

HELLO SOCIAL: INTELLECTUAL TRANSITIONS IN ARTIFICIAL INTELLIGENCE, GENERATIVE AI, AND SOCIETY - A BIBLIOMETRIC ANALYSIS (1972–2026*)

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ABSTRACT

*Artificial Intelligence (AI) has evolved beyond a predominantly technical field into an increasingly interdisciplinary domain with significant societal implications. This study presents a scientometric mapping of intellectual transitions in Artificial Intelligence, Generative AI and society over the period 1972–2026. Using about 29,000 bibliographic records from **Scopus and OpenAlex**, the study identifies AI publications demonstrating explicit societal relevance through the terms society, social, societal, and societies. The analysis combines quantitative text mining, text cleaning, normalisation, TF–IDF, topic modelling, network analysis and temporal trend analysis to examine the changing intellectual structure of AI–society scholarship. Titles, abstracts and keywords/concepts are used to identify dominant themes, conceptual relationships and patterns of societal engagement. Results indicate that societal AI research constitutes a relatively small component of the overall AI literature but has expanded substantially, particularly since the late 2010s and during the 2020s. Social concerns dominate the thematic structure, accompanied by ethics, public issues, policy, governance, trust, sustainability and inequality. The conceptual and disciplinary analyses reveal strong linkages among Computer Science, Artificial Intelligence, Psychology, Political Science, Sociology, Law, Engineering and Social Sciences. Generative AI emerges as an important recent inflection point in this intellectual transition. The study provides evidence-based insights into the evolving AI–society interface and its relevance to responsible AI, public policy and societal well-being.*

KEYWORDS: *Artificial Intelligence; Ai–Society; Scientometric Analysis; Generative Ai; Intellectual Transitions.*

1. INTRODUCTION

Artificial Intelligence (AI) has evolved from a predominantly technical and computational field into a broad interdisciplinary domain with increasingly significant societal dimensions. Contemporary AI research encompasses questions extending beyond algorithms, computation and technological innovation to include social systems, governance, ethics, public policy, sustainability, human well-being and applications across diverse sectors. However, the societal dimensions embedded within the expanding AI knowledge domain remain comparatively under-examined when viewed through large-scale bibliometric evidence. The present study addresses

this dimension through a scientometric mapping of AI–society research published between 1972 and 2026* (till January’2026).

The study draws upon two major scholarly databases, Scopus and Open Alex, to identify AI-related publications with explicit societal relevance. Publications containing terms such as society, social, societal, and societies are examined through quantitative text-mining and network-based approaches. Titles, abstracts and keywords/concepts are processed using cleaning, normalisation and Term Frequency–Inverse Document Frequency (TF–IDF) techniques, followed by topic modelling, network analysis and temporal trend analysis. The resulting intellectual-space maps, thematic structures and temporal patterns provide an empirical view of how societal engagement has developed within AI scholarship. By tracing intellectual transitions, conceptual relationships and emerging thematic structures, the study contributes evidence for understanding the changing relationship between AI and society and provides a basis for discussions surrounding responsible AI, public policy and societal well-being.

2. Background

Bibliometric analysis is the quantitative study of scholarly publications using statistical and mathematical techniques to examine patterns in scientific literature (Pritchard, 1969). It analyses authors, citations, journals, keywords, affiliations and publication trends to identify research productivity, influential contributions, collaboration structures and knowledge development (Zupic & Čater, 2015; Donthu et al., 2021). Contemporary bibliometric research increasingly combines science mapping, network analysis and thematic analysis to identify intellectual and conceptual structures (Aria et al., 2024; Tomczyk et al., 2024). Effective bibliometric studies also require systematic data cleaning, integration and tool selection (Lim et al., 2024; Öztürk et al., 2024). Such methods can reveal knowledge flows and the evolution of scientific communities (Aman & Gläser, 2024).

AI broadly refers to machine-based systems capable of generating outputs such as predictions, recommendations or decisions from given inputs, with varying levels of autonomy and adaptiveness (OECD, 2024). The concept originated in early work on the possibility of computationally simulating intelligent behaviour (McCarthy et al., 1955). Contemporary AI encompasses machine learning, deep learning, natural language processing, computer vision, robotics and generative AI, with applications extending across scientific, economic and social domains (Russell & Norvig, 2021; Triguero et al., 2024). Recent scholarship also highlights continuing conceptual debate concerning what constitutes intelligence in artificial systems (Ishii et al., 2024). Alongside technological opportunities, AI introduces questions concerning transparency, accountability, safety, human values and societal impacts, necessitating approaches to responsible development and governance (UNESCO, 2021; NIST, 2023).

OpenAlex is a fully open scholarly knowledge graph that provides interconnected information on research works, authors, sources, institutions, concepts and citations, and was developed as a successor to the Microsoft Academic Graph (Priem et al., 2022). Its freely accessible API and downloadable data infrastructure support large-scale, reproducible bibliometric and scientometric research (Harder, 2024; OpenAlex, 2026). Studies have demonstrated its usefulness for bibliometric mapping at author, institutional and national levels (Haunschild & Bornmann, 2024) and have examined its coverage relative to established databases such as Scopus and Web of Science (Culbert et al., 2024; Alperin et al., 2024). Comparative assessments also indicate strong coverage of research entities (Delgado-Quirós & Ortega, 2025), while recent

review work highlights both its growing importance and continuing metadata limitations (Forchino& Torres-Salinas, 2026).

3. Aim and Objectives

Aim

To map the intellectual transitions and societal engagement of Artificial Intelligence research from 1972 to 2026, using large-scale scientometric, text-mining and network-based analysis of Scopus and OpenAlex publications.

Objectives

- To identify AI publications demonstrating explicit societal relevance through the occurrence of terms including society, social, societal and societies.
- To examine the temporal development of AI–society scholarship and identify periods of changing research intensity.
- To analyse titles, abstracts and keywords/concepts using text cleaning, normalisation and TF–IDF procedures.
- To identify major thematic dimensions and conceptual structures through topic modelling.
- To investigate relationships among concepts and societal terms through network and co-word analysis.
- To map the evolving intellectual space of AI–society research and examine transitions between technical and interdisciplinary research domains.
- To identify patterns of societal engagement in AI scholarship and generate evidence relevant to responsible AI, public policy and societal well-being.

4. Data Sources and Methodology

The study adopts a scientometric methodology to investigate the intellectual development of AI–society research during 1972–2026. Two bibliographic databases, Scopus and OpenAlex, constitute the principal data sources. The presentation reports approximately 25,000 AI-related documents in Scopus and 3,074 AI documents in OpenAlex, from which publications containing explicit societal references were identified. The societal filtering incorporated the terms society, social, societal and societies. The presentation reports approximately 1,250 societal AI publications in the broad results summary and approximately 184 OpenAlex records with direct society/societies mention; the Scopus panel reports around 1,300 such records.

