Mapping Influence and Evolution in AI Research: A Citation Network Analysis of Top Universities (2015–Present)

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Abstract

The using of Artificial intelligence has been growing rapidly, and AI-based applications have become more extensive across all disciplines. Mapping citation patterns among journals and articles about AI from leading institutions can reveal how research influence, collaboration, and subdisciplines in AI have evolved as time goes by. This study analyzes the distribution of AI-related journals from the top ten universities over the past decade and explores the relationships between citation to identify any patterns and characteristics in the citation. Using bibliographic records collected from OpenAlex (online databases of publications), we construct a directed citation network, where each node represents AI related paper, and each edge represents a citation between papers. Centrality measures, community detection, and degree distribution are applied to reveal undiscovered patterns in the publication and citation behaviour of these institutions. The analysis reveals a scale-free network structure where the publication count, which was led by Stanford University, does not strictly correlate with citation impact, which is highest at Harvard University. Furthermore, “AI in Healthcare” is identified as a dominant subtopic, with a recent exponential growth navigated by network growth by Large Language Models. These discovery indicate that high-betweenness “bridge” papers are becoming crucial for integrating disconnected research communities. The study confirms a significant shift toward interdisciplinary collaboration, suggesting that future institutional influence will depend on producing trend-setting research that connects diverse domains rather than a mere publication count.

This analysis is done in the Submission branch of github repo: https://github.com/johaneshp/cosc421-final-project.git

Keywords: citation network analysis, artificial intelligence, machine learning, healthcare AI, educational technology, research impact, network centrality, community detection, bibliometrics

1 Introduction

1.1 Background and Motivation

Over the past decade, artificial intelligence has experienced unprecedented growth in both research output and practical applications. AI-related publications have increased globally by 57% from 2018 to 2022, making it one of the largest areas of research (Nature News, 2023). At the same time, the organizational adoption of AI has surged from 55% to 72% between 2023 and 2024 (Singla et al, 2024). This rapid expansion of AI-driven applications, from large language models like ChatGPT to highly specialized systems in healthcare, underscores the technology's transformative impact across virtually every industry. As AI research continues to grow, understanding the structural foundation of this field through citation patterns is critical in identifying influential work, emerging subfields, and future research directions.

Due to the extensive growth in AI publications, there remains a significant gap in understanding how citation relationships among leading research institutions reveal the underlying dynamics of knowledge distribution and collaborative networks in this rapidly evolving field. While certain papers and researcher teams are frequently evaluated for impact, systematic analysis of citation networks from top-tier institutions can uncover structural patterns that go beyond individual contributions and reveal how research influence spreads across subfields, shaping the trajectory of AI development. Moreover, the recent emergence of groundbreaking technologies, such as large language models, requires an examination of whether traditional patterns of citation and influence persist or whether new paradigm shifts are reshaping the research landscape.

1.2 Research Objectives

In this context, the aim of this study is to analyze the citation network of AI-related publications from the top ten leading universities over the past decade (2015-2025). Specifically, we set out to address the following research questions:

1. **RQ1**: Which papers are the most impactful in the AI research landscape?
2. **RQ2**: What subtopics have the highest concentration of research and how do they cluster into communities?
3. **RQ3**: Which institutions have the most research output and impact?
4. **RQ4**: What are the foundational papers that have sustained relevance over time?
5. **RQ5**: What are the emerging trends and where is newer research headed?

1.3 Contributions

This study analyzes 2,610 published research papers collected from OpenAlex and examines their distribution across institutions and subtopics. The 3,757 directed citation relationships among these papers form a citation network that enables us to apply network analysis techniques, including degree distributions, centrality measures, and community detection, to identify structural patterns and influential works. Through mapping the citation landscape of leading AI research institutions, this study provides insights into:

- How research influence is distributed across institutions and papers
- How interdisciplinary subfields emerge and interact through citation patterns
- How bridge papers connect disparate research communities
- The evolution of AI research trends from 2015 to 2024

The findings of this study have direct practical implications for understanding the ever-evolving dynamics of AI research in its current form and identifying emerging directions that may help shape the future of this field.

2 Related Work

Previous research has used bibliometric and network-based methods to understand the evolution of artificial intelligence research. However, few studies specifically examine citation structures within top universities or consider how recent developments, such as large language models, reshape them. Building on this literature, our study uses institutional citation networks to examine both influence and emerging subfields in contemporary AI research.

2.1 Bibliometric Analysis of AI Research

Mardiani and Iswahyudi (Mardiani and Iswahyudi, 2023) use a bibliometric approach to map the AI research landscape. They examine publication volumes, country-level contributions, and topic clusters. Their results confirm rapid evolution and thematic differences in AI. However, they accumulate output at the global level, without analyzing differences in citation structures across leading universities or their links to specific subtopics. Their data also spans a much wider period (1974-2023) than ours, diluting the impact of recent LLM advances and detracting from current research trends.

