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AI-Driven Entrepreneurship Research (2023–2026): Bibliometric Trends, Thematic Evolution, and a Future Research Agenda

Acep Supriadi[1*], Asep Mahpudz[2], Ade Budhi Salira[3], Harfandi Harfandi[4]
[1,2,3]Universitas Pendidikan Indonesia, Bandung, Indonesia
[4]Universitas Islam Negeri Sjech M.Djamil Djambek Bukittinggi, Bukittinggi, Indonesia

*Corresponding Author
e-mail: acepsupriadi@upi.edu

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Abstract: This study maps publication trends, intellectual structure, thematic evolution, and future research directions in Scopus-indexed conference papers, book chapters, and books on AI-driven entrepreneurship. Using a bibliometric and science-mapping approach, the analysis draws on metadata for 2,119 documents from 1,248 sources indexed in Scopus during 2023–2026, comprising 6,139 authors, 5,072 author keywords, and 9,890 Keywords Plus terms. Performance analysis, co-authorship, co-citation, bibliographic coupling, keyword co-occurrence, and thematic-evolution mapping were conducted using Bibliometrix/Biblioshiny and VOSviewer, with Python-based verification of key figures. Publications grew 22.02% annually, with 3.17 authors per document on average and a 22.27% international co-authorship rate; India and China emerged as leading centers of productivity and collaboration. Publication sources remain dominated by conference proceedings, book chapters, and Lecture Notes series, a pattern reflecting the document-type restriction applied during retrieval. The intellectual structure links entrepreneurship theory, innovation, technology management, decision-making, and computing systems, with artificial intelligence as the most central theme; keyword trends show a gradual, still-emerging rise in generative-AI and hybrid-AI terms alongside continued dominance of core AI and machine-learning concepts. A stratified two-rater relevance screening of a 327-record sample (Cohen's $\kappa = 0.707$) indicates that about 51% of the retrieved corpus is substantively relevant to AI-driven entrepreneurship, so the mapped patterns should be read as a provisional, database-bounded picture. The study proposes a future research agenda testing how AI capabilities shape opportunity recognition, creativity, business-model innovation, financing access, performance, and sustainability, while calling for stronger theory, longitudinal evidence, and attention to ethics and governance.

Keywords: Artificial intelligence, AI-driven entrepreneurship, Bibliometric analysis, Thematic evolution, Science mapping

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INTRODUCTION

The development of artificial intelligence (AI) has transformed the entrepreneurial landscape from activities that relied primarily on intuition, experience, and human resources to processes that are increasingly data-driven, algorithmic, and human–machine collaborative. Technologies such as machine learning, natural language processing, predictive analytics, and generative AI now enable entrepreneurs to identify market opportunities, predict consumer behavior, automate business processes, develop products, and validate business models more quickly and efficiently. Because technology no longer functions merely as a supporting tool but actively shapes opportunities, decision-making, and value creation, these changes have expanded the conception of digital entrepreneurship (Nambisan, 2017; Shepherd & Majchrzak, 2022). AI is also seen as capable of improving decision quality, business performance, entrepreneurship education, and entrepreneurs' ability to exploit opportunities (Giuggioli & Pellegrini, 2023).

Research on AI-driven entrepreneurship, however, has not kept pace with its rapid adoption in practice. The field spans entrepreneurship, innovation management, information systems, finance, education, marketing, and sustainability, producing disagreement over whether AI is a resource, a dynamic capability, a decision-making actor, or part of an entrepreneurial ecosystem. Prior studies confirm that this research has grown rapidly but remains largely conceptual and descriptive, without a deep theoretical foundation (Blanco-González-Tejero et al., 2023; Uriarte et al., 2026). It is likewise unclear which countries, institutions, and documents have most shaped the field, or how its focus has shifted from digitalization and machine learning toward generative AI, human–AI collaboration, ethics, privacy, and governance. AI can strengthen entrepreneurial capability, yet it also carries risks, algorithmic bias, technological dependence, loss of decision-making autonomy, and irresponsible use (Shepherd & Majchrzak, 2022; Obschonka et al., 2025), and Cristofaro et al. (2026) show that its benefits for decision quality are conditional on how sector knowledge is balanced against intuition and analysis, not automatic.

At least four recent studies map a substantially similar domain. Blanco-González-Tejero et al. (2023) analyzed 520 publications indexed in Dimensions.ai through July 2022 using semantic analysis and NLP, without network-based science mapping. Boateng et al. (2024) mapped Scopus-indexed publications and reported cross-country productivity differences but did not examine thematic evolution or bibliographic coupling. Uriarte et al. (2026) combined bibliometric analysis with a systematic review of 345 Scopus articles through 2023, emphasizing fragmentation and a developed-country orientation without extending post-2023 or offering a multilevel agenda. Retamal-Saavedra et al. (2026) mapped the same field and proposed a cognitive agenda overlapping with the intended contribution here, requiring explicit differentiation. Three further recent bibliometric mappings reinforce this picture without altering it: Siddiqui et al. (2024) and Redondo-Rodríguez et al. (2024) each map the AI-entrepreneurship intersection using different databases and clustering tools, while Kumar and Singh (2025) narrow the focus specifically to AI-driven startups; none of these isolates the conference-paper, book-chapter, and book segment analyzed here or extends observation into the partial 2026 period. Building on these studies, this research's contribution is threefold: it extends the observation window through July 2026 (with the partial final year explicitly bounded); it integrates co-citation, coupling, and keyword co-occurrence in a single design applied to the conference-paper, book-chapter, and book segment of the Scopus record, a composition none of the four comparisons isolates; and it translates the resulting clusters into a multilevel agenda spanning individual, team, ecosystem, and institutional levels. Because the topical relevance of this corpus has not been independently validated (see Method and Limitations), the contribution is presented as scoped and database-bounded rather than as definitive coverage of the field.

This research is urgent because academics, entrepreneurs, educators, investors, and policymakers need a systematic knowledge map of AI's benefits and risks in entrepreneurship; without it, research risks duplication and unclear theoretical direction. Bibliometric methods are well suited to this task because they can identify publication trends, influential actors, collaborative networks, intellectual structures, and conceptual developments across large literatures (Donthu et al., 2021), and the findings can also help guide AI policies that are inclusive, responsible, and adapted to entrepreneurial ecosystems in both developed and developing countries.

Artificial intelligence refers to computing technologies that perform tasks once requiring human intelligence, learning from data, recognizing patterns, making predictions, generating content, and producing recommendations. In entrepreneurship, AI functions not merely as an automation tool but as a strategic resource reshaping opportunity identification, decision-making, and value creation, marking a shift toward AI-driven entrepreneurship, activity in which processes and decisions are substantially shaped by AI (Nambisan, 2017). Obschonka and Audretsch (2020) argue that AI, big data, and entrepreneurship together open a new research and practice era, converting data into knowledge that supports market prediction, customer segmentation, and strategy development, while also creating tension between algorithmic logic grounded in past patterns and entrepreneurship's inherently uncertain, future-oriented nature. Across the entrepreneurial process, opportunity identification, resource mobilization, business establishment, and growth, AI can process market data, consumer behavior, and social-media signals to surface unmet needs and deepen evaluation through simulation and risk analysis, though over-reliance on historical data can reduce opportunity originality; decision quality therefore depends not only on AI sophistication but also on entrepreneurial knowledge, creativity, experience, and judgment (Townsend & Hunt, 2019; Shepherd & Majchrzak, 2022). AI can nonetheless reduce experimentation costs and accelerate learning, a dynamic consistent with effectuation theory's emphasis on using available means to iteratively shape opportunities under uncertainty rather than relying solely on prediction (Sarasvathy, 2001). Chalmers et al. (2021) note that AI can influence organizational design and new-venture outcomes, though benefits are unevenly distributed, as firms with more data and capital are better positioned to capture them.

From a resource-based perspective, AI's value emerges from its integration with quality data, business knowledge, human skills, and organizational processes rather than from mere ownership, since the technology is relatively accessible and replicable; AI-driven entrepreneurship research is accordingly shifting from questions of technology adoption toward the formation of AI capability, the ability to obtain data, operate the technology, combine human and machine knowledge, and convert AI outputs into business action. Giuggioli and Pellegrini (2023) show AI functioning as an enabling technology alongside other Industry 4.0 technologies, with its benefits depending heavily on entrepreneurs' ability to connect the technology to market needs. This capability is further shaped by the entrepreneurial ecosystem: infrastructure, data access, financing, education, and government support determine how far entrepreneurs can use AI, with ecosystems anchored by universities and investors producing more AI-based ventures, consistent with the view of entrepreneurial ecosystems as sets of interdependent actors and institutions that jointly enable productive entrepreneurship (Stam, 2015), while limited connectivity and financing widen gaps between developed- and developing-country entrepreneurs. Boateng et al. (2024) show that AI-and-entrepreneurship research spans diverse disciplines and networks but that productivity and influence remain unevenly distributed, pointing to a need for work comparing how institutional environment and digital readiness shape AI adoption. Use of AI is not without cost: automation can displace jobs, and concentration of data and technology in large firms can crowd out small businesses. Chalmers et al. (2021) warn AI can disintermediate businesses unable to adapt, and Obschonka et al. (2025) argue predictive and generative AI require stronger theory, methods, and regulation; governance needs transparency, accountability, and human oversight throughout the AI lifecycle (Papagiannidis et al., 2025).

Therefore, this research, titled "AI-Driven Entrepreneurship Research in Scopus-Indexed Conference Papers, Book Chapters, and Books (2023–2026): Bibliometric Trends, Thematic Evolution, and a Future Research Agenda," aims to map publication trends within this Scopus-indexed, document-type-bounded corpus, identify the social, intellectual, and conceptual structures of the research, analyze thematic evolution and emerging themes, and formulate a future research agenda. This research is expected to yield a more integrative understanding of the development of AI-driven entrepreneurship and provide a theoretical and methodological basis for further research into the relationships among AI technology, entrepreneurial behavior, business innovation, and entrepreneurial ecosystems, combining publication-performance indicators and science-mapping techniques to identify key actors, intellectual foundations, conceptual relationships, and theme evolution. Based on these objectives, this study formulated three research questions: (1) What is the development of publications, author productivity, journal sources, institutions, countries, and patterns of scientific collaboration in research on AI-driven entrepreneurship? (2) What is the intellectual and conceptual structure of AI-driven entrepreneurship research based on co-citation analysis, bibliographic coupling, and keyword co-occurrence? and (3) What are the main clusters, thematic evolutions, research trends, knowledge gaps, and future research directions in the field of AI-driven entrepreneurship?