The methodological workflow consists of four principal stages. First, AI-related publications were filtered for societal relevance. Second, textual information from titles, abstracts and keywords/concepts was processed through cleaning, normalisation and TF–IDF procedures. TF–IDF and is a statistical text-mining technique used to assess the importance of a term within a document relative to its occurrence across a collection of documents. TF measures how frequently a term occurs within an individual document, whereas IDF assigns lower weights to terms occurring across many documents and relatively higher weights to terms that are more distinctive. The combined weighting scheme helps identify terms that are particularly representative of specific documents or thematic groups (Salton & Buckley, 1988). TF–IDF

weights can also be interpreted in relation to the relevance and discriminative value of terms within information retrieval and text analysis (Wu et al., 2008). In bibliometric research, TF-IDF is therefore useful for identifying salient keywords, concepts and thematic vocabulary from titles, abstracts and keywords.

Third, analytical techniques including topic modelling, network analysis and temporal trend analysis were applied to identify thematic structures, conceptual associations and changes through time. Topic modelling and co-word/network approaches were used to characterise the intellectual space and thematic transitions.

Finally, the outputs were interpreted through intellectual-space maps, thematic transitions and societal engagement patterns. The presentation combines temporal graphs, heatmaps, keyword/concept frequency plots, co-word networks, conceptual-flow diagrams, cluster distributions and bibliographic profiles as can be seen in Figure 1.

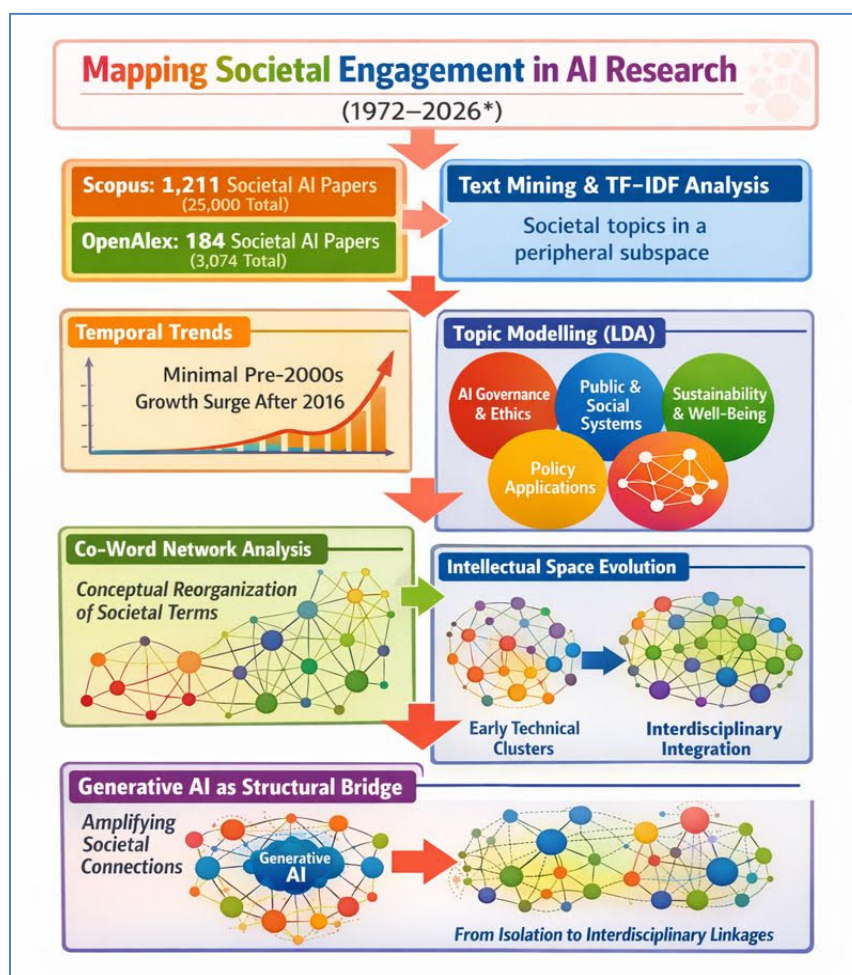


Figure 1. Mapping Societal Engagement in AI Research (1972–2026)

Source- Author, 2026

This framework provides the overall conceptual and methodological architecture of the study. It positions societal engagement within the much larger AI publication universe and connects data filtering with text mining, TF-IDF analysis, topic modelling, co-word network analysis and

intellectual-space evolution. The framework also identifies major thematic areas—AI governance and ethics, public and social systems, sustainability and well-being, and policy applications. A further component presents Generative AI as a structural bridge capable of amplifying societal connections and interdisciplinary linkages. Thus, the figure establishes a progression from bibliographic identification and quantitative text analysis to interpretation of intellectual transitions, showing how technical AI research can be examined through a broader societal lens.

5. Results

Following outputs were obtained:

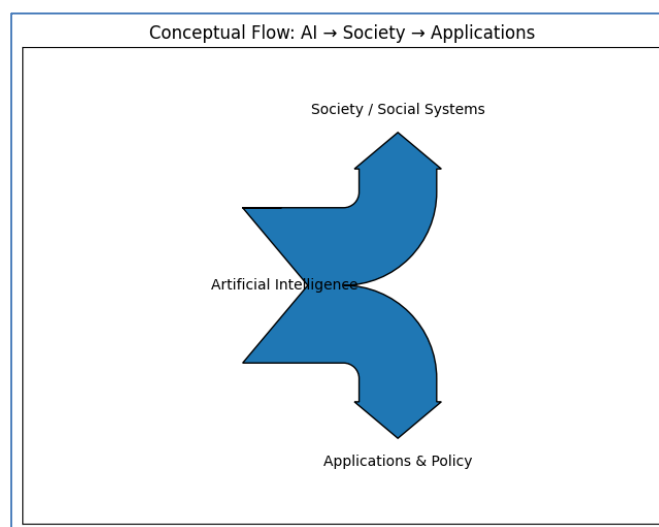


Figure 2. Conceptual Flow: AI → Society → Applications

Source- Author, 2026

The conceptual-flow diagram places Artificial Intelligence at the centre of a relationship linking Society/Social Systems with Applications and Policy (Figure 2). The visual structure represents AI as an intermediary between societal contexts and practical or policy-oriented outcomes. This is consistent with the study framework, where AI is examined not simply as a technological domain but as a knowledge field interacting with social structures. The upper component, Society/Social Systems, represents the societal context in which AI develops and operates, while Applications & Policy represents downstream areas of use and governance. The figure therefore provides a compact conceptual representation of the movement from technological knowledge toward societal application and institutional engagement.