Similarly, Costa and Frigori (Costa and Frigori, 2024) expand this line of work by analyzing an AI citation network to study complexity and phase transitions over time. They use measures such as Shannon entropy of paper titles and changes in average degree to identify structural shifts. While their study shows that citation networks undergo rapid reconfiguration during major technological advances, it focuses on global temporal dynamics rather than institutional influence or 'bridge' papers within subfields. Additionally, collecting data only up to 2020 means their study misses the network impact of the latest research.

2.2 Citation Networks and Impact Metrics

Other research has focused on citation networks and impact metrics to find what works best. For example, Fiala and Tutoky (Fiala and Tutoky, 2017) compare PageRank-based metrics and raw citation counts performance in predicting award-winning researchers in computer science, using author-level citation network. From the research, it is concluded that PageRank is better in identifying high impact contributors and shows the value of network-aware measures for evaluating influence. However, their work does not address PageRank's connection to institutional citation patterns or community structure in AI-specific research

Costa and Frigori's (Costa and Frigori, 2024) treatment of citation networks as complex systems also encourages the use of centrality and connectivity metrics to detect structural key points. However, their analysis does not incorporate community detection of distinct subtopics, leaving open questions about how influence and field specialization are distributed across leading research teams.

2.3 Large Language Models as an Emerging AI Frontier

Fan et al. (Fan et al, 2024) conducted a bibliometric review of large language model research from 2017 to 2023, synthesizing more than 5,000 publications to characterize growth trends, application domains, and collaboration patterns around LLMs. Their findings highlight LLMs as a rapidly expanding and highly interdisciplinary subfield, but the study treats LLM work largely through publication and topical statistics rather than through explicit citation network analysis or institutional comparison.

Alongside broader AI bibliometric studies, Fan et al.'s (Fan et al, 2024) review suggests that LLMs are a major driver of recent research. Even so, previous work has not examined how LLM-related publications reshape citation network topology or create high-betweenness 'bridge' papers that link previously separate communities. Addressing this gap is essential for understanding how emerging transformative technologies redistribute influence among established institutions.

2.4 Research Gap and Contribution of This Study

The existing bibliometric and citation-network studies collectively explain global growth patterns, thematic shifts, and author-level impact in AI. However, they provide limited insight into how citations influence community structure and how trend-setting papers are organized within the top research universities over the last decade. Additionally, previous work rarely combines PageRank, degree-based metrics, and community detection in a single institutional network or systematically tracks how LLM-related research contributes to the formation of influential papers across subfields.

This study addresses these gaps by constructing a directed citation network of AI-related publications from the top 10 universities. It applies PageRank and centrality measures to identify influential papers and institutions, and uses community detection to reveal dominant and interdisciplinary subtopics, such as AI in healthcare and education. Focusing on the 2015-2025 period and examining high-betweenness papers, the analysis links technological shifts to measurable changes in network structure and institutional influence connections that prior bibliometric and citation-based work did not capture.

3 Dataset and Methodology

3.1 Data Collection

Our dataset contains AI-related journals from top ten universities from the OpenAlex database. The data collection involves filtering the institution of first author, publication year from 2015-2025, subtopics, and referenced work. It includes the title, authors, and the filtered columns.

All data analyses in this study were conducted in R on a personal computer. We first filtered the raw datasets obtained from OpenAlex, which initially contained over 60,000 publication records and approximately 100,000 citation pairs. The filtering process removed invalid or incomplete entries—specifically, papers lacking essential metadata such as titles, research topics, or institutional affiliations, as well as citation links involving these records.

After data cleaning and validation, our dataset contains:

- **Total papers**: 2,610 papers
- **Connected component**: 1,582 papers with at least one citation connection
- **Citation edges**: 3,757 directed citations
- **Research subtopics**: AI in Healthcare, AI in Law, AI and Decision Support System, Natural Language Processing, and others

The network statistics are presented in Table A1 in the Appendix.

3.2 Network Construction

We formulate a directed citation network where:

- **Nodes**: Each node represents a research paper
- **Edges**: A directed edge from paper A to paper B indicates that A cites B
- **Attributes**: Node attributes include publication year, institution, subtopic, and citation counts

The network shows typical properties of citation networks (Newman, 2001):

- **Scale-free distribution**: Degree distribution follows a power law (Barabási and Albert, 1999)
- **Small-world property**: Short average path length despite high clustering
- **Directed structure**: Citations flow from newer to older papers

The overall citation network by institution is shown in Figure A1 in the Appendix.

Because 1,028 publications in the cleaned dataset cite only works published prior to 2015, the initial "overall network" contains a substantial number of isolated nodes. To enable more effective structural analysis, we partitioned the dataset into two components: nodes_isolated, representing the isolated publications with no citation links within the 2015–2025 scope, and nodes_connected (along with the corresponding edge_connected dataset), representing the remaining publications that participate in at least one citation relationship in the constructed network.

