degree centrality offers a robust first-order measure of structural importance, a complementary betweenness and closeness centrality analysis, for instance via network analysis software such as Gephi, would further refine the identification of bridging keywords and is suggested as an avenue for future bibliometric refinement. The density visualization (Figure 5) further confirms this pattern, with the brightest zones concentrated around 'artificial intelligence,' 'students,' and 'entrepreneurship education,' visually corroborating their central and high-density positioning within the network.

5.Discussion

The findings of this study carry significant theoretical, methodological, and managerial implications that extend well beyond the bibliometric mapping exercise itself.

From a theoretical standpoint, the exponential growth of publications after 2022 confirms that generative AI has fundamentally disrupted the intellectual landscape of academic entrepreneurship research, calling for new conceptual frameworks capable of capturing the cognitive, creative, and institutional dimensions of AI-augmented entrepreneurship (Obschonka et al., 2025). The classical frameworks mobilized in this study: Schumpeter's (1942) creative destruction, Knight's (1921) uncertainty theory, and Sarasvathy's (2001, 2008) effectuation logic remain relevant but require adaptation to account for the affordances of large language models, No-Code tools, and AI-assisted prototyping, which fundamentally alter the conditions under which student-entrepreneurs identify opportunities, mobilize resources, and create value. This reconfiguration is empirically visible in the thematic structure identified in Section 4.4, where "artificial intelligence" emerges as the central structural connector of the semantic network (39 direct connections, TLS 313), bridging pedagogical clusters (e.g., "engineering education," "curricula") and entrepreneurial clusters (e.g., "entrepreneurship education," "entrepreneurial intention") rather than remaining confined to a single thematic silo. In this sense, AI does not merely accelerate existing entrepreneurial processes; it reconfigures them at their core, consistent with its conceptualization as a general-purpose technology (Nambisan et al., 2019; Obschonka & Audretsch, 2020).

From a geographic standpoint, the dominance of China and other Asian economies in the corpus raises important questions about the transferability of findings to other institutional and cultural contexts. As shown in Section 4.3, the nine most productive countries jointly account for 131 of the 165 documents in the corpus (79%), with China alone contributing 61 publications (37%). This pronounced concentration suggests that existing models of AI-driven academic entrepreneurship may reflect the specific conditions of high-investment digital university ecosystems, and caution should be exercised when generalizing these findings to institutional contexts with different levels of digital infrastructure or research investment (Pedro et al., 2019). This geographic concentration constitutes both a limitation of the current literature and a call for broader, more geographically diverse empirical research on AI-driven university entrepreneurship.

From a pedagogical standpoint, the strong thematic co-occurrence among generative AI, entrepreneurial intention, and entrepreneurial self-efficacy, reflected in the high link strength connecting "entrepreneurship education" (TLS 192) to the AI-centered cluster in Table 3, confirms that AI-enriched learning environments can meaningfully enhance students' venture creation intentions and capabilities (Xie & Wang, 2025). However, the simultaneous emergence of debates around academic integrity, assessment redesign, and the risk of AI becoming a cognitive crutch rather than a scaffold (Wang et al., 2024; Cotton et al., 2024; Miserandino, 2025) signals that the pedagogical integration of AI in entrepreneurship education requires careful institutional design. Universities must therefore develop governance frameworks that maximize the transformative potential of AI while preserving the authenticity of learning and entrepreneurial experience.

From a managerial perspective, the results highlight the urgency of redesigning university support structures: incubators, technology transfer offices, and entrepreneurship curricula to integrate AI literacy, data engineering skills, and effectual approaches to venture creation (Sarasvathy, 2001), particularly in view of the pronounced geographic concentration of research and innovation capacity identified in Section 4.3. Building human capital tailored to the demands of the AI era thus emerges as a core strategic priority for university governance worldwide (Becker, 1964), and one that requires coordinated action across academic, institutional, and policy levels.