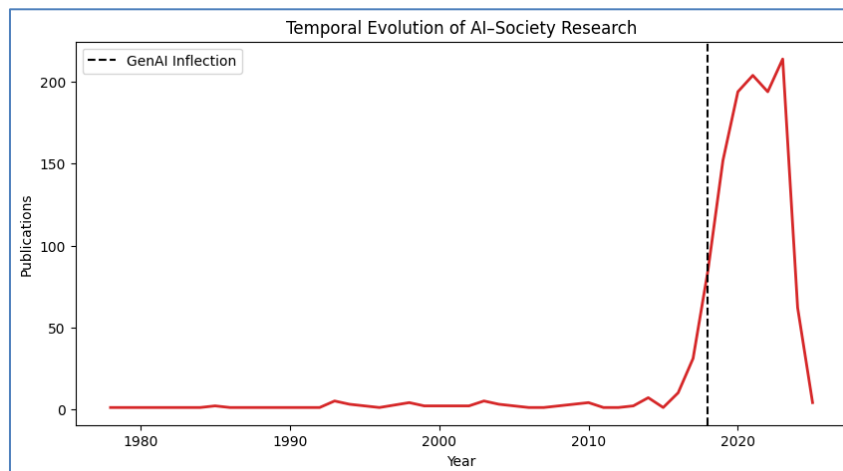


Figure 3. Temporal Evolution of AI-Society Research — OpenAlex

Source- Author, 2026

In Figure 3., the temporal series shows relatively low AI-society publication activity across the earlier decades, followed by a sharp increase after the mid-2010s. Output accelerates strongly around the late 2010s and reaches more than 200 publications in the early 2020s. The vertical marker identifies a “GenAI inflection”, highlighting the period associated with the recent transformation of AI research. The final observations show a sharp fall in the last displayed year, which should be interpreted cautiously because 2026 represents an ongoing publication period. Overall, the figure provides temporal evidence that societal engagement in AI has become substantially more visible during the contemporary phase of AI development.

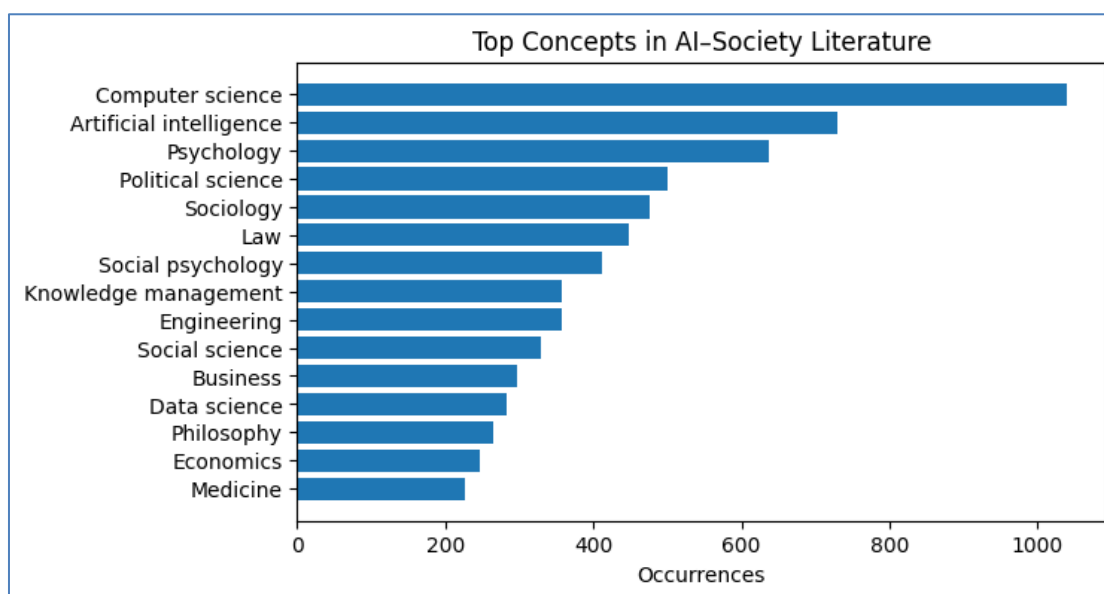


Figure 4. Top Concepts in AI-Society Literature — OpenAlex

Source- Author, 2026

The concept-frequency distribution is headed by Computer Science and Artificial Intelligence, demonstrating that the societal literature retains a strong computational foundation (Figure 4.).

Psychology is the next prominent domain, followed by Political Science, Sociology and Law. Social Psychology and Knowledge Management form additional substantial components, with Engineering, Social Science, Business, Data Science, Philosophy, Economics and Medicine also represented. The distribution demonstrates considerable disciplinary breadth. While Computer Science and AI remain the core conceptual categories, the strong presence of psychology, political science, sociology and law indicates increasing engagement with human behaviour, institutions, regulation and social consequences. The figure therefore illustrates the interdisciplinary expansion of AI–society scholarship.

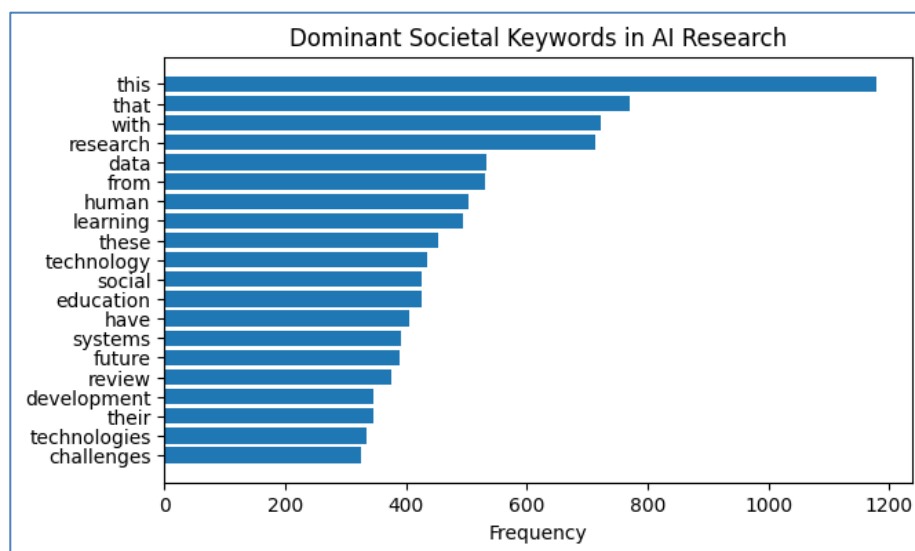


Figure 5. Dominant Societal Keywords in AI Research

Source- Author, 2026

The keyword-frequency graph in Figure 5. shows a broad vocabulary surrounding societal engagement in AI research. High-frequency terms include “research”, “data”, “human”, “learning”, “technology”, “social”, “education”, “systems”, “future”, “development”, “technologies” and “challenges”, alongside common textual terms. The substantive vocabulary is significant because it connects technical AI processes with human and institutional settings. In particular, the appearance of human, social, education and challenges indicates that the literature addresses AI beyond computational performance alone. The frequency distribution therefore reflects a research environment in which technical terminology coexists with human-centred and societal concerns, supporting the study’s interpretation of an expanding AI–society knowledge domain.