3.2.1 Isolated Data Analysis

For the nodes_isolated dataset, we focused on examining the distribution of these publications across research topics and institutional affiliations. This analysis allowed us to identify the predominant research areas represented among the isolated papers, as well as the institutions that contributed most frequently to this subset of the data.

3.2.2 Non Isolated Data Analysis

The nodes_connected dataset, together with its corresponding edge_connected dataset, constitutes the primary focus of this study. For this subset of the data (1,582 nodes and 3,730 directed edges), we conducted analyses of topic and institutional distributions, as well as structural properties including the average in-degree, the overall in-degree and out-degree distribution, and the component structure of the network. From this examination, we identified the largest connected component, which serves as the foundation for the subsequent stages of analysis. The visualization of network without isolated nodes can be observed in Figure A2 in the Appendix

3.2.3 Largest Connected Component

The largest connected component contains 1,433 nodes and 3,634 directed edges, meaning that the vast majority of the nodes_connected dataset is encompassed within this component. Therefore, we treat the in-depth analysis of this component as representative of the overall structure of the dataset.

3.2.4 Power-Law Degree Distribution

Figure A3 in the Appendix illustrates the scale-free nature of the citation network. The log-log plots show a linear relationship between degree and frequency, characteristic of power-law distributions (Barabási and Albert, 1999). This proves that most papers receive few citations (low in-degree) while a small number of highly influential papers receive many citations, following the "preferential attachment" principle where well-cited papers are more likely to receive additional citations.

3.3 Analysis Methods

We conduct several network analysis techniques:

3.3.1 Centrality Measures

- **PageRank** (Brin and Page, 1998): Measure paper importance based on citation quality
- **Degree Centrality**: Counts direct citations (in-degree) and references (out-degree)
- **Betweenness Centrality**: Identifies bridge papers connecting different research communities
- **Closeness Centrality**: Measures how quickly information spreads from a paper

3.3.2 Community Detection

We use the Louvain algorithm (Blondel et al, 2008) to identify research communities based on citation patterns. This unsupervised method reveals natural groupings of papers that cite each other more frequently than expected by chance.

3.3.3 Temporal Analysis

We analyze how citation patterns evolve over three time periods:

- **Early period (2015-2018)**: Foundation papers and initial AI boom
- **Middle period (2019-2021)**: Consolidation and deep learning maturation
- **Recent period (2022-2025)**: Large language models and new paradigms

4 Results

4.1 RQ1: Most Impactful Papers

We identify the most impactful papers using PageRank, which considers not just the number of citations, but the quality of those citations. The top 10 most impactful papers by PageRank are presented in Table A2 in the Appendix. However, we agree that the pagerank numbers produced is extremely small, so we also consider other metrics such as betweenness and indegree, normalized it, and add all of them. The top 10 papers by combined normalized metrics are shown in Table A3 in the Appendix.

Key Findings:

- The most impactful papers are in the subtopics of healthcare such as AI in interpreting medical dataset, medicine, diagnostic accuracy
- Papers from the 2018-present period dominate the top rankings, indicating their foundational role
- High PageRank papers often serve as methodological foundations cited across different AI subfields

4.2 RQ2: Research Communities and Subtopics

Community detection reveals distinct research clusters within the citation network. The top subtopics by detected community are shown in Table A4 in the Appendix, and the research distribution by subtopic in the connected component is visualized in Figure A4 in the Appendix.

Key Findings:

- **AI in Healthcare** is the most dominant topic in the research communities with highest concentration of papers
- Clear clustering occurs around application domains (healthcare, education) and technical areas (Games, NLP Techniques, Material Science, Law)
- The existence of a few different subtopics in one community shows interdisciplinary collaboration

4.3 RQ3: Institutional Research Output and Impact

We analyze both the number and impact of research from different institutions. Research output by institution is shown in Figure A5, and the institutional comparison of volume versus impact is presented in Figure A6 in the Appendix.

Key Findings:

- **Stanford University** leads in publication quantity within the connected component
- Even though Stanford University is leading in terms of paper counts, Harvard University is leading with highest pagerank. It means that number of papers does not reflect the quality.
- **Research impact** (measured by citation counts and PageRank) does not perfectly correlate with volume
- Some institutions shows exceptional research quality and influence as evidenced by their high citation rates

4.4 RQ4: Foundation Papers with Sustained Relevance

We identify older papers that maintain high closeness centrality and continue to receive citations from recent work. Foundation papers sorted by year and closeness centrality are shown in Table A5 and papers most cited by recent work are presented in Table A6 in the Appendix.

Key Findings:

- Foundation papers from 2015-2017 maintain high relevance through sustained citation by recent work
- High closeness centrality indicates these papers remain central to ongoing research discussions

4.5 RQ5: Emerging Trends and Future Directions

We analyze recent research trends by examining publication patterns and high-betweenness papers from 2020-2025. Research output by time period is shown in Table A7, and recent papers with highest betweenness centrality are presented in Table A8 in the Appendix. The citation network colored by research subtopic is shown in Figure A7 in the Appendix.