METHOD

This study used a descriptive quantitative approach through bibliometric analysis and science-mapping methods. Bibliometric analysis measured publication development, author productivity, document influence, and the contributions of journals, institutions, countries, and collaboration patterns in AI-driven entrepreneurship research, while science mapping identified the field's social, intellectual, and conceptual structures through co-authorship, co-citation, bibliographic coupling, and keyword co-occurrence analysis. Combining performance analysis with science mapping enables a field's development, influential actors, collaboration patterns, intellectual foundations, and emerging themes to be uncovered (Donthu et al., 2021). This approach was chosen because AI-and-entrepreneurship research has grown rapidly and is dispersed across management, entrepreneurship, information systems, computer science, education, and public policy, and it enables systematic analysis of publication metadata while reducing the subjectivity of narrative reviews. The research proceeded through five stages: defining scope, developing the search strategy, collecting and filtering documents, cleaning metadata, and conducting bibliometric analysis and visualization.

Research data were obtained from Scopus, chosen for its structured bibliographic metadata, titles, abstracts, keywords, author names, affiliations, countries, publication sources, year, citation counts, and bibliographies, needed to analyze publication performance and build bibliometric networks. The search used the Advanced Search TITLE-ABS-KEY field code combined with a DOCTYPE code to limit document types. Data were collected on a single day (28 July 2026) to avoid within-collection changes in document and citation counts. Publication years were left unrestricted at the search stage to avoid imposing an arbitrary starting point and to let the corpus itself reveal when Scopus-indexed conference papers, book chapters, and books combining these terms first appear, with the end point set at the search date.

The search strategy combined two concept groups: artificial-intelligence technology and entrepreneurial activity. The search string was: TITLE-ABS-KEY ((“artificial intelligence” OR “generative artificial intelligence” OR “generative AI” OR “AI-driven” OR “AI-enabled” OR “machine learning” OR “deep learning” OR “natural language processing” OR “large language model*” OR “predictive analytic*” OR “intelligent system*” OR “expert system*” OR “computer vision”) AND (entrepreneur* OR entrepreneurship OR “entrepreneurial activit*” OR “entrepreneurial process*” OR “entrepreneurial opportunity*” OR “entrepreneurial decision*” OR “entrepreneurial ecosystem*” OR “new venture*” OR “venture creation” OR “business creation” OR startup* OR “start-up*” OR “technology venture*”)) AND DOCTYPE (cp OR ch OR bk). The search was not limited by country or field, given the study's aim to map global, multidisciplinary trends; records were limited to English language. On verification against the exported metadata, the DOCTYPE clause restricted document type to conference paper, book chapter, and book rather than article and review article; this is reported here so the eligibility criteria match the analyzed corpus and the search remains reproducible.

Although the year field was unrestricted, the retrieved corpus begins in 2023, verified directly against the raw Scopus export: of 2,137 records returned by the DOCTYPE (cp OR ch OR bk) query, zero predate 2023 (2023: 275; 2024: 523; 2025: 841; 2026: 498, as of 28 July 2026); the corpus's temporal boundary reflects what Scopus actually returns for this term set and document-type restriction, not a concealed cutoff. Two factors plausibly explain this: several central search terms ("generative AI," "AI-driven," "large language model*") entered common scholarly usage only from around 2022, concentrating matches from 2023 onward; and the DOCTYPE restriction concentrates the corpus in proceedings series (notably Lecture Notes in Networks and Systems, the largest single source at 102 of 2,119 records) predominantly indexed from 2023 onward. The same query limited to articles and reviews would likely return earlier records, though that comparison was not run and is noted as a scope boundary. Figure 1 presents the PRISMA flow diagram (Page et al., 2021) used to report this research, including removal of non-English and duplicate/republished records identified during screening.

The 2,119-document corpus in Table 1 and the 2,122-record figure used in earlier network-analysis tables have been reconciled against the raw Scopus export; the discrepancy is a deduplication-method artifact. Of 2,137 records returned, 2,130 are English-language, among which 11 pairs (22 records) are duplicate or republished records sharing an identical title but differing in Scopus EID, year, or source. A case-insensitive title match removes all 11 pairs, yielding 2,119 documents (conference paper: 1,100; book chapter: 749; book: 270, matching Table 1); a case-sensitive match catches only 8 of the 11 (three differ solely in capitalization), leaving 2,122. The 2,119-document, case-insensitive-deduplicated corpus is therefore adopted for all results; country-, institution-, and keyword-level statistics (Tables 2, 3, 6) were recomputed on this corpus (Table 2's China count corrected from 197 to 196), while the co-citation and bibliographic-coupling networks (Tables 4, 5) are unaffected in cluster structure.

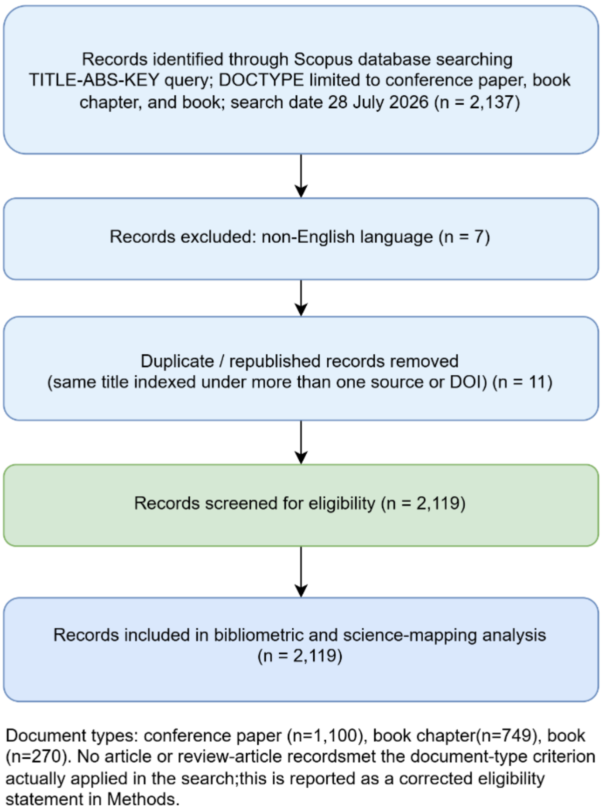

Figure 1. Systematic Literature Review Flow

Source: Author's Own Work

Document metadata were exported from Scopus in CSV and BibTeX formats, selecting citation, bibliographical, abstract/keyword, and funding fields; for co-citation and bibliographic-coupling analyses, data were exported alongside the cited-reference list, with BibTeX used in Bibliometrix/Biblioshiny (Aria & Cuccurullo, 2017) and CSV used in VOSviewer and manual checking. Data were cleaned and standardized, removing duplicates, unifying author-name and institution/country-name variants, and aligning synonymous keywords (e.g., artificial intelligence/AI, startup/start-up) via a thesaurus file, while excluding generic terms (study, article, research) from keyword mapping. Similarly named authors were checked against affiliation, field, and publication record to reduce misidentification.

To make the science-mapping procedures reproducible, the following protocol was applied. Descriptive indicators (Table 1), publication trends, and author/country counts were computed from the cleaned metadata using Python 3.11 (pandas 2.2.2, numpy 1.26); country attribution used the last comma-separated affiliation element, and international collaboration meant affiliations spanning two or more countries. Co-citation and bibliographic-coupling networks (Figures 6–7) were generated in VOSviewer 1.6.20 using full counting, with a minimum of 20 citations per cited reference for co-citation and a minimum of 5 documents/50 total link strength per source for coupling, retaining only the largest connected component; clustering used VOSviewer's default VOS technique (resolution = 1.00) (van Eck et al., 2010; Waltman et al., 2010). The keyword co-occurrence network (Figure 8) combined Author and Index Keywords after thesaurus normalization, retaining the 40 highest-frequency terms with a minimum co-occurrence of 15 documents. The thematic map (Figure 9) was generated in R 3.4 using Bibliometrix 4.3.2/Biblioshiny via co-word analysis with Louvain community detection. Because Bibliometrix's default split confounds change with an unequal window, thematic evolution (Figure 10) and trends (Figure 11) were computed across three periods, 2023–2024, 2025, 2026 (partial), with 2026 as a preliminary signal.

Because the search strategy retrieves records based on co-occurring AI- and entrepreneurship-related terms rather than a substantive topical assessment, the corpus required documented relevance screening, remaining the single most important validity issue in the study (see Limitations). Inclusion criteria required that a record's title, abstract, or author keywords establish a substantive link between an AI-related technology and an entrepreneurial actor, process, or outcome, rather than incidental co-occurrence (e.g., a computer-vision paper mentioning “startup” only in a funding acknowledgement). Second, a stratified random sample of records (stratified by document type and year, 95% confidence, 5% margin of error, requiring approximately n = 327 for a corpus this size) underwent independent title-and-abstract screening by two raters, with inter-rater agreement reported via Cohen's kappa and disagreements resolved by a third rater. Third, the resulting precision estimate (proportion judged substantively relevant) is reported explicitly; if precision fell materially below an acceptable threshold, full-corpus screening or a refined query would follow, with every result recomputed on the validated corpus.

This protocol has been executed: a stratified random sample of 327 records (95% confidence, 5% margin of error) was drawn from the reconciled 2,119-document corpus and independently screened by two raters using title, abstract, and author keywords only. Inter-rater agreement was substantial (Cohen's $\kappa = 0.707$ across Relevant/Not Relevant/Borderline, rising to $\kappa = 0.749$ with Borderline collapsed into Not Relevant; raw agreement 84.7%), and the 50 disagreements were resolved by a third reading. The validated sample yielded 163 records relevant, 157 not relevant, and 7 borderline, an estimated corpus-wide precision of approximately 51%. Screening identified a specific false-positive mechanism: “startup” frequently refers to a software/container/hardware/process startup (e.g., Kubernetes initialization, FaaS cold-start latency) rather than a business venture, a distinction the search string cannot make; other false positives involved entrepreneurship terms used only as incidental tags in unrelated engineering, medicine, or education papers. This precision suits the scope of a broad TITLE-ABS-KEY mapping study rather than a fully verified systematic review, and is reported as a transparent, quantified limitation. Extending screening to all 2,119 records and recomputing every result is recommended for a definitive future replication, noted in the Limitations.

RESULTS AND DISCUSSION

Results

This research aimed to map the development of global scientific publications, identify the social, intellectual, and conceptual structures of the research, analyze thematic evolution, and formulate a future research agenda in the field of AI-driven entrepreneurship. The indicators used to address the research objectives included publication growth, author productivity, collaboration networks, co-citation, bibliographic coupling, keyword co-occurrence, and thematic evolution.