Several methodological limitations should be acknowledged. First, the present study relies exclusively on the Scopus database; although Scopus provides broad coverage of management and innovation research, future studies could assess the robustness of the findings by comparing the results with those obtained from complementary databases such as Web of Science. Second, the corpus is restricted to documents indexed in English, which may underrepresent relevant research published in other languages on AI-driven university entrepreneurship (Van Raan, 2005). Third, citation-based indicators used throughout this study (e.g., Total Citations, CiteScore) are inherently affected by institutional and journal notoriety effects, whereby established venues and well-known research groups tend to accumulate citations more rapidly regardless of the intrinsic quality of individual contributions; this effect should be considered when interpreting the impact rankings presented in Table 1. Taken together, these limitations suggest that the present findings should be read as an indicative mapping of a rapidly evolving research field rather than a definitive or fully representative account of global scholarly activity on AI-driven university entrepreneurship.

6. Conclusion, and Limitations

Through a bibliometric analysis of 165 Scopus-indexed articles published between 2019 and 2025, this study provides a structured mapping of the scientific landscape at the intersection of artificial intelligence and academic entrepreneurship within university ecosystems. The results point to three major findings. First, scientific output has grown exponentially, particularly after 2022, driven by the widespread diffusion of generative AI tools and large language models, which have reshaped the research agenda in higher education (Farrokhnia et al., 2023; Sahar & Munawaroh, 2025). Second, global production remains heavily concentrated in a small number of countries, led by China (37% of the corpus), with the nine most productive countries jointly accounting for 79% of all publications, highlighting a pronounced geographic concentration of research activity. Third, the thematic structure of the field has evolved significantly beyond its initial computational focus, with "artificial intelligence" acting as a central structural connector between pedagogical and entrepreneurial sub-themes, consistent with its conceptualization as a general-purpose technology (Nambisan et al., 2019; Obschonka & Audretsch, 2020).

Theoretically, this article combines classical innovation frameworks: Schumpeter (1942), Knight (1921), and Sarasvathy (2001, 2008), with the realities of the digital economy, suggesting that AI may act not merely as a sector-specific tool but as a force that reshapes aspects of the entrepreneurial university model (Etzkowitz, 2013) and contributes to new pathways for human capital development (Becker, 1964). Given the exploratory and descriptive nature of the bibliometric method employed, this contribution should be understood as an indicative conceptual repositioning rather than a definitive theoretical redefinition and warrants further validation through empirical and qualitative research. Methodologically, the transparent PRISMA protocol, grounded in established bibliometric methods (Zupic & Čater, 2015; Donthu et al., 2021), offers a replicable template that future researchers can adapt and extend to other intersecting fields.

From a managerial perspective, these findings call for a redesign of university support structures: incubators, technology transfer offices, and entrepreneurship curricula to integrate AI literacy, generative AI tools, and effectual approaches to venture creation (Sarasvathy, 2001). University decision-makers should also prioritize institutional frameworks that balance the transformative potential of AI with the challenges of academic integrity and equitable access (Cotton et al., 2024; Miserandino, 2025).

This study is not without limitations. Its exclusive reliance on Scopus may exclude relevant contributions indexed in other databases such as Web of Science or Google Scholar. Furthermore, its purely quantitative bibliometric design does not capture the qualitative and contextual dimensions of AI adoption in university ecosystems. The manual filtering stage of the corpus was conducted without independent double-coding, which may introduce a degree of subjectivity in inclusion and exclusion decisions; future replications should incorporate inter-coder reliability checks. Additionally, the search equation, while designed to maximize thematic relevance, relies on a fixed set of keywords that may have excluded studies using alternative terminology (e.g., "AI-enabled entrepreneurship" or "smart university ecosystems"), which future studies could address through iterative or expert-validated query refinement.

Future research should therefore combine multiple databases, integrate qualitative and mixed methods approaches, and pursue more targeted empirical designs. For instance, a comparative qualitative study examining how university incubators in different institutional contexts, such as Moroccan and East Asian institutions, adopt generative AI tools in entrepreneurship support programs would provide contextually grounded insight that a purely bibliometric approach cannot capture. Given the rapid pace of AI development, future bibliometric analyses should also adopt shorter update cycles and incorporate emerging themes such as explainable AI, AI ethics in education, and the long-term impact of generative AI on entrepreneurial ecosystems.

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