Key Findings:

- **Exponential growth** in AI publications from 2022-2024, particularly in Large Language Models
- Recent bridge papers with high betweenness centrality connect previously distinct research areas
- Moving towards the application of LLM and AI for the application of health and medicine research
- Emerging trend toward **interdisciplinary applications**: healthcare AI, educational technology, and AI ethics

5 Discussion

5.1 Principal Findings

Our citation network analysis of AI research from top universities reveals several important patterns:

1. **Scale-free network structure**: The citation network exhibits a power-law degree distribution, where a small number of highly cited papers coexist with many papers receiving few citations (Barabási and Albert, 1999). This confirms the "rich get richer" phenomenon in academic citations (Wang and Barabási, 2021).
2. **Volume-impact disconnect**: While Stanford leads in publication volume, research impact (measured by PageRank and citations) is distributed across institutions, with Harvard University leading with the highest PageRank. This suggests that quality and timing of research matter more than quantity.
3. **Healthcare AI dominance**: AI in Healthcare emerges as the largest and most connected research community, reflecting the field's practical importance and interdisciplinary nature.
4. **Foundation papers maintain relevance**: Papers from 2015-2018 introducing fundamental architectures continue to receive citations from recent work, indicating their sustained importance as AI research evolves.
5. **Paradigm shift toward LLMs**: The 2022-2024 period shows explosive growth in publications, driven primarily by Large Language Models and their applications across domains.
6. **Rise of bridge papers**: Recent high-betweenness papers increasingly serve to connect different research communities, suggesting a trend toward more integrated, interdisciplinary AI research.

5.2 Implications

These findings have several practical implications:

For Researchers: Understanding the network structure helps identify foundational papers, emerging trends, and opportunities for interdisciplinary work. High-betweenness positions indicate opportunities to bridge research gaps.

For Institutions: Publication volume alone does not guarantee research impact. Strategic focus on trend-setting research and interdisciplinary collaboration may be more important than maximizing output.

For Funding Agencies: The dominance of healthcare AI and the rise of bridge papers suggest that supporting interdisciplinary research could yield high-impact outcomes.

For the AI Field: The sustained relevance of foundation papers alongside rapid growth in new paradigms (LLMs) indicates that AI research builds cumulatively while also experiencing periodic paradigm shifts.

5.3 Future Work

Several directions for future research emerge from this study:

1. **Temporal dynamics**: Longitudinal analysis tracking how individual papers' centrality measures evolve over time (Wang and Barabási, 2021)
2. **Author networks**: Analyzing collaboration networks alongside citation networks to understand how research influence spreads through both ideas and people (Newman, 2001)
3. **Content analysis**: Combining network analysis with natural language processing to analyze the semantic content of highly central papers (Chen, 2006)
4. **Predictive modeling**: Using early citation patterns to predict which papers will become foundational
5. **Global comparison**: Expanding the analysis to include institutions from more countries and regions

6 Conclusion

This study analyzed the citation patterns of AI-related publications from top-tier research institutions over the past decade to understand the structural evolution of the field. By constructing and analyzing a directed citation network, we aimed to identify influential institutions, dominant research subtopics, and the emergence of trend-setting papers.

The analysis revealed a scale-free network structure with small-world properties, where only 60.6% of papers formed a connected component. Key findings indicate a distinction between quantity and quality: while Stanford University led in publication volume (119 papers), Harvard University demonstrated the highest citation impact. Furthermore, community detection identified "AI in Healthcare and Education" as the most prominent research cluster. A significant exponential growth in research output was observed from 2022 to 2023, driven largely by the advent of Large Language Models (LLMs). Specifically, recent papers with high betweenness centrality, such as "Large language models in medicine," were identified as critical bridges connecting disparate research communities.

The implications of these findings suggest a pivotal shift in the AI research landscape toward interdisciplinary integration. The prominence of high-betweenness papers indicates that future institutional influence will likely depend on producing "bridge" research that connects diverse domains—such as medicine and computer science—rather than merely increasing publication volume. The study confirms that LLMs are not just a volume driver but a foundational technology reshaping research directions.

There are limitations to this study. The exclusion of cited papers published prior to 2015 resulted in a disintegrated network with many isolated nodes, limiting the scope of connectivity analysis. Additionally, the 2025 data remains incomplete, causing an artificial decline in the most recent period. Future research should expand the dataset to include a broader historical range to capture long-term citation lineages. Moreover, future work will track the long-term trajectory of the identified trend-setting papers to validate whether these bridge works successfully establish enduring, independent research subfields.