Table 1. Main Information

Description	Results
Main Information About Data	
Timespan	2023:2026
Sources (Journals, Books, etc.)	1,248
Documents	2,119
Annual Growth Rate (%)	22.02
Document Average Age	1.27
Average citations per doc	1.628
References	94,688
Document Contents	
Keywords Plus (ID)	9,890
Author's Keywords (DE)	5,072
Authors	
Authors	6,139
Authors of single-authored docs	393
Authors Collaboration	
Single-authored docs	413
Co-Authors per Doc	3.17
International co-authorships (%)	22.27
Document Types	
Book	270
Book chapter	749
Conference paper	1,100

Source: Author Analysis using Python (pandas), based on the verified Scopus export

Table 1 presents bibliometric data for 2023–2026: 2,119 documents from 1,248 sources, a 22.02% annual growth rate, 1.27-year average document age, and 1.628 citations per document, involving 6,139 authors (3.17 per document on average), 22.27% international collaboration, and 413 single-authored documents. By document type, the corpus comprised 1,100 conference papers, 749 book chapters, and 270 books.

Publication Trends, Productivity, and Scientific Collaboration

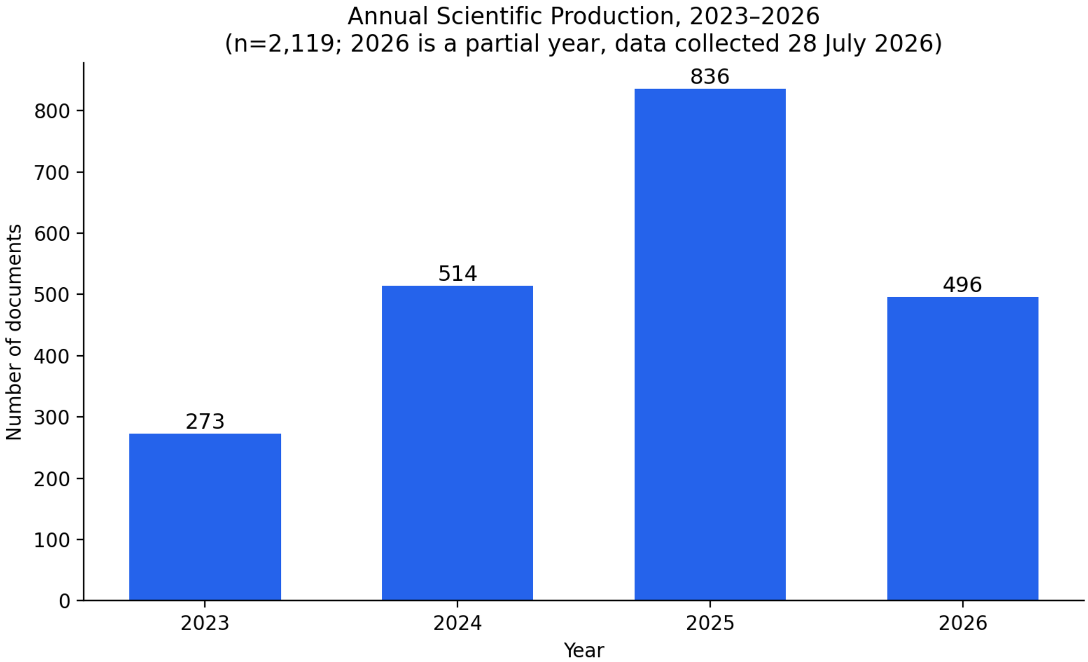

Figure 2. Publication Development
Source: Author Analysis using Python (matplotlib), based on the verified Scopus export

Figure 2 shows publications rising from 273 in 2023 to 514 in 2024 and peaking at 836 in 2025, signaling growing academic attention to AI-entrepreneurship integration; the 496 recorded for 2026 reflects ongoing data collection rather than declining interest (search conducted 28 July 2026).

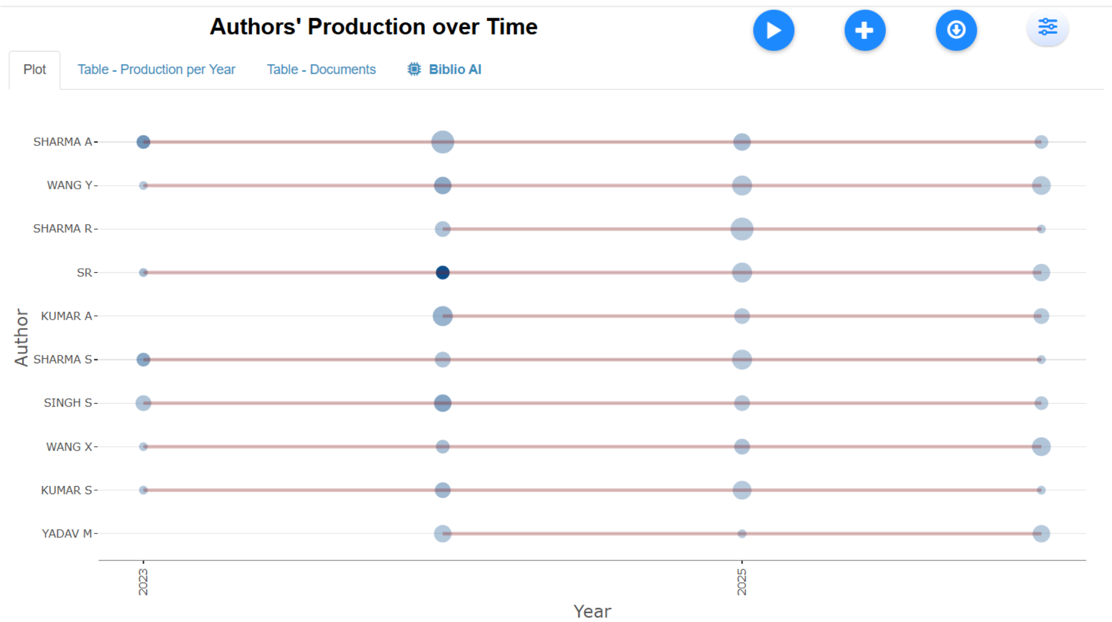

Figure 3. Author Productivity
Source: Author Analysis using R Studio Biblioshiny

Figure 3 shows a mixed author-productivity pattern during 2023–2026, with most authors contributing more in 2024–2025; Sharma A., Wang Y., Sharma R., and Kumar A. are relatively consistent contributors. Circle size reflects publication count, and color intensity reflects citation influence in a given year.

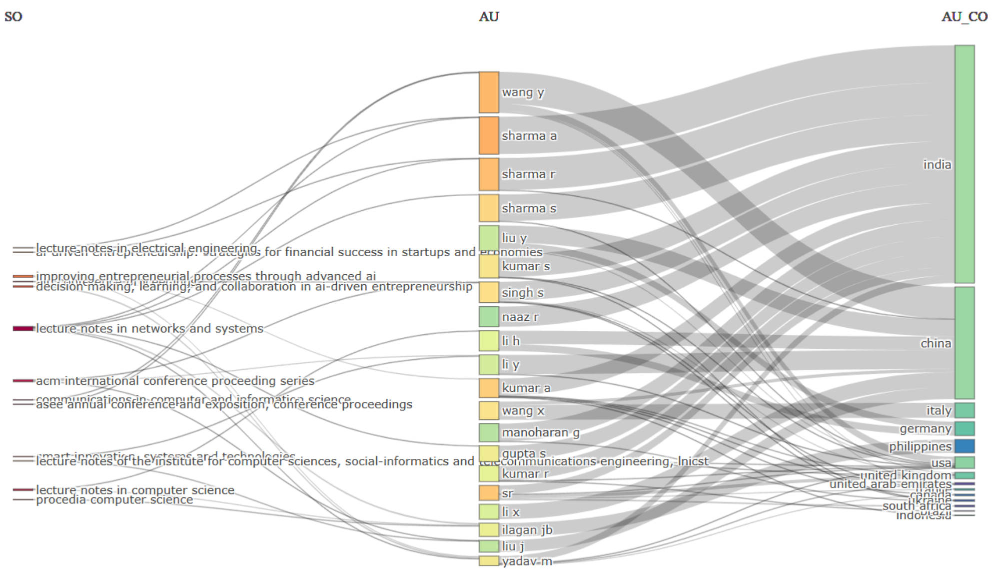

Figure 4. Three-Field Plot
Source: Author Analysis using R Studio Biblioshiny

Figure 4 illustrates relationships among publication sources, authors, and countries. Authors such as Wang Y., Sharma A., Sharma R., Sharma S., Liu Y., and Kumar S. show strong publication ties, with India and China as major contributors; sources remain dominated by proceedings and the Lecture Notes series, showing that this topic disseminates largely through conference and technology publications.

Figure 5. Map of Author Collaboration between Countries
Source: Author Analysis using R Studio Biblioshiny

Figure 5 shows extensive cross-border collaboration networks spanning Asia, Europe, the Americas, Africa, and Australia, with India as the most dominant center, strongly tied to the United States, China, Europe, and Australia, though collaboration intensity remains concentrated among high-productivity countries.

Table 2. Top 10 Country Collaboration and Author Productivity

No	Country	Documents	Total Link Strength	Citations
1	India	604	241	961
2	United States	257	149	785
3	China	196	33	196
4	United Kingdom	106	108	316
5	Italy	80	67	148
6	Germany	78	58	157
7	Indonesia	78	20	183
8	Canada	51	56	62
9	Malaysia	51	67	133
10	France	44	77	145

Source: Computed on the raw Scopus CSV export

Table 3 reports institution-level counts, closing the gap left by the preceding author- and country-level results reported for Research Question 1.