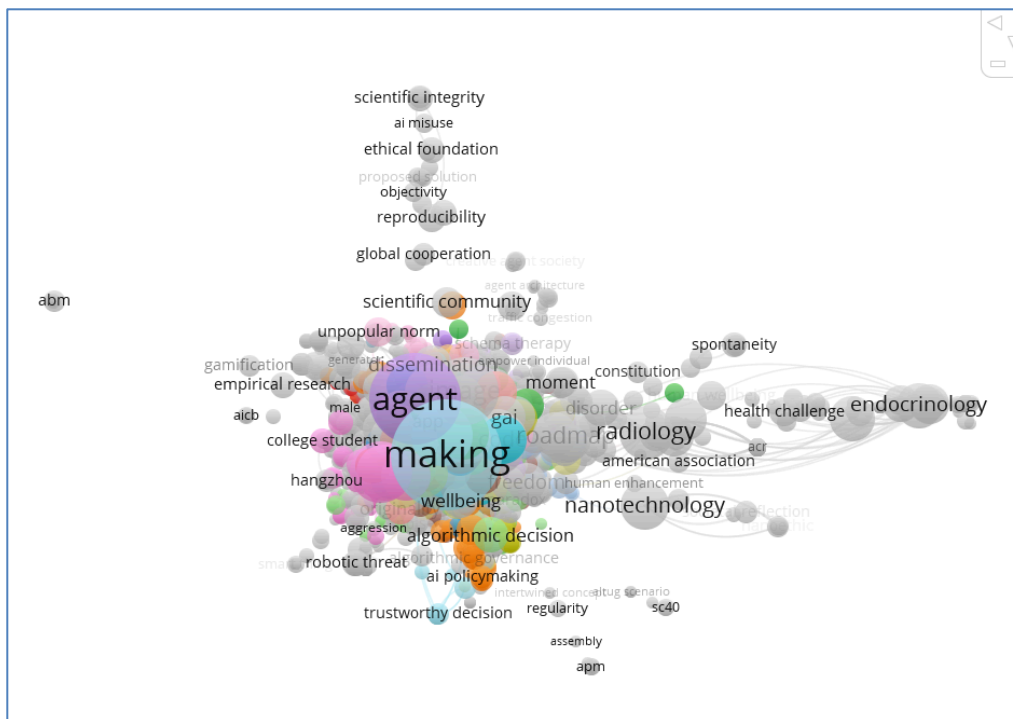


Figure 6. Conceptual Network of AI-Society Research — OpenAlex

Source- Author, 2026

The network visualisation in Figure 6. presents a dense web of concepts associated with AI and society. The central region contains highly interconnected terms, while peripheral concepts extend outward through multiple links. The structure indicates that technical AI concepts are connected with social, human-centred and application-oriented terminology rather than forming isolated research compartments. The density of the network is particularly important because it visually demonstrates conceptual integration across different areas of scholarship. The network also supports the intellectual-space interpretation adopted in the study: AI-society research contains a shared conceptual core but simultaneously incorporates specialised topics. The figure therefore provides network-level evidence for the interdisciplinary character of contemporary AI-society scholarship.

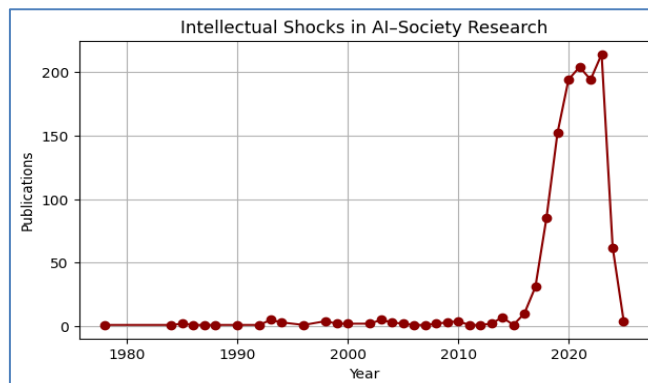


Figure 7. Intellectual Shocks in AI-Society Research

Source- Author, 2026

The time-series representation of intellectual shocks shows a long period of comparatively low publication activity followed by a pronounced acceleration during the late 2010s and early 2020s. In Figure 7., the curve rises rapidly and reaches its strongest values in the most recent part of the series. This pattern indicates that the AI-society knowledge domain experienced a relatively recent structural expansion rather than a uniformly gradual increase across the entire study period. The concentration of activity in the contemporary period is consistent with the wider temporal results in the presentation. The figure therefore identifies a clear phase of intensified intellectual production and provides temporal context for subsequent thematic and network analyses.

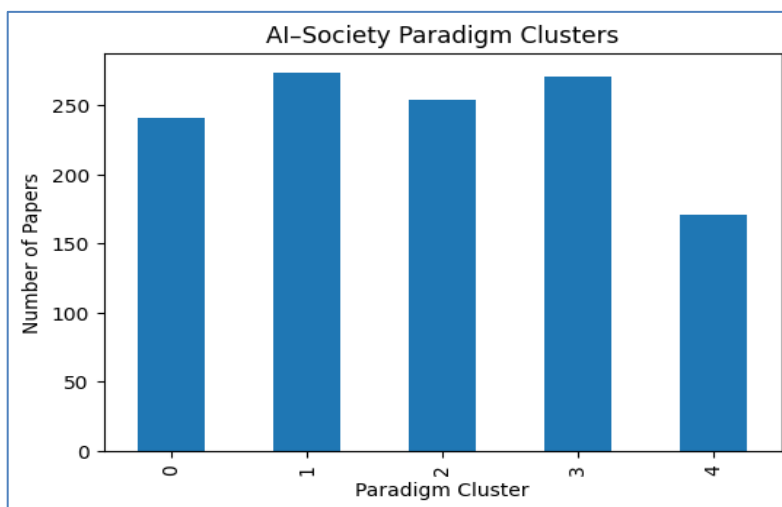


Figure 8. AI-Society Paradigm Clusters

Source- Author, 2026

The cluster chart in Figure 8. identifies five paradigmatic groupings, numbered 0 to 4, with different levels of representation. Clusters 1 and 3 are the largest, each approaching or exceeding approximately 270 papers, while Cluster 2 contains slightly more than 250. Cluster 0 contains around 240 papers and Cluster 4 is smaller, at roughly 170 papers. The distribution indicates that AI-society scholarship is not concentrated within a single intellectual paradigm. Instead, several substantial clusters coexist, suggesting differentiated research configurations within the broader

field. The comparatively smaller fifth cluster may represent a more specialised component. Overall, the figure demonstrates internal diversification of the AI–society research landscape.

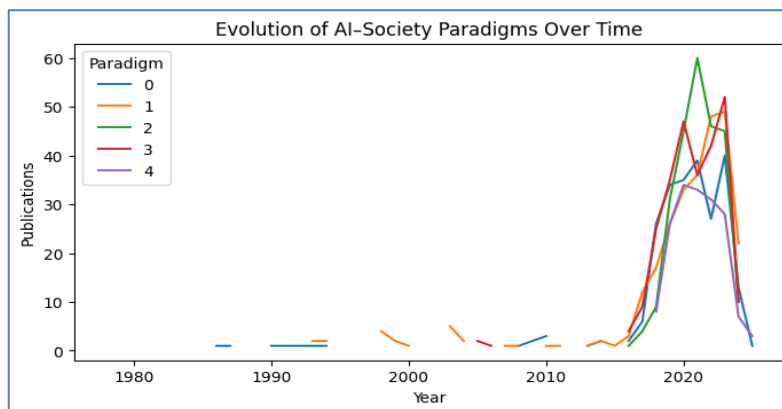


Figure 9. Evolution of AI–Society Paradigms Over Time

Source- Author, 2026

The temporal cluster plot in Figure 9. shows that the identified paradigms have little representation during much of the earlier period but become increasingly visible during the 2010s and rise sharply in the early 2020s. The different coloured trajectories indicate that the paradigms do not develop identically: some reach stronger peaks at particular years, while others show smaller or later increases. The convergence of several trajectories during the recent period indicates simultaneous expansion of multiple research configurations. This pattern supports the interpretation that the growth of AI–society scholarship has involved diversification rather than the emergence of a single dominant theme. The figure therefore links cluster structure with its temporal evolution.