Appendix A Tables, Graphs, and Figures

A.1 Network Statistics and Visualizations

Table A1: Network Basic Statistics

Metric	Value
Total Nodes	1582.0000000
Total Edges	3757.0000000
Average Degree	4.7496839
Average In-Degree	2.3748420
Average Out-Degree	2.3748420
Network Density	0.0015021
Network Diameter	10.0000000
Average Path Length	3.1484370
Number of Weakly Connected Components	58.0000000
Number of Strongly Connected Components	1569.0000000

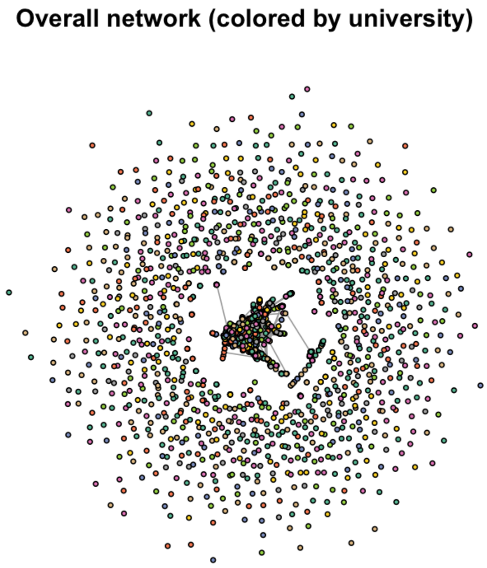

Fig. A1 Overall Citation Network by Institution

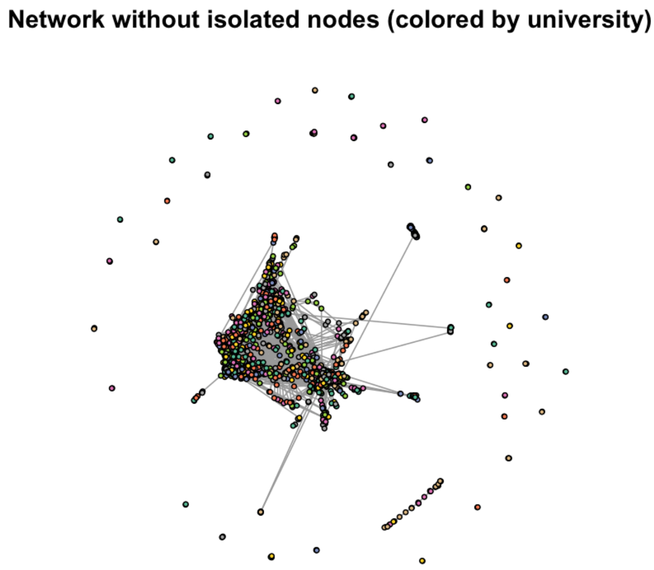

Fig. A2 Overall Citation Network (Non-Isolated)

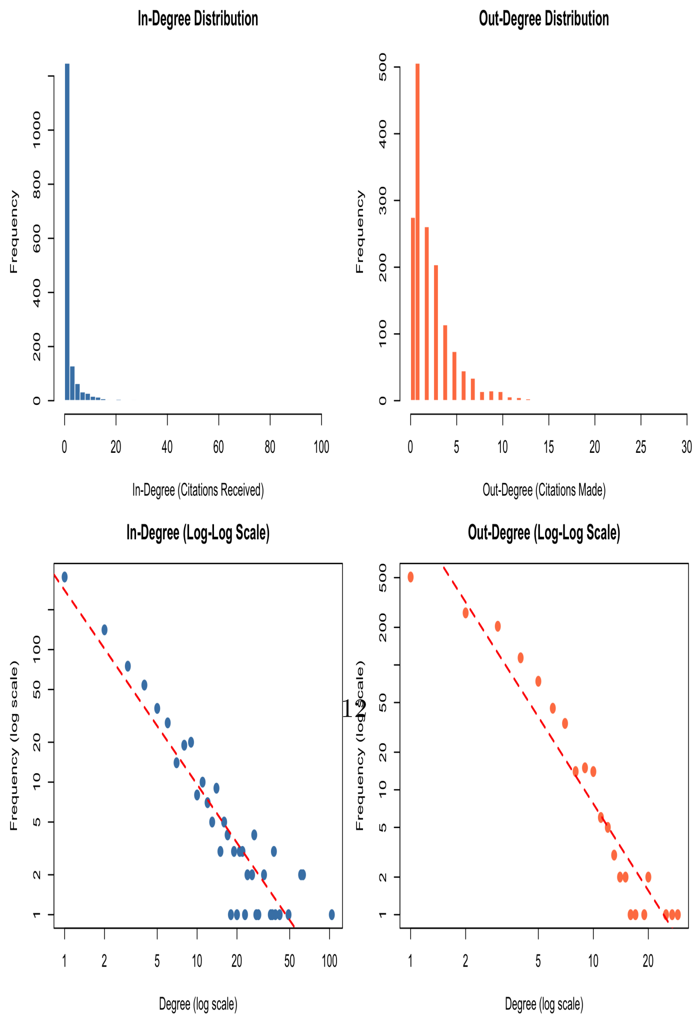

Fig. A3 Degree Distribution Showing Power-Law Property. The log-log plots (bottom panels) show linear trends, confirming power-law distribution characteristic of scale-free networks.