Table 3. Top 10 Most Productive Institutions

No	Institution	Documents	International Collaboration (%)	Citations
1	Lovely Professional University (India)	35	57.1	43
2	Bina Nusantara University (Indonesia)	29	10.3	59
3	Amity University (India)	23	34.8	39
4	O.P. Jindal Global University (India)	20	100.0	27
5	Chandigarh University (India)	16	12.5	16
6	Galgotias University (India)	13	15.4	29
7	Graphic Era Deemed to Be University (India)	12	0.0	113
8	Sharda University (India)	10	60.0	54
9	SR University (India)	10	40.0	24
10	Ateneo de Manila University (Philippines)	10	0.0	17

Source: Computed on the raw Scopus CSV export

Intellectual and Conceptual Structure of AI-Driven Entrepreneurship Research

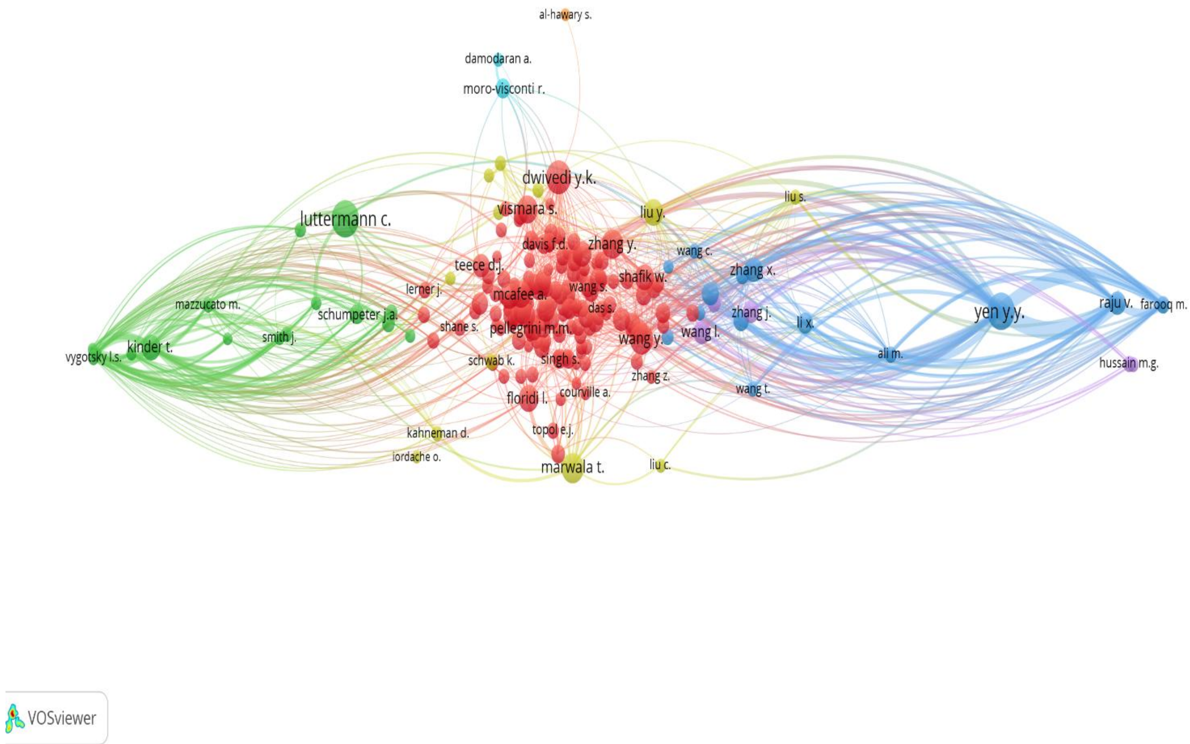

Figure 6. Co-Citation Analysis
Source: Author Analysis using VOSviewer

Figure 6's co-citation network shows three main clusters: green (classic entrepreneurial literature, e.g., Schumpeter), red (AI and entrepreneurial decision-making), and blue (technology and AI applications), with link density signaling growing intellectual linkage between entrepreneurial theory and digital technology.

Table 4. Top 10 Co-Citation Network Among the 27 References Cited ≥20 Times in the Corpus

No	First-Cited-Author, Year (as parsed)	Times Cited Within Corpus	Co-Citation Cluster	Total Link Strength	Likely Corresponds To
1	Ronanki R., 2018	45	1 – AI/technology-management literature	114	Davenport & Ronanki (2018)
2	Audretsch D.B., 2020	45	2 – AI and entrepreneurial decision-making	85	Obschonka & Audretsch (2020)
3	Carter S., 2021	41	2 – AI and entrepreneurial decision-making	77	Chalmers, MacKenzie & Carter (2021)
4	Majchrzak A., 2022	29	2 – AI and entrepreneurial decision-making	77	Shepherd & Majchrzak (2022)
5	Pellegrini M.M., 2023	47	2 – AI and entrepreneurial decision-making	75	Giuggioli & Pellegrini (2023)
6	Rust R.T., 2021	25	1 – AI/technology-management literature	73	Rust & Huang (2021)
7	Rust R.T., 2018	23	1 – AI/technology-management literature	73	Huang & Rust (2018)

No	First-Cited-Author, Year (as parsed)	Times Cited Within Corpus	Co-Citation Cluster	Total Link Strength	Likely Corresponds To
8	Haenlein M., 2019	23	1 – AI/technology-management literature	71	Haenlein & Kaplan (2019)
9	Williams M.D., 2021	25	1 – AI/technology-management literature	67	Dwivedi et al. (2021)
10	McAfee A., 2017	30	1 – AI/technology-management literature	67	Brynjolfsson & McAfee (2017)

The full co-citation network contains 27 reference nodes, each cited at least 20 times, consistent with the Method's threshold. All retained nodes formed a single connected component and were resolved into four clusters through Louvain community detection: Cluster 1 (n = 11; AI and technology-management literature, including Davenport and Ronanki (2018), Brynjolfsson and McAfee (2017), Huang and Rust (2018), and Haenlein and Kaplan (2019)); Cluster 2 (n = 8; AI and entrepreneurial decision-making literature, including Obschonka and Audretsch (2020), Chalmers et al. (2021), Shepherd and Majchrzak (2022), and Giuggioli and Pellegrini (2023)); Cluster 3 (n = 5; entrepreneurship and strategy foundations, including Nambisan (2017), Barney (1991), and Shane and Venkataraman (2000)); and Cluster 4 (n = 3; technology-adoption and behavioral theory, including Davis's (1989) Technology Acceptance Model and Ajzen's (1991) Theory of Planned Behavior). Clusters 1–3 correspond to the blue, red, and green clusters previously described in Figure 6, now supported by quantitative link-strength measures, whereas Cluster 4 represents a smaller grouping identified through this additional analysis.

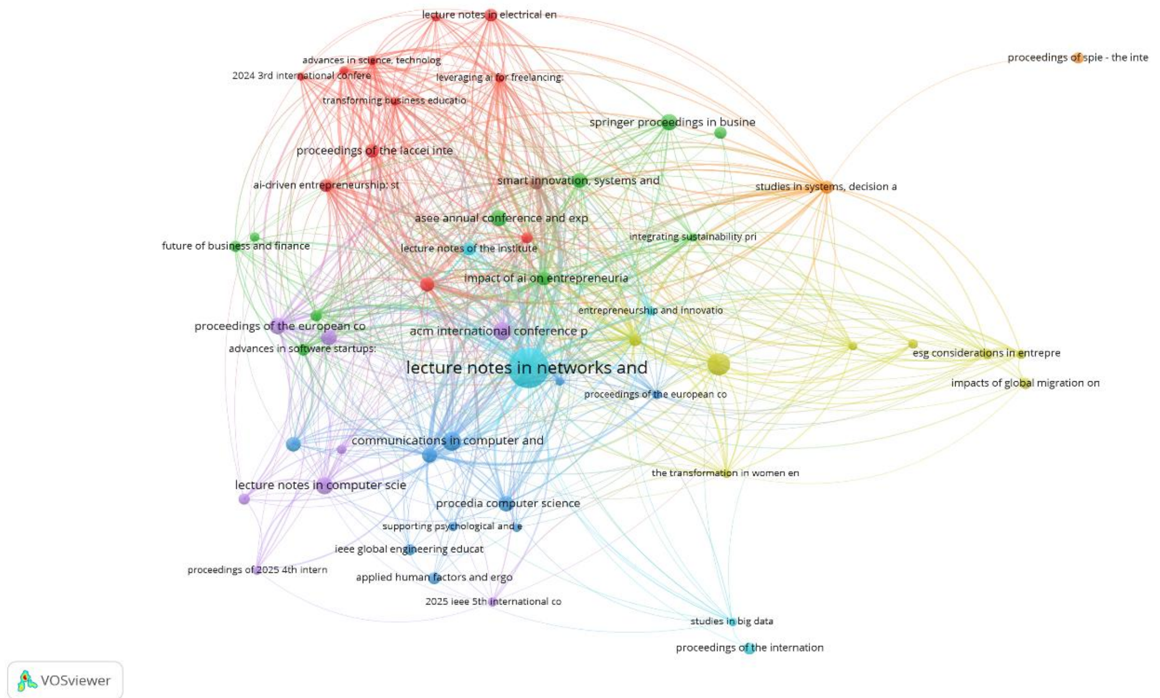

Figure 7. Bibliographic Coupling
Source: Author Analysis using VOSviewer

The bibliographic-coupling network shows Lecture Notes in Networks and Systems as the most central node, strongly linked to other proceedings, with clusters spanning AI-based entrepreneurship, smart innovation, sustainability, and entrepreneurial transformation, confirming the field's multidisciplinary nature, though proceedings still dominate.

Table 5. Top 7 Bibliographic-Coupling Network Among Sources with ≥5 Documents and Coupling TLS ≥50

No	Source	Documents	Coupling Cluster	Total Link Strength
1	Lecture Notes in Networks and Systems	102	2 – Computing/technical proceedings	1,157
2	Impact of AI on Entrepreneurial Leadership	12	4 – AI-driven entrepreneurial leadership & marketing	708
3	Decision Making, Learning, and Collaboration in AI-Driven Entrepreneurship	14	4 – AI-driven entrepreneurial leadership & marketing	505
4	Contributions to Management Science	9	3 – Sustainability, ESG & management science	477
5	AI-Powered Entrepreneurial Marketing and Communication	11	4 – AI-driven entrepreneurial leadership & marketing	461
6	Improving Entrepreneurial Processes through Advanced AI	12	1 – AI-driven entrepreneurial process & startup practice	420
7	Leveraging AI for Freelancing: Current and Future Prospects	6	1 – AI-driven entrepreneurial process & startup practice	319

The full network (41 sources meeting the ≥5-document and ≥50-TLS thresholds, all within a single connected component) resolves into four Louvain clusters: Cluster 1 (n = 13; AI-driven entrepreneurial process and startup practice, e.g., Improving Entrepreneurial Processes through Advanced AI, Leveraging AI for Freelancing); Cluster 2 (n = 11; computing/technical proceedings, e.g., Lecture Notes in Networks and Systems, Lecture Notes in Computer Science); Cluster 3 (n = 9; sustainability, ESG, and management science, e.g., Contributions to Management Science, Navigating ESG in Global Entrepreneurial Ecosystems); and Cluster 4 (n = 8; AI-driven entrepreneurial leadership and marketing, e.g., Impact of AI on Entrepreneurial Leadership, AI-Powered Entrepreneurial Marketing and Communication). These four clusters correspond closely to Figure 7's descriptive labels, now grounded in a real, clustered network rather than visual description alone.