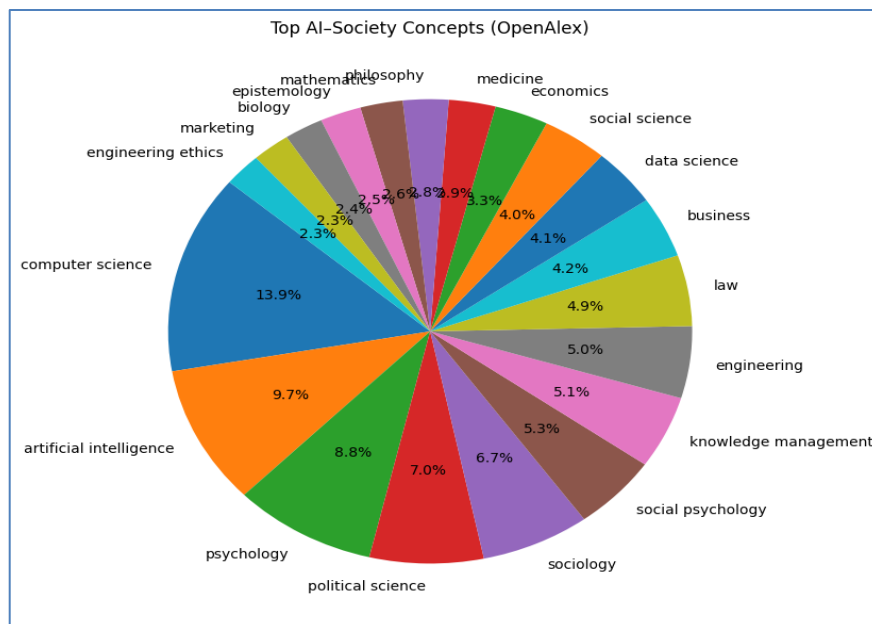


Figure 10. Top AI–Society Concepts — OpenAlex

Source- Author, 2026

The pie chart in Figure 10. provides a proportional view of the principal concepts represented in the OpenAlex AI–society literature. Computer Science and Artificial Intelligence occupy the largest sectors, confirming their foundational position. Psychology, Political Science and Sociology form prominent social-science components, while Law, Social Psychology, Knowledge Management, Engineering, Social Science and Business contribute additional shares. Data Science, Philosophy, Economics and Medicine are also represented. The visual balance between technical and social-science domains demonstrates that societal AI research remains anchored in computation while simultaneously drawing on multiple fields concerned with people, institutions and social systems. The chart therefore complements the frequency bar graph by showing the relative distribution of disciplinary concepts.

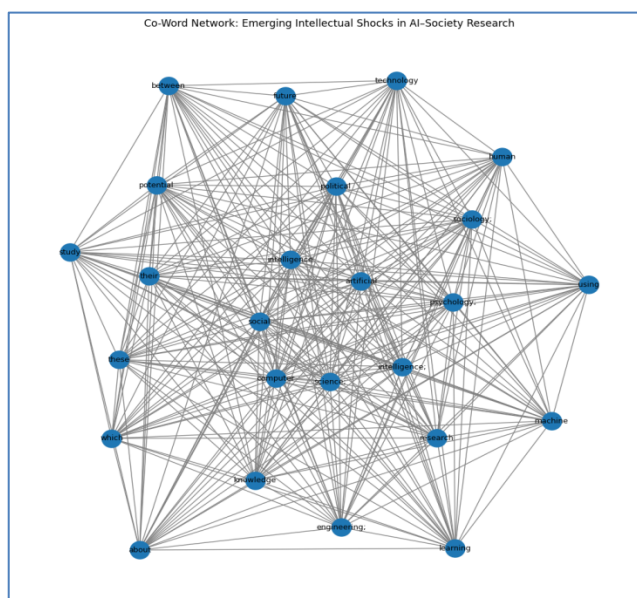


Figure 11. AI–Society Conceptual Network

Source- Author, 2026

The co-occurrence network shows numerous interconnected nodes distributed across a compact intellectual structure. The network contains central concepts with several links to surrounding nodes, indicating that the most visible ideas are repeatedly associated across publications. The interconnected structure suggests that AI–society research combines technological concepts with social, behavioural and application-related concerns as shown in Figure 11. Rather than producing isolated thematic islands, the network shows considerable overlap among concepts. This supports the interpretation that the field is becoming increasingly interdisciplinary. The network also provides a visual basis for identifying central and peripheral concepts, with central nodes representing ideas that participate in multiple conceptual relationships across the literature.

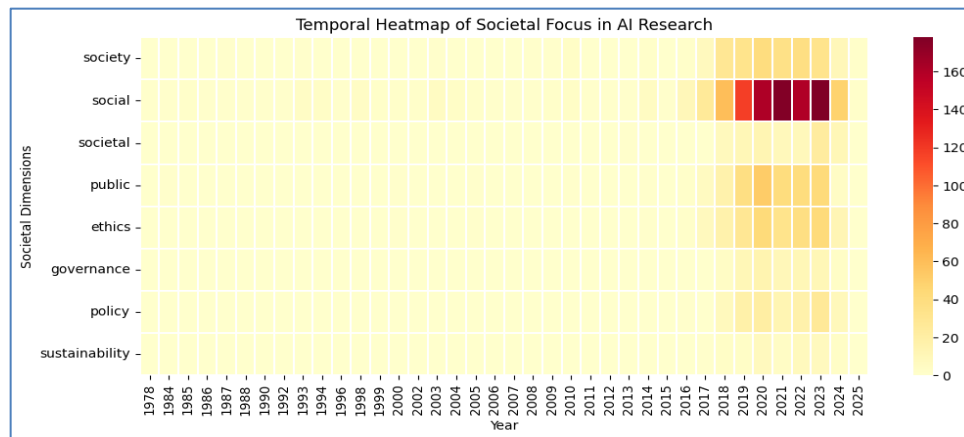


Figure 12. Temporal Heatmap of Societal Focus in AI Research — OpenAlex

Source- Author, 2026

The heatmap (Figure 12.) shows weak societal-term intensity across much of the earlier study period, followed by a clear increase toward the right-hand side of the timeline. The strongest concentration occurs during the recent years, particularly for the social dimension. Society, societal, public, ethics and governance also become increasingly visible, although at different intensities. Sustainability remains comparatively weaker across the displayed period. The figure is valuable because it combines temporal and thematic information in a single representation: it shows not only that societal research increased, but also that different societal dimensions emerged with varying strengths. The recent concentration supports the broader finding of intensified societal engagement in AI scholarship.