A.2 RQ1: Most Impactful Papers

Table A2: Top 10 Most Impactful Papers by PageRank

Title	First Author	Year	PageRank
Artificial intelligence in healthcare	Kun-Hsing Yu	2018	0.0370
Developing specific reporting guidelines for diagnostic accuracy studies assessing AI interventions: The STARD-AI Steering Group	Viknesh Sounderajah	2020	0.0297
Framing the challenges of artificial intelligence in medicine	Kun-Hsing Yu	2018	0.0181
Artificial intelligence (AI) systems for interpreting complex medical datasets	Rb Altman	2017	0.0160
Potential Liability for Physicians Using Artificial Intelligence	W. Nicholson Price	2019	0.0144
The "inconvenient truth" about AI in healthcare	Trishan Panch	2019	0.0127
Large language models in medicine	Arun James Thirunavukarasu	2023	0.0115
AI in health and medicine	Pranav Rajpurkar	2022	0.0105
AI-Assisted Decision-making in Healthcare	Tamra Lysaght	2019	0.0101
An Ethics Framework for Big Data in Health and Research	Vicki Xafis	2019	0.0095

Table A3: Top 10 Papers by Combined Normalized Metrics

Title	Year	PageRank	In-Degree	Betweenness	Combined
Large language models in medicine	2023	0.306	1.000	0.812	2.117
Artificial intelligence in healthcare	2018	1.000	0.587	0.250	1.837
AI in health and medicine	2022	0.278	0.587	0.672	1.536
The shaky foundations of large language models and foundation models for electronic health records	2023	0.169	0.308	1.000	1.476
Foundation models for generalist medical artificial intelligence	2023	0.222	0.606	0.519	1.346
Multimodal biomedical AI	2022	0.173	0.250	0.749	1.172
Developing specific reporting guidelines for diagnostic accuracy studies assessing AI interventions: The STARD-AI Steering Group	2020	0.800	0.308	0.000	1.108
Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: the CONSORT-AI extension	2020	0.250	0.606	0.018	0.873
Potential Liability for Physicians Using Artificial Intelligence	2019	0.386	0.365	0.000	0.751

Creation and Adoption of Large Language Models in Medicine	2023	0.123	0.279	0.335	0.737

A.3 RQ2: Research Communities and Subtopics

Table A4: Top Subtopics by Detected Community

Community	Subtopic	Papers
1	Artificial Intelligence in Healthcare and Education	209
1	Machine Learning in Healthcare	34
1	Artificial Intelligence in Healthcare	2
2	Artificial Intelligence in Healthcare and Education	70
2	Machine Learning in Healthcare	9
2	Artificial Intelligence in Healthcare	3
3	Machine Learning in Materials Science	46
4	Artificial Intelligence in Healthcare and Education	145
4	Machine Learning in Healthcare	9
4	Artificial Intelligence in Healthcare	5
5	Artificial Intelligence in Healthcare and Education	138
5	Machine Learning in Healthcare	16
5	Machine Learning and Data Classification	1
6	Machine Learning in Healthcare	2
6	Natural Language Processing Techniques	1
7	Machine Learning in Healthcare	35
7	Artificial Intelligence in Healthcare and Education	5
7	Artificial Intelligence in Healthcare	1
8	Artificial Intelligence in Healthcare and Education	111
8	Machine Learning in Healthcare	11