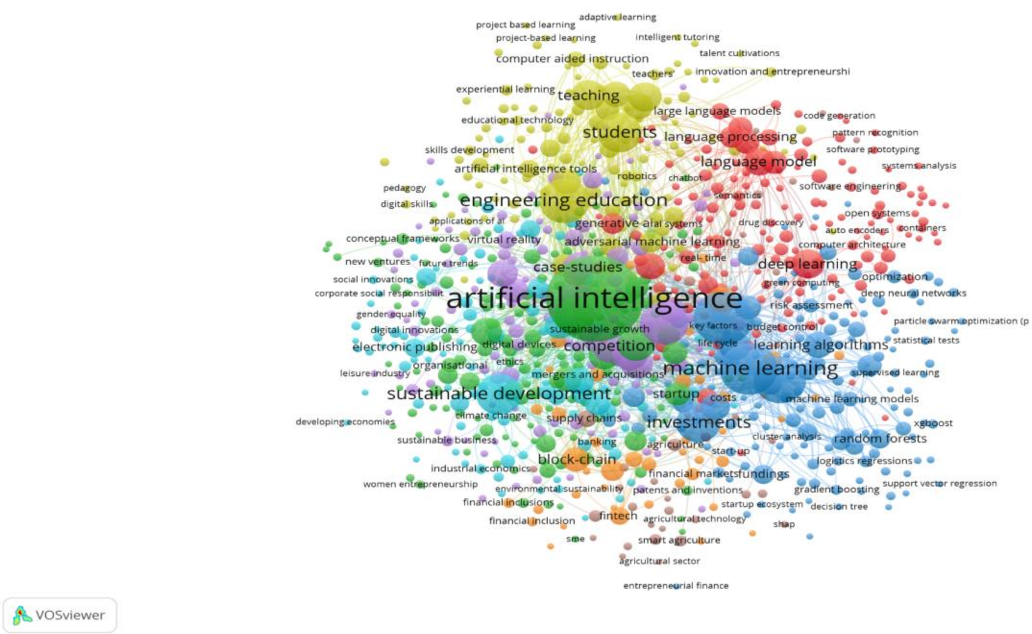

Figure 8. Keyword Co-Occurrence
Source: Author Analysis using VOSviewer

Figure 8 shows artificial intelligence as the most central theme, closely connected to machine learning, deep learning, and engineering education, with clusters spanning education, investment/finance, sustainable development, and innovation/startups, confirming multidisciplinary integration of technology, education, finance, and sustainability.

Table 6. Top 9 Keyword Occurrence and Co-Occurrence-Based Link Strength

No	Keyword	Occurrences (documents)	Total Link Strength (min. co-occurrence = 15)
1	Artificial intelligence	918	2,334
2	Machine learning	396	1,073
3	Learning systems	349	1,315
4	Engineering education	252	786
5	Decision making	236	701
6	Sustainable development	211	539
7	Deep learning	108	67
8	Blockchain	89	121
9	Generative artificial intelligence	26	0 (no pairing reaches the 15-document co-occurrence threshold)

Source: Author Analysis

Thematic Evolution, Research Clusters, and Future Research Directions

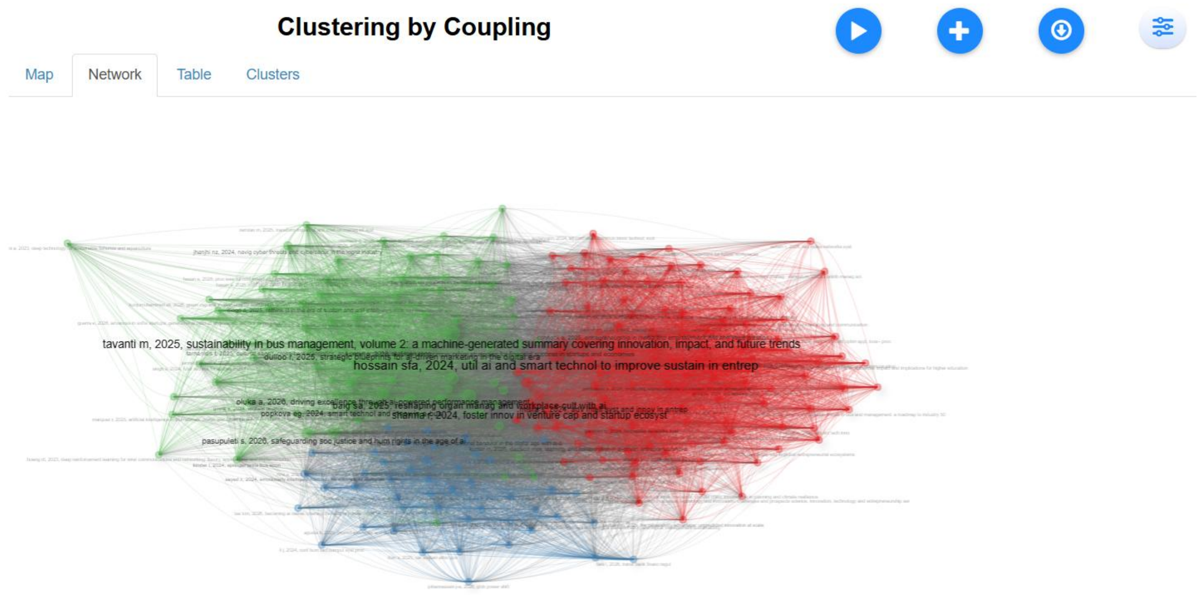

Figure 9. Main Clusters
Source: Author Analysis using R Studio Biblioshiny

Figure 9's green cluster focuses on sustainability and AI-based innovation; the red cluster covers smart technology, digital entrepreneurship, and venture capital; and the blue cluster covers ethical and social issues of AI, human rights, social justice, and technology governance.

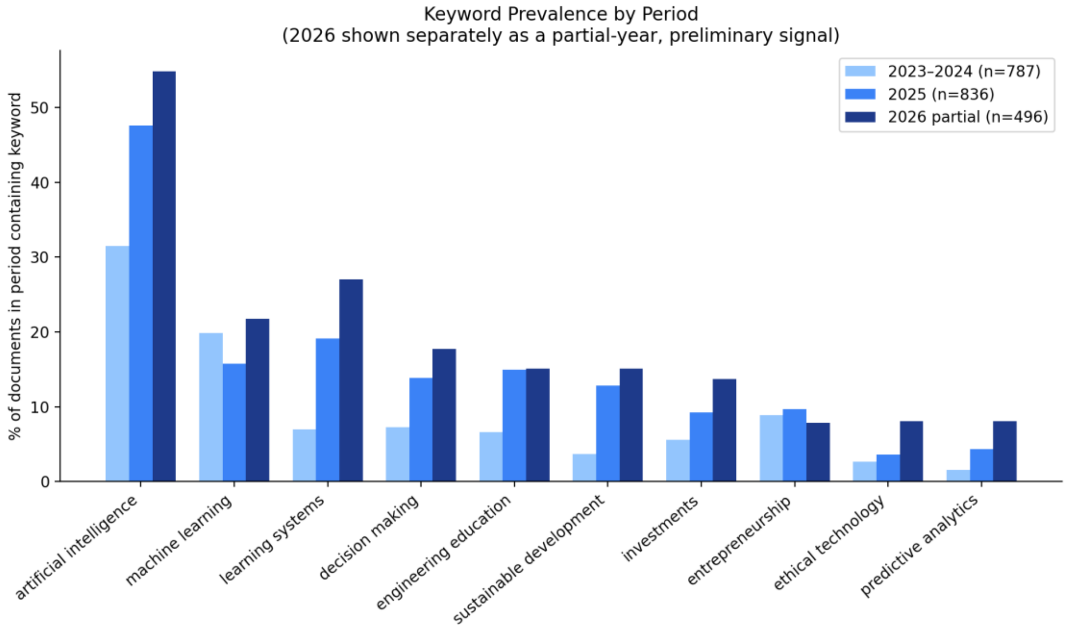

Figure 10. Thematic Evolution
Source: Author Analysis using Python (matplotlib), based on the normalized keyword set

Figure 10 compares keyword prevalence across three explicit periods (2023–2024, n=787; 2025, n=836; 2026 partial, n=496) rather than Bibliometrix's default unbalanced split. Artificial intelligence, machine learning, and decision-making remain dominant throughout, rising steadily; generative-AI and hybrid terms remain a small, modestly rising share (about 3% to 5%), read as an early signal given 2026's incompleteness.

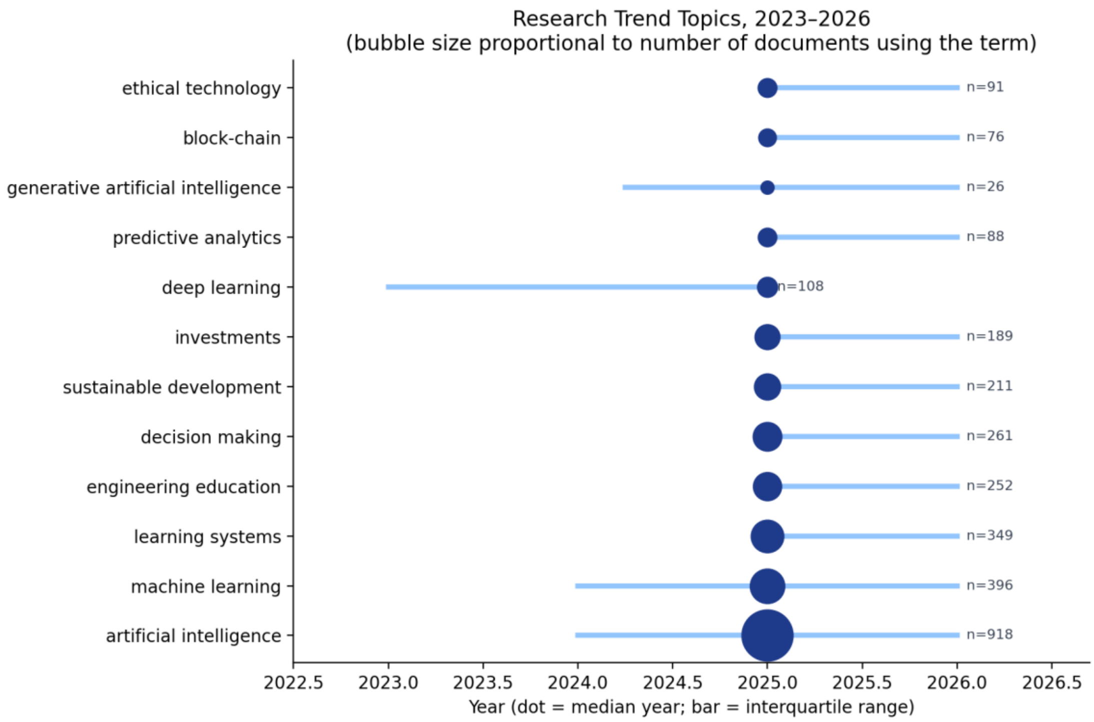

Figure 11. Research Trends
Source: Author Analysis

The dominant term is artificial intelligence (n=918), followed by machine learning (n=396) and learning systems (n=349), confirming a sustained AI focus. Decision making, engineering education, and sustainable development form a second tier (n=189–261), while generative artificial intelligence (n=26) and blockchain (n=76) appear later, with a median year of 2025, reflecting their more recent, still-emerging status. Deep learning shows the widest interquartile range, indicating consistent use across 2023–2026.