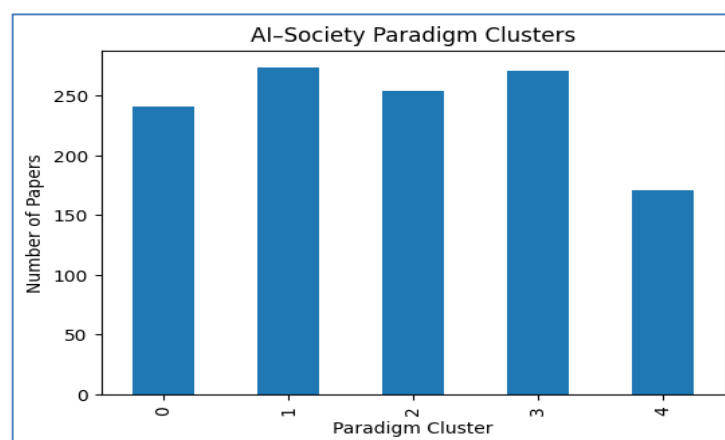


Figure 13. AI-Society Paradigm Clusters — OpenAlex

Source- Author, 2026

The second cluster representation confirms the five-cluster structure identified in the analysis. In Figure 13., Clusters 1 and 3 are again the largest groups, followed by Cluster 2 and Cluster 0, while Cluster 4 is distinctly smaller. The similarity of the distribution across the two visual representations strengthens the consistency of the clustering result. The five-group configuration indicates that AI-society research consists of several substantial intellectual configurations rather than one homogeneous body of literature. Differences in cluster size show that some paradigms

have accumulated more publications than others. However, all five groups contribute to the overall intellectual structure and should be viewed as components of a diversified research landscape.

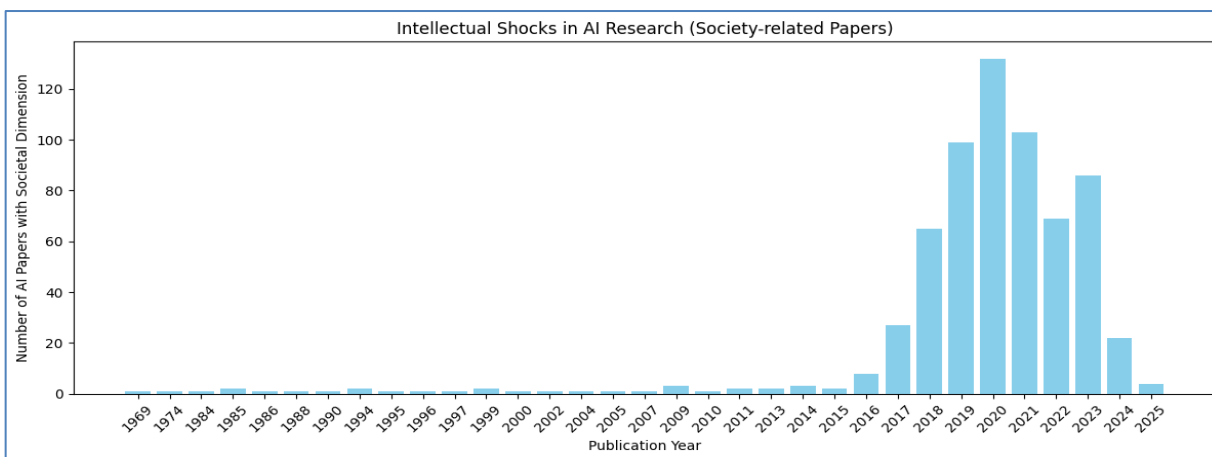


Figure 14. Intellectual Shocks in AI–Society Research — Temporal Distribution

Source- Author, 2026

This publication-frequency in Figure 14. provides another temporal representation of the intellectual expansion identified in the study. The early part of the series remains close to the baseline, with relatively little activity visible across the decades. A strong concentration appears in the later years, with a sequence of rapidly increasing observations followed by a decline at the end of the series. The shape indicates that the growth of AI–society scholarship is highly concentrated in the contemporary period. It also reinforces the need to distinguish complete historical years from the incomplete final year when interpreting the apparent decline. The figure provides a concise temporal summary of the field’s recent acceleration.

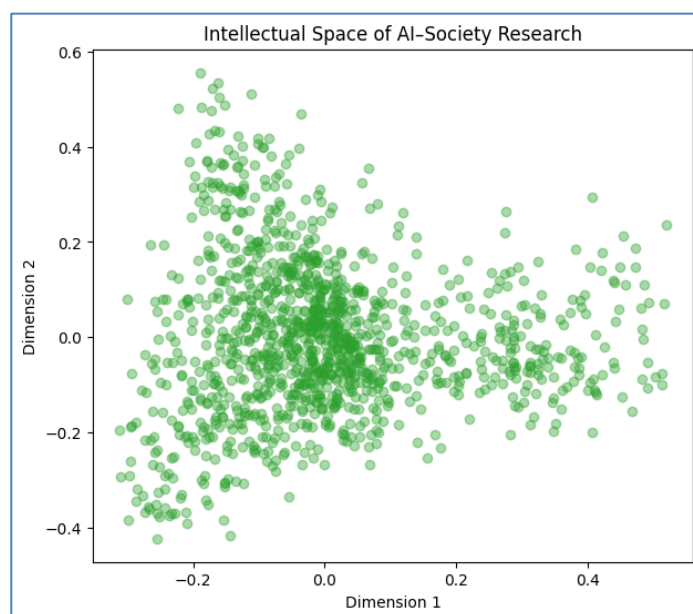


Figure 15. Intellectual Space of AI–Society Research — OpenAlex

Source- Author, 2026

The two-dimensional intellectual-space plot shows a large concentration of observations within a broad central region, with additional observations extending along both dimensions. The distribution does not form sharply isolated groups; instead, substantial overlap occurs around the central area. Figure 15. suggests the presence of a shared conceptual core within AI–society research alongside specialised thematic or disciplinary extensions. The peripheral observations indicate additional areas of intellectual differentiation. The plot therefore complements the cluster analysis by representing the continuous spatial relationship among publications rather than only assigning them to discrete groups. Overall, it portrays AI–society scholarship as a connected but multidimensional knowledge space.