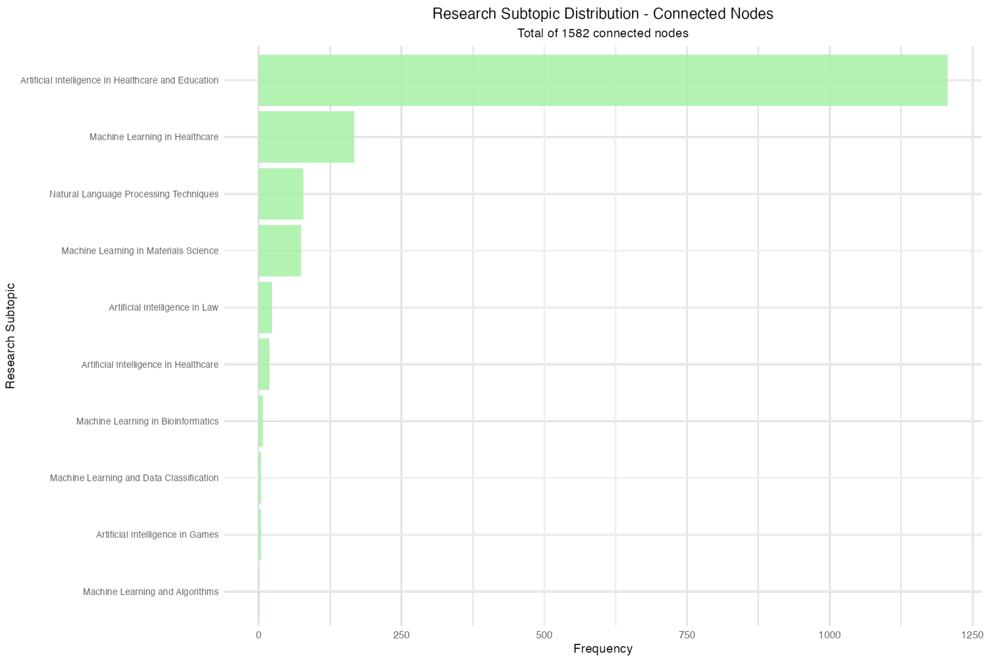

Fig. A4 Research Distribution by Subtopic in Connected Component

A.4 RQ3: Institutional Research Output and Impact

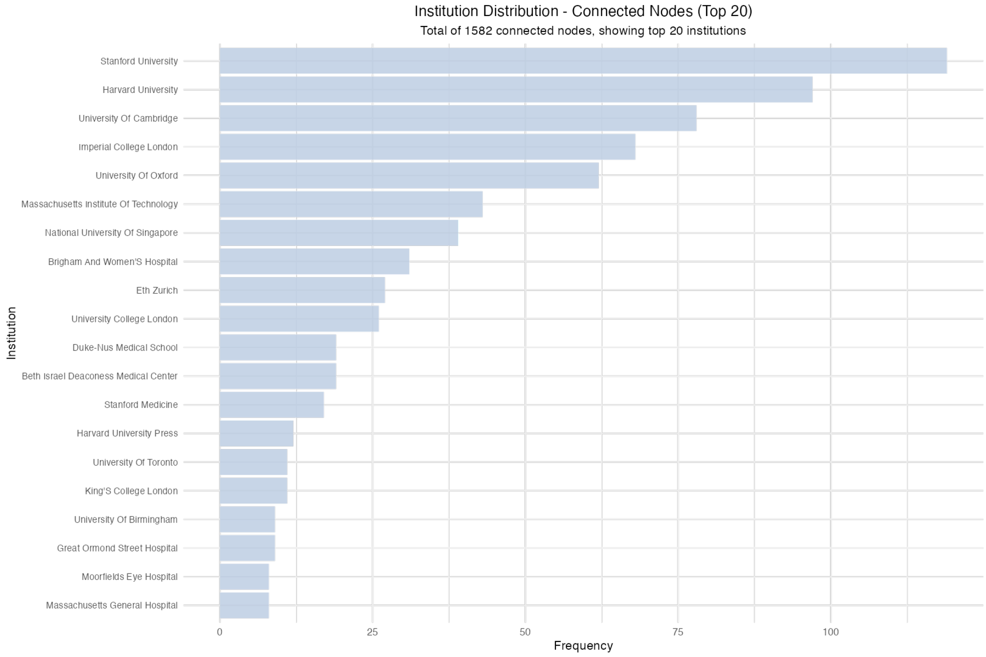

Fig. A5 Research Output by Institution

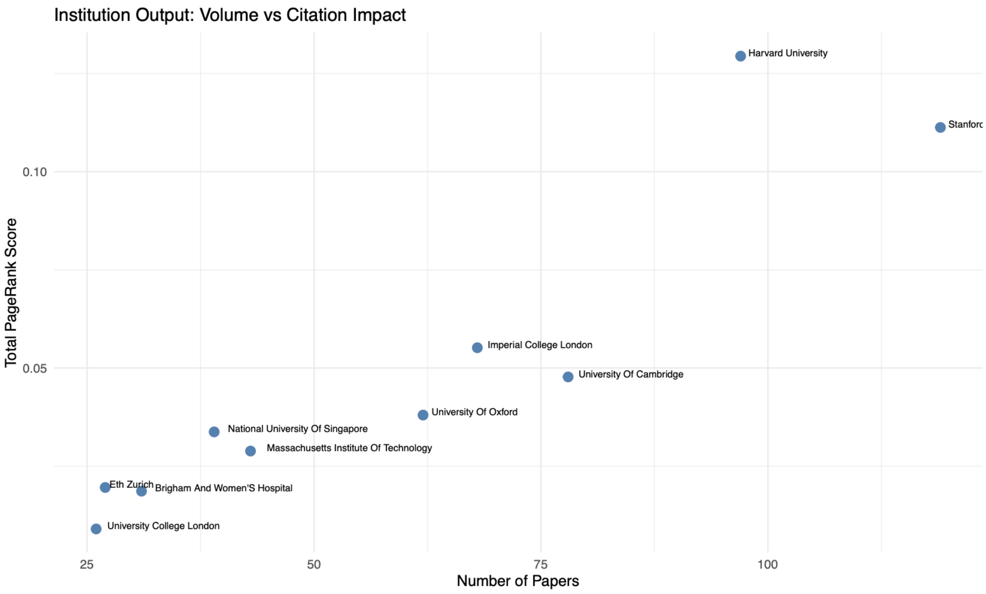

Fig. A6 Institutional Comparison: Volume vs Impact

A.5 RQ4: Foundation Papers with Sustained Relevance

Table A5: Foundation Papers Sorted by Year and Closeness Centrality

Title	Year	Closeness	In-Degree
Exploring big educational learner corpora for SLA research	2015	1.0000	1
Incremental Dependency Parsing and Disfluency Detection in Spoken Learner English	2015	0.3333	1
How to Train good Word Embeddings for Biomedical NLP	2016	0.3333	1
AI as evaluator: Search driven playtesting of modern board games	2017	1.0000	0
Findings of the VarDial Evaluation Campaign 2017	2017	0.2000	3
A Report on the 2017 Native Language Identification Shared Task	2017	0.1667	1
Investigating the cross-lingual translatability of VerbNet-style classification	2017	0.0044	1
What This Computer Needs Is a Physician	2017	0.0002	13
Artificial intelligence (AI) systems for interpreting complex medical datasets	2017	0.0002	1

Segmenting and POS tagging Classical Tibetan using a memory-based tagger	2018	1.0000	1

Table A6: Papers Most Cited by Recent Work (2020-2025)

Title	Year	Total Citations	Recent Citations
What This Computer Needs Is a Physician	2017	13	4
How to Train good Word Embeddings for Biomedical NLP	2016	1	1
Investigating the cross-lingual translatability of VerbNet-style classification	2017	1	1
Exploring big educational learner corpora for SLA research	2015	1	0