Based on the mapping of the intellectual structure and thematic evolution above, twenty future research directions were formulated across the individual, team/organizational, ecosystem, and institutional levels, as summarized in Table 7.

Table 7. Future Research Directions in the Field of AI-Based Entrepreneurship

No	Future Research Theme	Research Gap	Suggested Research Question(s)	Key Constructs / Variables	Context and Unit of Analysis	Suggested Methods
1	AI and entrepreneurial opportunity recognition	Whether AI enhances opportunity novelty or merely reproduces historical patterns remains unclear.	How does AI use affect the number, novelty, feasibility, and quality of opportunities identified by entrepreneurs?	AI use, information quality, industry knowledge	Prospective entrepreneurs, startup founders, new ventures, technology and non-technology sectors	Experiments, laboratory studies, process analysis
2	Human–AI collaboration in decision-making	The relationship among algorithmic recommendations, entrepreneurial intuition, and sector knowledge is insufficiently understood.	How do entrepreneurs combine intuition and AI recommendations when evaluating opportunities?	Quality of AI recommendations, intuition, experience	Individual entrepreneurs, founding teams, angel investors, small-business managers	Factorial experiments, scenario studies, think-aloud protocols
3	Generative AI and entrepreneurial creativity	Generative AI's effect on creativity is ambiguous, potentially expanding ideas while also homogenizing them.	Does the use of generative AI improve the creativity and originality of business ideas?	GenAI use, prompt quality, AI literacy	Entrepreneurship students, novice entrepreneurs, innovation teams, creative industries	Controlled experiments, pretest–posttest designs, content analysis of AI outputs
4	AI and business model innovation	Studies discuss AI's potential more than how it changes value creation, delivery, and capture mechanisms.	How does AI transform startups' value propositions, customer relationships, cost structures, and revenue streams?	AI capabilities, dynamic capabilities, business model innovation	Startups, SMEs, digital firms, family businesses	Comparative case studies, longitudinal surveys, fuzzy-set QCA

No	Future Research Theme	Research Gap	Suggested Research Question(s)	Key Constructs / Variables	Context and Unit of Analysis	Suggested Methods
5	AI and new venture performance	The causal link between AI adoption and venture performance is weakly established, given mostly conceptual or cross-sectional evidence.	Does AI adoption improve sales growth, productivity, innovation, and new-venture survival?	AI adoption, productivity, innovation	Startups and SMEs at different stages of growth	Panel data, difference-in-differences, propensity score matching
6	AI capabilities and competitive advantage	As AI access widens, advantage increasingly depends on integrating AI with data, people, and processes.	Which AI capabilities are difficult for competitors to imitate?	AI capabilities, data quality, human capital	AI-based startups, digital SMEs, platform firms	Scale development, cross-country surveys, SEM
7	AI, effectuation, and causation	Whether AI encourages predictive planning or supports flexible experimentation under uncertainty is unclear.	How does AI affect the use of effectuation and causation logics?	AI use, effectuation, causation	Nascent entrepreneurs, early-stage startups, innovation projects	Experiments, longitudinal process studies, repeated interviews
8	AI in entrepreneurial finance	Algorithmic investor decisions may improve selection efficiency while reinforcing bias against particular groups or ventures.	How does AI influence investors' decisions when selecting startups?	Algorithmic assessment, venture quality, investment bias	Venture capital, angel investors, crowdfunding platforms, financial institutions	Audit experiments, transaction-data analysis, predictive modeling
9	Responsible AI and startup governance	AI-governance frameworks built for large corporations may not fit startups' different constraints and pressures.	How can startups implement transparency, accountability, privacy, security, and algorithmic fairness with limited resources?	Transparency, explainability, fairness	AI startups, fintech, health-tech, edtech, digital platforms	Case studies, design science, policy analysis
10	AI dependence,	Intensive AI use may	Does dependence on	AI dependence,	Novice and experienced	Longitudinal studies,

No	Future Research Theme	Research Gap	Suggested Research Question(s)	Key Constructs / Variables	Context and Unit of Analysis	Suggested Methods
	deskilling, and entrepreneurial autonomy	reduce entrepreneurs' judgment, learning capacity, and independence.	AI lead to a decline in entrepreneurial skills and critical thinking?	automation bias, skills	entrepreneurs, students, self-employed workers	experiments, behavioral measures
11	AI and entrepreneurship education	No robust pedagogical model yet integrates AI without weakening experiential learning.	How can AI be used to develop opportunity recognition, creativity, business planning, and decision-making?	AI literacy, entrepreneurial competence, creativity	Students, lecturers, university incubators, SME training participants	Quasi-experiments, randomized controlled trials, mixed methods
12	AI and inclusive entrepreneurship	Studies set mainly in developed countries leave unclear whether AI narrows or widens entrepreneurial inequality.	Does AI reduce entry barriers for women, young people, persons with disabilities, and entrepreneurs in disadvantaged regions?	Access to AI, digital inclusion, human capital	Women entrepreneurs, rural entrepreneurs, the informal sector, vulnerable groups	Cross-country studies, multilevel surveys, participatory research
13	AI-driven entrepreneurship in developing countries	Existing theories were largely developed in ecosystems with advanced infrastructure, data, capital, and regulation.	How do limitations in infrastructure, data quality, culture, and institutions influence AI adoption?	AI readiness, institutions, digital infrastructure	Developing countries, including Indonesia and the ASEAN region	Cross-country comparative studies, multilevel analysis, institutional case studies
14	AI-driven entrepreneurial ecosystems	Research still focuses on individual entrepreneurs or firms, underexplaining interactions among ecosystem actors.	How do ecosystem actors collaborate to support the creation and growth of AI-driven ventures?	Government support, universities, investors	Cities, regions, industrial clusters, national ecosystems	Social network analysis, multilevel studies, spatial analysis
15	AI policy and regulation for new ventures	Regulation's effects on startup innovation are inconsistent across sectors and government levels.	How does AI regulation affect compliance costs, innovation, investment, and startup legitimacy?	Regulatory intensity, compliance costs, regulatory uncertainty	Startups in high- and low-risk sectors; local, national, regional levels	Comparative policy analysis, policy experiments, natural experiments

No	Future Research Theme	Research Gap	Suggested Research Question(s)	Key Constructs / Variables	Context and Unit of Analysis	Suggested Methods
16	AI, sustainability, and social entrepreneurship	AI is assumed to support sustainability, yet its environmental and social costs remain underexamined.	How does AI help entrepreneurs pursue economic, social, and environmental goals simultaneously?	AI capabilities, sustainability orientation, green innovation	Social enterprises, green startups, agritech, energy and waste-management ventures	Life-cycle assessment, longitudinal studies, SEM
17	AI and founding team dynamics	Most studies focus on individual entrepreneurs despite founding teams generally making key decisions.	How does AI affect task allocation, conflict, coordination, power, and creativity within founding teams?	AI use, team coordination, task conflict	Startup founding teams and new-venture development teams	Multilevel studies, team observation, conversation analysis
18	Long-term effects of AI on startup employment	Evidence on automation, job creation, and organizational change remains predominantly short-term.	How does AI change workforce requirements and startup organizational design over the long term?	Automation intensity, job design, skill requirements	Startups and SMEs in knowledge-intensive and labor-intensive sectors	Panel data, cohort studies, job analysis
19	Comparing predictive AI and generative AI	The literature often treats all AI technologies as one category despite differing functions and consequences.	How do predictive AI and generative AI differ in their effects on opportunity recognition, creativity, risk evaluation, and venture performance?	Predictive AI, generative AI, creativity	Entrepreneurs, startups, investors, incubators	Comparative experiments, factorial designs, field studies
20	Measuring AI-driven entrepreneurship	No widely accepted definition or instrument distinguishes ordinary AI adoption from genuinely AI-driven entrepreneurship.	What are the core dimensions of AI-driven entrepreneurship?	AI intensity, process integration, algorithmic autonomy	Entrepreneurs and firms across sectors and countries	Conceptual development, Delphi studies, scale development

Source: Author Analysis

Each item in Table 7 was derived by connecting a specific pattern already reported in the Results, a keyword's occurrence rank, a cluster's composition, a document-type or collaboration imbalance, or an explicit conceptual gap noted when discussing that pattern, to a corresponding proposed research direction, rather than being asserted independently of the mapping. Table 8 makes this derivation explicit for every item so that the agenda is auditable rather than only plausible. Where an item's evidence basis rests on a term's absence from the top-40 keyword co-occurrence network or on a low occurrence count, this absence indicates limited representation within the present, document-type-bounded corpus rather than a demonstrated gap in the wider literature; the items below are accordingly presented as an evidence-informed research agenda derived from bibliometric patterns together with the substantive literature already cited in the Introduction and Discussion, not as gaps proven exclusively through bibliometric absence.

Table 8. Evidentiary Basis for the Proposed Future Research Agenda

No	Agenda Item (Table 2)	Bibliometric or Conceptual Evidence Basis
1	Opportunity recognition	Dense AI-decision-making keyword linkage (Figure 8); opportunity quality itself remains untested by co-occurrence alone (Townsend & Hunt, 2019; Shepherd & Majchrzak, 2022).
2	Human–AI decision-making	Co-citation cluster (Figure 6, red) links AI and entrepreneurial decision-making, without a sub-cluster distinguishing collaborative from substitutive AI use.
3	Generative AI creativity	Low occurrence of "generative artificial intelligence" (n = 26) versus "artificial intelligence" (n = 918, Figure 11) indicates a thin, emerging sub-literature.
4	Business model innovation	Keyword cluster combining AI and investment/business terms (Figure 8) shows no matching causal or longitudinal-method markers in the corpus.
5	New venture performance	Corpus dominance of conference papers (n = 1,100/2,119) and short average document age (1.27 years, Table 1) indicate a largely conceptual evidence base.
6	Competitive advantage	Bibliographic-coupling cluster on "smart innovation" and "business education" (Figure 7) has no corresponding resource-based-view keyword among the top-40 terms.
7	Effectuation and causation	Effectuation/causation terms have limited representation among the top-40 co-occurrence terms (Figure 8) despite prominent process terms, motivating this link.
8	Entrepreneurial finance	The "investment and entrepreneurship finance" keyword cluster (Figure 8) co-occurs with AI terms without algorithmic-bias-specific sub-nodes.
9	Startup governance	An ethics/governance cluster appears descriptively in Figure 9 (blue cluster) without governance-specific measurement keywords among the top-40 terms.
10	Dependence and deskilling	Limited representation of "deskilling" or "autonomy" among top-40 keywords despite an AI-ethics/social-impact cluster (Figure 9) and the citation-age caveat in the Discussion.
11	Entrepreneurship education	"Engineering education" is a second-tier high-frequency keyword (n = 189–261, Figure 11) co-occurring with AI but framed technically rather than pedagogically.
12	Inclusive entrepreneurship	The country-collaboration map (Figure 5) concentrates among India, China, the United States, and Europe, with limited visible representation from Africa and Latin America.
13	Developing-country entrepreneurship	Same collaboration-concentration pattern as item 12, combined with the Discussion's note on the dominance of high-technological-capacity countries.
14	Entrepreneurial ecosystems	Bibliographic-coupling cluster on "entrepreneurial transformation" and "computing applications" (Figure 7) lacks an explicit multi-actor ecosystem sub-cluster.