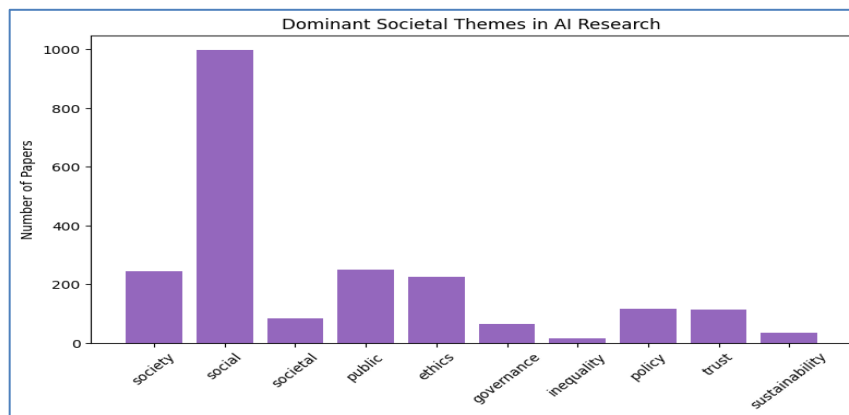


Figure 16. Dominant Societal Themes in AI Research

Source- Author, 2026

The thematic-frequency graph shows a very strong dominance of the social dimension, with approximately 1,000 papers in the displayed results. Society and public themes occur at considerably lower but still substantial levels, followed by ethics as is visible in Figure 16. Policy and trust occupy intermediate positions, while governance, sustainability and inequality are represented by smaller counts. The distribution indicates that broad social engagement forms the largest thematic component, while more specific institutional, ethical and developmental concerns constitute smaller thematic spaces. Importantly, the presence of ethics, policy, trust and governance demonstrates that societal AI scholarship extends beyond generic references to society and incorporates concerns about institutions, responsibility and the consequences of AI deployment.

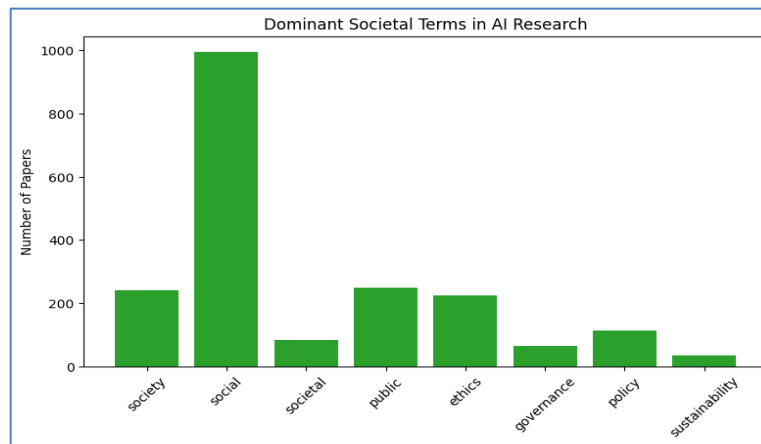


Figure 17. Dominant Societal Terms in AI Research

Source- Author, 2026

The bar chart in Figure 17. confirms the strong predominance of the term “social”, which approaches approximately 1,000 papers in the displayed results. Society and public occur at roughly similar, substantially lower levels, while ethics also has a strong presence. Policy, societal, governance and sustainability appear progressively lower in the distribution. This result demonstrates that broad societal terminology dominates the identified corpus, but the literature also contains more specific concepts relating to ethics and governance. The distinction among social, society and societal is analytically useful because it shows that societal engagement is expressed through several linguistic forms. The figure therefore reinforces the thematic concentration identified in the accompanying analysis.

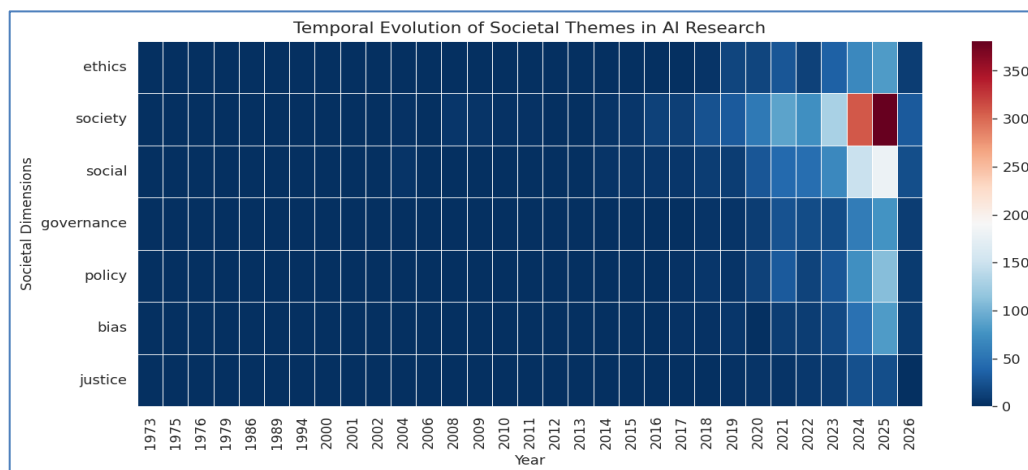


Figure 18. Temporal Evolution of Societal Themes in AI Research — Scopus

Source- Author, 2026

The Scopus heatmap shows very limited societal-term intensity during the earlier decades, followed by a pronounced increase toward the most recent years. In Figure 18.,the strongest values occur in the late 2010s and 2020s, particularly for social and society. Ethics, governance, policy, bias and justice also become more visible toward the end of the timeline. The pattern indicates a broadening of societal concerns: the literature moves from general social terminology toward more specific ethical, institutional and justice-related themes. The concentration of strong

values in the recent period corresponds with the overall publication expansion and demonstrates that the growth of AI–society scholarship has also involved diversification of societal themes.

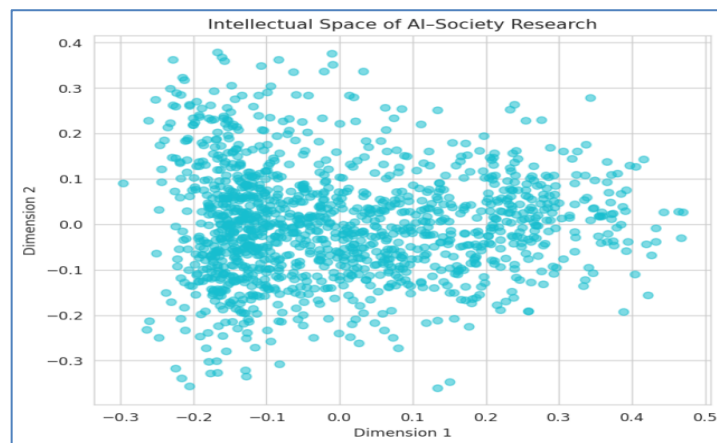


Figure 19. Intellectual Space of AI–Society Research — Scopus

Source- Author, 2026

The Scopus intellectual-space plot contains a large concentration of observations distributed across two dimensions, with a broad central and left-of-centre cluster and additional observations extending toward positive Dimension 1 values. The points overlap substantially, indicating that the intellectual structure is connected rather than divided into completely separate thematic islands in Figure 19. The broad distribution reflects the incorporation of multiple disciplinary and application-oriented perspectives into the AI–society literature. The figure therefore complements the OpenAlex intellectual-space analysis while providing a Scopus-based representation. Together, the two databases indicate that AI–society scholarship occupies a multidimensional conceptual environment characterised by a common core and diversified extensions.