Incremental Dependency Parsing and Disfluency Detection in Spoken Learner English	2015	1	0
AI as evaluator: Search driven playtesting of modern board games	2017	0	0
Findings of the VarDial Evaluation Campaign 2017	2017	3	0
A Report on the 2017 Native Language Identification Shared Task	2017	1	0
Artificial intelligence (AI) systems for interpreting complex medical datasets	2017	1	0
Segmenting and POS tagging Classical Tibetan using a memory-based tagger	2018	1	0

A.6 RQ5: Emerging Trends and Future Directions

Table A7: Research Output by Time Period

Period	Number of Papers
Early (2015-2018)	93
Middle (2019-2021)	509
Recent (2022-2024)	1436

Table A8: Recent Papers with Highest Betweenness Centrality (Bridge Papers)

Title	Year	Betweenness	In-Degree
The shaky foundations of large language models and foundation models for electronic health records	2023	5287.65	32

Large language models in medicine	2023	4291.82	104
Multimodal biomedical AI	2022	3960.81	26
AI in health and medicine	2022	3551.09	61
Foundation models for generalist medical artificial intelligence	2023	2744.23	63
QUEST-AI: A System for Question Generation, Verification, and Refinement using AI for USMLE-Style Exams	2023	2034.00	2
Creation and Adoption of Large Language Models in Medicine	2023	1768.98	29
Ensuring that biomedical AI benefits diverse populations	2021	1747.33	2
A Systematic Review of Testing and Evaluation of Healthcare Applications of Large Language Models (LLMs)	2024	1740.67	3
AI recognition of patient race in medical imaging: a modelling study	2022	1354.80	28

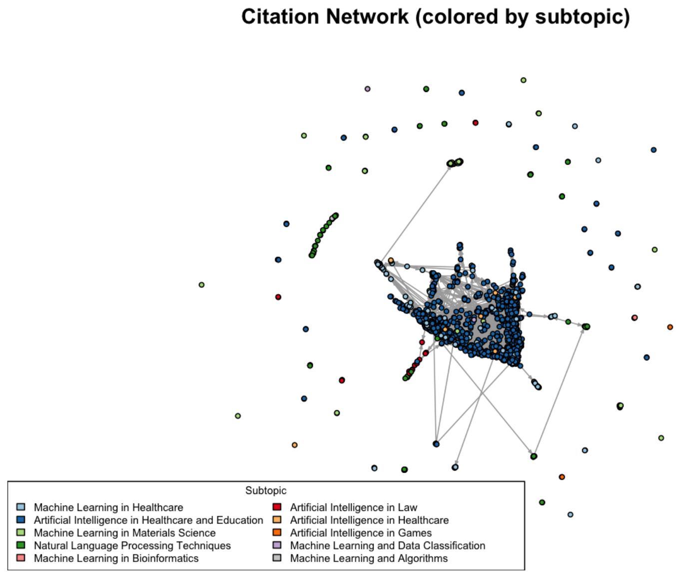

Fig. A7 Citation Network Colored by Research Subtopic

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