No	Agenda Item (Table 2)	Bibliometric or Conceptual Evidence Basis
15	AI policy and regulation	"Regulation" and "policy" have limited representation among the top-40 co-occurrence terms (Figure 8) despite governance appearing qualitatively in the Figure 9 blue cluster.
16	Sustainability and social entrepreneurship	"Sustainable development" is a second-tier high-frequency keyword (n = 189–261, Figure 11) co-occurring with AI but without quantitative environmental-impact sub-metrics.
17	Founding team dynamics	Team- or group-level keywords have limited representation among the top-40 terms, consistent with the individual/firm-level framing dominant in the retrieved set.
18	AI and employment	The 2023–2026 window and 1.27-year average document age (Table 1) mean the corpus cannot itself support long-term employment claims.
19	Predictive vs. generative AI	The large occurrence asymmetry between "artificial intelligence"/"machine learning" (n = 918/396) and "generative artificial intelligence" (n = 26, Figure 11) motivates disaggregating these categories.
20	Measuring AI-driven entrepreneurship	A standardized "AI intensity" keyword has limited representation among the top-40 terms despite AI being the single most central node (Figure 8), conceptual centrality unmatched by operational measurement.

Table 7 groups the research directions into four levels of analysis. At the individual level, research needs to examine the creativity, intuition, knowledge, trust, dependency, and competence of AI-driven entrepreneurs. At the team and organizational level, attention is directed to AI capabilities, business model innovation, governance, job design, and startup performance. At the ecosystem level, research needs to analyze the relationships between governments, universities, investors, technology companies, and supporting institutions. At the institutional level, research should examine how regulations, culture, digital inequalities, and country characteristics influence the development of AI-based entrepreneurship. Further research also needs to move from conceptual and cross-sectional studies to experiments, panel data, longitudinal process studies, multilevel analysis, and mixed methods. This approach is important for distinguishing correlations from causal relationships and for explaining how AI's impact varies across the stages of opportunity recognition, business establishment, growth, and sustainability. The use of various theories, such as effectuation theory, dynamic capabilities, the resource-based view, institutional theory, human capital theory, and entrepreneurial ecosystem theory, can deepen the explanation of how and under what conditions AI produces benefits or risks for entrepreneurs.

Discussion

The results on publication development, author productivity, and scientific collaboration show that AI-driven entrepreneurship research grew very rapidly during 2023–2026: 2,119 documents across 1,248 sources, at an annual growth rate of 22.02%. The involvement of 6,139 authors and an average of 3.17 authors per document reflects the field's collaborative nature, though an international-collaboration rate of 22.27% suggests most cooperation remains national or regional. India and China dominate productivity and collaboration networks, with the United States, European countries, and Australia as key knowledge-exchange partners,consistent with Boateng et al. (2024), who found AI-and-entrepreneurship research evolving across diverse country and disciplinary networks with unevenly distributed influence. The dominance of conference papers, book chapters, and the Lecture Notes series indicates the field remains in an early, computer-science- and engineering-driven stage, reinforcing Uriarte et al.'s (2026) conclusion that this literature is growing explosively yet remains conceptually and methodologically fragmented. The lower 2026 count should not be read as declining interest, since the observation year was still ongoing and Scopus indexing incomplete at the time of collection (Boateng et al., 2024; Chalmers et al., 2021; Uriarte et al., 2026).

Regarding intellectual and conceptual structure, co-citation, bibliographic coupling, and keyword co-occurrence together show that entrepreneurship theory, innovation, decision-making, learning, and computational technology form the field's intellectual core. The co-citation network connects classical entrepreneurial thinking on innovation and value creation with contemporary literature positioning AI as an entrepreneurial resource, enabler, and cognitive partner, supporting Shepherd and Majchrzak (2022), who note that AI can augment opportunity recognition while also posing risks such as algorithmic dependence, bias, and destructive entrepreneurial action. The centrality of the Lecture Notes in Networks and Systems series in bibliographic coupling (Table 5) indicates the field remains strongly shaped by technology and conference-proceedings publications. Conceptually, artificial intelligence is the main node (n = 918; Table 6) connected to machine learning, deep learning, language models, engineering education, investment, and sustainable development,associating AI with opportunity recognition, decision-making, and business-model innovation rather than treating it solely as automation, though this remains a co-occurrence statement rather than evidence of how AI actually functions. Giuggioli and Pellegrini (2023) affirm AI supports decision quality, opportunity identification, and performance, while Blanco-González-Tejero et al. (2023) show the field spans themes not yet integrated; the knowledge structure is thus multidisciplinary but still requires theoretical consolidation (Blanco-González-Tejero et al., 2023; Giuggioli & Pellegrini, 2023; Shepherd & Majchrzak, 2022). The co-citation network itself (Table 4) is further anchored by an AI-in-business and AI-in-service literature (Davenport & Ronanki, 2018; Huang & Rust, 2018; Rust & Huang, 2021; Haenlein & Kaplan, 2019; Dwivedi et al., 2021; Brynjolfsson & McAfee, 2017) not previously cited in this manuscript, confirming with corpus-internal evidence that this field is intellectually dependent on general management and information-systems AI scholarship rather than a fully self-contained citation base. Relative to existing reviews, the present mapping converges with Boateng et al. (2024) and Uriarte et al. (2026) on the field's fragmented character and with Blanco-González-Tejero et al. (2023) on its conceptual orientation, while diverging by extending the window into 2025–2026, isolating the conference-paper, book-chapter, and book segment, and contributing the quantified cluster structure (Tables 4, 5) and corpus-internal evidence that this literature draws substantially on general AI-in-business scholarship.

Regarding thematic evolution, three main cluster directions were identified: business innovation and sustainability; smart technology and startup ecosystems; and ethics, education, governance, and social impact. Consistent with the three-period comparison in Figure 10, artificial intelligence, machine learning, and decision-making remain dominant across 2023–2024, 2025, and the partial year 2026, while generative-AI and hybrid-related terms show only a modest, gradual rise (from roughly 3% of documents in 2023–2024 to roughly 5% in 2025–2026),an early, still-developing signal rather than a confirmed thematic shift, given the incomplete final observation year. Generative AI can reduce information asymmetry, generate alternative ideas, and support early-stage problem-solving, though these benefits depend on field knowledge, prompt quality, and entrepreneurs' ability to evaluate AI outputs (Li et al., 2025); experimental evidence outside the entrepreneurship literature similarly finds that generative AI can raise individual creative output while narrowing the diversity of ideas produced collectively, a tension directly relevant to Cluster 3's open questions about generative AI and entrepreneurial creativity (Doshi & Hauser, 2024). Future research needs to move from descriptive studies toward experiments, panel data, and longitudinal designs testing AI's influence on creativity, opportunity recognition, and performance, with greater attention to human–AI collaboration, algorithmic bias, and responsible governance. The dominance of high-technological-capacity countries also points to a need for research in developing countries, MSMEs, the informal sector, women entrepreneurs, and regions with limited digital infrastructure,a gap consistent with recent SME-focused bibliometric evidence showing that AI-adoption research for smaller firms remains concentrated in developed economies despite AI's demonstrated role in supporting SME innovation and competitiveness (Yesuf & Fields, 2025),in line with Obschonka et al. (2025), who call for new theoretical and empirical foundations for understanding AI's transformation of entrepreneurship, and Uriarte et al. (2026), who emphasize more diverse theories, contexts, and methods (Li et al., 2025; Obschonka et al., 2025; Uriarte et al., 2026).

These patterns should also be read against alternative, non-substantive explanations before being treated as evidence of field-level structure. The dominance of conference proceedings and the Lecture Notes series may partly reflect the corpus composition and disciplinary scope of the database queried rather than a genuine editorial preference of the field. Citation-based measures such as co-citation strength are subject to citation-age effects, structurally disadvantaging recently published clusters regardless of substantive importance. Because the final observation year is incomplete, any apparent shift in keyword prominence toward that year is also consistent with partial indexing rather than a genuine agenda change. These alternative explanations do not eliminate the value of the mapping but bound how strongly its patterns should be interpreted as evidence of substantive change in the field.

CONCLUSION

This bibliometric study concludes that, within the bounded corpus of 2,119 Scopus-indexed conference papers, book chapters, and books analyzed, AI-driven entrepreneurship research grew rapidly during 2023–2026, at 22.02% annually, involving 6,139 authors; these figures describe the retrieved and cleaned dataset rather than a fully validated global map, given the corpus's relevance-validation limits noted in the Method. Publication activity peaked in 2025, while 2026 figures should be read cautiously since the observation period had not fully ended. The field is collaborative (3.17 authors per document on average), though the 22.27% international-collaboration rate suggests room for more cross-border cooperation; India and China are emerging production and collaboration centers, with the United States, European countries, Australia, and several developing countries shaping the wider network. Intellectually, the field integrates classical entrepreneurial theory, innovation, technology management, and decision-making; bibliographic coupling shows the dominance of conference proceedings and the Lecture Notes series, indicating an early stage shaped by engineering and computer science, while keyword co-occurrence identifies AI as the central node connecting technology, education, finance, and sustainability. Across the three observation periods (2023–2024, 2025, 2026 partial), generative-AI and hybrid-related terms show only a modest, gradual rise alongside continued dominance of artificial intelligence, machine learning, and decision-making,an early, still-emerging signal rather than a confirmed thematic shift, given the incomplete final year. Three main clusters were identified: business innovation and sustainability; smart technology and startup ecosystems; and ethics, education, governance, and social impact. Future research needs to move from mapping technological potential to empirically testing how AI affects opportunity recognition, decision-making, and performance; this mapping does not itself evaluate infrastructure, supply-chain, or policy outcomes, noted as directions the clusters point toward rather than established findings.

Theoretically, this research contributes to the digital entrepreneurship literature by showing that the mapped literature increasingly conceptualizes AI as a resource, capability, cognitive partner, and ecosystem building block rather than only an operational tool,though confirming these roles would require evidence beyond bibliometric mapping. The findings indicate a need to integrate resource-based view, dynamic capabilities, effectuation, and entrepreneurial ecosystem theory to explain AI's impact more comprehensively, and to distinguish predictive from generative AI, since each supports prediction and creativity through different mechanisms. Methodologically, the dominance of conceptual and conference-based studies points to a need for more longitudinal surveys, experiments, and mixed methods to test causal relationships between AI use and entrepreneurial outcomes, alongside valid instruments for measuring AI capability and integration level.

The following practical, educational, and policy points are implications drawn from the mapped literature and proposed agenda rather than findings directly tested by the present design. For entrepreneurs, excellence depends less on access to AI applications than on integrating technology with data, knowledge, and human judgment; entrepreneurs need AI literacy, the ability to verify algorithmic results, and human-supervision mechanisms so AI expands opportunities without displacing intuition and ethics. For entrepreneurship education, institutions need to integrate AI through project-based learning, business simulations, and generative-AI experimentation, teaching not only tool use but data literacy, critical thinking, algorithmic ethics, privacy, intellectual-property rights, and risk evaluation, so students use AI creatively and responsibly rather than simply relying on its outputs.

For policymakers, governments need to build an AI-based entrepreneurship ecosystem through infrastructure, data access, skills training, and university–industry–investor collaboration, while ensuring transparency, data security, and accountability. Special support is needed for MSMEs, women entrepreneurs, rural businesses, and technology-limited groups so AI development does not widen the entrepreneurial gap. Socially, AI can increase inclusion and access to opportunity, but can also produce bias, dependence, and digital inequality; its development must balance economic growth with social protection and human values, directing human–AI collaboration toward broader social benefit rather than efficiency alone.

Future research is recommended to move beyond descriptive and conceptual designs toward experiments, panel data, and longitudinal approaches that systematically test how AI capabilities influence opportunity recognition, creativity, business-model innovation, financing access, performance, and sustainability across individual, organizational, ecosystem, and institutional levels of analysis, with study designs and sample requirements specified in light of the effect sizes and gaps identified within the mapped clusters rather than a generic call for larger samples.

Limitations

This study has several limitations that should be considered when interpreting the findings. First, the analysis relies exclusively on the Scopus database and English-language documents, which may have resulted in the omission of relevant studies indexed in other databases or published in other languages. Second, the inclusion of conference papers, book chapters, and books as eligible document types influences the composition of the corpus and may produce patterns that differ from those obtained through an article- or review-only approach.

Third, although a broad search strategy was adopted to capture the interdisciplinary nature of AI-driven entrepreneurship research, the retrieved documents may include studies in which AI and entrepreneurship-related terms appear together without representing a primary focus on AI-driven entrepreneurial processes. Therefore, some degree of thematic heterogeneity within the corpus remains unavoidable. Fourth, despite applying standardization procedures for authors, institutions, countries, and keywords, bibliometric disambiguation remains subject to uncertainty; consequently, institutional and collaboration analyses should be interpreted as conservative representations rather than exhaustive measures.

Fifth, network-based analyses, including co-citation, bibliographic coupling, and keyword clustering, are sensitive to parameter choices such as thresholds, counting methods, and clustering algorithms. Although robustness checks and independent calculations were conducted, variations in analytical settings may influence the resulting network structures and cluster interpretations. Sixth, the retrieved corpus contains no records published before 2023, and the final observation year is incomplete due to ongoing indexing processes. Accordingly, temporal patterns involving recent years, particularly 2026, should be interpreted as preliminary rather than definitive.

REFERENCES

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Aria, M., & Cuccurullo, C. (2017). Bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics, 11*(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

Barney, J. B. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Blanco-González-Tejero, C., Ribeiro-Navarrete, B., Cano-Marín, E., & McDowell, W. C. (2023). A systematic literature review on the role of artificial intelligence in entrepreneurial activity. *International Journal on Semantic Web and Information Systems, 19*(1), 1–16. https://doi.org/10.4018/IJSWIS.318448

Boateng, S. L., Penu, O. K. A., Budu, J., Boateng, R., Marfo, J. S., Anning-Dorson, T., & Broni, F. E. J. (2024). Mapping the research on artificial intelligence and entrepreneurship: A bibliometric review from the Scopus database. *International Journal of E-Entrepreneurship and Innovation, 14*(1), 1–24. https://doi.org/10.4018/IJEEI.343790

Brynjolfsson, E., & McAfee, A. (2017). The business of artificial intelligence. *Harvard Business Review, 95*(1), 1–11.

Chalmers, D., MacKenzie, N. G., & Carter, S. (2021). Artificial intelligence and entrepreneurship: Implications for venture creation in the Fourth Industrial Revolution. *Entrepreneurship Theory and Practice, 45*(5), 1028–1053. https://doi.org/10.1177/1042258720934581

Cristofaro, M., Giardino, P. L., & Muldoon, J. (2026). Entrepreneurial decision-making in the age of AI: Sector knowledge at the balance of intuition and analysis. *Technology in Society, 85*, Article 103200. https://doi.org/10.1016/j.techsoc.2025.103200

Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review, 96*(1), 108–116.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research, 133*, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070

Doshi, A. R., & Hauser, O. P. (2024). Generative AI enhances individual creativity but reduces the collective diversity of novel content. *Science Advances, 10*(28), Article eadn5290. https://doi.org/10.1126/sciadv.adn5290

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, Article 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Giuggioli, G., & Pellegrini, M. M. (2023). Artificial intelligence as an enabler for entrepreneurs: A systematic literature review and an agenda for future research. *International Journal of Entrepreneurial Behavior & Research, 29*(4), 816–837. https://doi.org/10.1108/IJEBR-05-2021-0426

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review, 61*(4), 5–14. https://doi.org/10.1177/0008125619864925

Huang, M.-H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research, 21*(2), 155–172. https://doi.org/10.1177/1094670517752459

Kumar, K., & Singh, B. (2025). Artificial intelligence in the startup world: A bibliometric study of emerging trends and themes. *Abhigyan, 43*(4), 315–337. https://doi.org/10.1177/09702385251349614

Li, Y., Ring, J. K., Jin, D., & Bajaba, S. (2025). Elevating entrepreneurship with generative artificial intelligence. *Journal of Innovation & Knowledge, 10*(6), Article 100820. https://doi.org/10.1016/j.jik.2025.100820

Nambisan, S. (2017). Digital entrepreneurship: Toward a digital technology perspective of entrepreneurship. *Entrepreneurship Theory and Practice, 41*(6), 1029–1055. https://doi.org/10.1111/etap.12254

Obschonka, M., & Audretsch, D. B. (2020). Artificial intelligence and big data in entrepreneurship: A new era has begun. *Small Business Economics, 55*(3), 529–539. https://doi.org/10.1007/s11187-019-00202-4

Obschonka, M., Grégoire, D. A., Nikolaev, B., Ooms, F., Lévesque, M., Pollack, J. M., & Behrend, T. S. (2025). Artificial intelligence and entrepreneurship: A call for research to prospect and establish the scholarly AI frontiers. *Entrepreneurship Theory and Practice, 49*(3), 620–641. https://doi.org/10.1177/10422587241304676

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McGuinness, L. A., ... Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, Article n71. https://doi.org/10.1136/bmj.n71

Papagiannidis, E., Mikalef, P., & Conboy, K. (2025). Responsible artificial intelligence governance: A review and research framework. *The Journal of Strategic Information Systems, 34*, Article 101885. https://doi.org/10.1016/j.jsis.2024.101885

Redondo-Rodríguez, M. D., Díaz-Garrido, E., Perez-Bustamante Yábar, D. C., & Ramón-Jerónimo, M. A. (2024). Entrepreneurship and artificial intelligence: A bibliometric analysis. *The Journal of Technology Transfer, 50*(4), 1840–1872. https://doi.org/10.1007/s10961-024-10165-8

Retamal-Saavedra, C. D., Andrade-Valbuena, N. A., & Contreras-Navarro, J. E. (2026). Artificial intelligence in entrepreneurship: Mapping a fragmented field and advancing a cognitive research agenda. *Journal of Management & Organization*. Advance online publication. https://doi.org/10.1017/jmo.2026.10082

Rust, R. T., & Huang, M.-H. (2021). *The feeling economy: How artificial intelligence is creating the era of empathy*. Palgrave Macmillan. https://doi.org/10.1007/978-3-030-52977-2

Sarasvathy, S. D. (2001). Causation and effectuation: Toward a theoretical shift from economic inevitability to entrepreneurial contingency. *Academy of Management Review, 26*(2), 243–263. https://doi.org/10.5465/AMR.2001.4378020

Shane, S., & Venkataraman, S. (2000). The promise of entrepreneurship as a field of research. *Academy of Management Review, 25*(1), 217–226. https://doi.org/10.5465/amr.2000.2791611

Shepherd, D. A., & Majchrzak, A. (2022). Machines augmenting entrepreneurs: Opportunities and threats at the nexus of artificial intelligence and entrepreneurship. *Journal of Business Venturing, 37*(4), Article 106227. https://doi.org/10.1016/j.jbusvent.2022.106227

Siddiqui, D., Mumtaz, U., & Ahmad, N. (2024). Artificial intelligence in entrepreneurship: A bibliometric analysis of the literature. *Journal of Global Entrepreneurship Research, 14*, Article 13. https://doi.org/10.1007/s40497-024-00385-5

Stam, E. (2015). Entrepreneurial ecosystems and regional policy: A sympathetic critique. *European Planning Studies, 23*(9), 1759–1769. https://doi.org/10.1080/09654313.2015.1061484

Townsend, D. M., & Hunt, R. A. (2019). Entrepreneurial action, creativity, and judgment in the age of artificial intelligence. *Journal of Business Venturing Insights, 11*, Article e00126. https://doi.org/10.1016/j.jbvi.2019.e00126

Uriarte, S., Baier-Fuentes, H., Espinoza-Benavides, J., & Inzunza-Mendoza, W. (2026). Artificial intelligence technologies and entrepreneurship: A hybrid literature review. *Review of Managerial Science, 20*(1), 251–299. https://doi.org/10.1007/s11846-025-00839-4

van Eck, N. J., Waltman, L., Dekker, R., & van den Berg, J. (2010). A comparison of two techniques for bibliometric mapping: Multidimensional scaling and VOS. *Journal of the American Society for Information Science and Technology, 61*(12), 2405–2416. https://doi.org/10.1002/asi.21421

Waltman, L., van Eck, N. J., & Noyons, E. C. M. (2010). A unified approach to mapping and clustering of bibliometric networks. *Journal of Informetrics, 4*(4), 629–635. https://doi.org/10.1016/j.joi.2010.07.002

Yesuf, Y., & Fields, Z. (2025). Artificial intelligence adoption as a driver of innovation and competitiveness in SMEs: A bibliometric and systematic review. *F1000Research, 14*, Article 1187. https://doi.org/10.12688/f1000research.171494.1