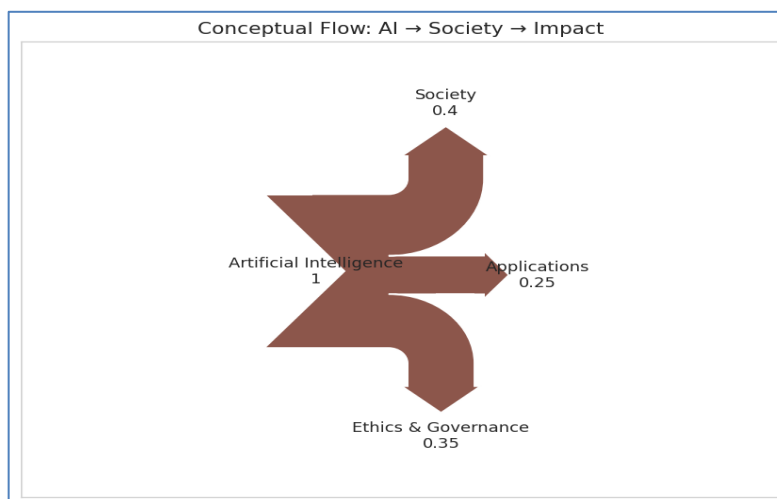


Figure 20. Conceptual Flow: AI → Society → Impact — Scopus

Source- Author, 2026

The Scopus conceptual-flow diagram in Figure 20., places Artificial Intelligence at the centre of three displayed dimensions: Society, Applications, and Ethics & Governance. The weights

shown in Figure are 0.40 for Society, 0.25 for Applications and 0.35 for Ethics & Governance. The values sum to 1.0 and indicate the relative conceptual emphasis represented by the diagram. Society is the largest component, followed by Ethics & Governance and Applications. The visual therefore presents AI as a central mechanism connecting social systems, practical applications and normative or institutional concerns. It provides a compact synthesis of the Scopus results and supports the broader interpretation of an increasingly societal and governance-oriented AI knowledge domain.

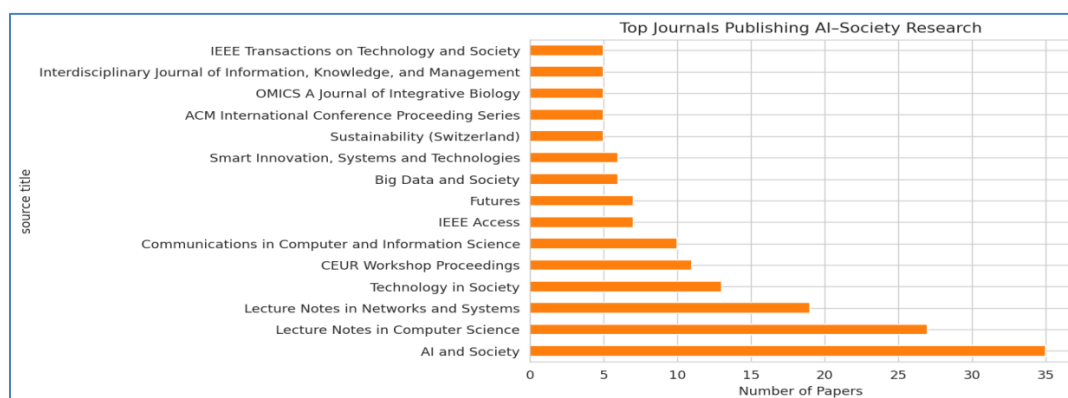


Figure 21. Top Journals Publishing AI-Society Research — Scopus

Source- Author, 2026

The journal distribution identifies AI and Society as the leading displayed outlet, with approximately 35 papers. Lecture Notes in Computer Science follows with around 27 papers, while Lecture Notes in Networks and Systems contributes approximately 19. Technology in Society, CEUR Workshop Proceedings and Communications in Computer and Information Science also appear prominently, followed by IEEE Access, Futures, Big Data and Society, Smart Innovation, Systems and Technologies and Sustainability. The distribution in Figure 21 demonstrates that AI-society research is communicated through both specialist society-oriented journals and technically oriented computing outlets. This combination is consistent with the interdisciplinary structure of the field and its connection between technological research and societal inquiry.

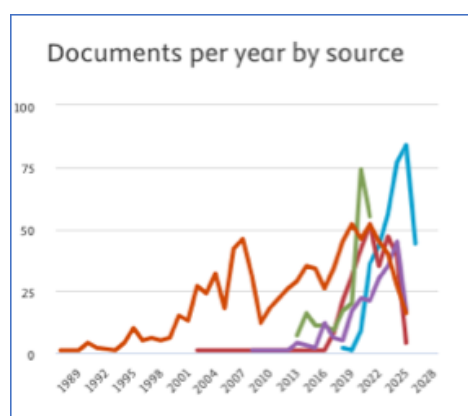


Figure 22. Documents per Year by Source

Source- Author, 2026

The source-wise temporal graph (Figure 22.) illustrates increasing publication activity across the contributing sources, particularly during the 2010s and early 2020s. The individual source trajectories differ considerably: some show earlier growth, while others begin rising more strongly after approximately 2015. Several series reach pronounced peaks around 2020–2025, with the highest displayed trajectory approaching the mid-80s. The variation demonstrates that the expansion of AI–society scholarship has occurred across multiple publication streams rather than through a single source. At the same time, differences in source trajectories indicate that publication activity is not uniform through time. The figure provides a source-level view of the field’s recent expansion.



Figure 23. Documents by Author

Source- Author, 2026

The author distribution is strongly influenced by the “No Author ID found” category, which is substantially larger than the named authors in the displayed chart. Among identified contributors, Wang, F.Y. is the most visible, followed by Floridi, L., Tyagi, A.K., Fukuda, T. and others with much smaller counts. This pattern indicates that the literature is dispersed across many individual contributors rather than concentrated among a small group of highly prolific authors. The large unidentified category is also methodologically important because incomplete author identifiers can affect productivity calculations. Consequently, Figure 23. is best interpreted as a bibliographic profile of the available records rather than a definitive ranking of author influence.

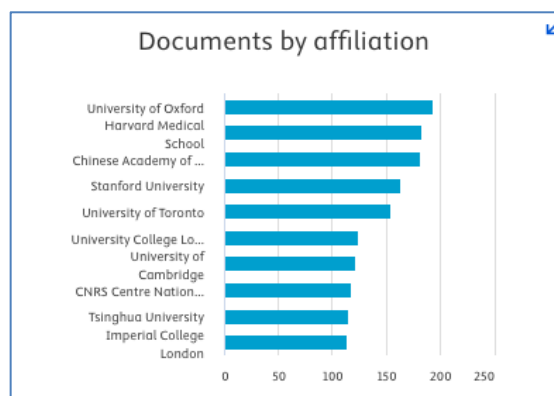


Figure 24. Documents by Affiliation

Source- Author, 2026

The affiliation graph shows substantial representation from internationally prominent academic institutions. The University of Oxford occupies the highest displayed position, followed closely by Harvard Medical School and the Chinese Academy of Sciences or related Chinese institutional grouping. Stanford University and the University of Toronto are also prominent, followed by University College London, the University of Cambridge, CNRS-related institutions, Tsinghua University and Imperial College London. The pattern indicates that AI–society scholarship is institutionally diverse and strongly connected with major research universities and organisations. The distribution also demonstrates international participation across North America, Europe and Asia, consistent with the global character of contemporary AI research in Figure 24.

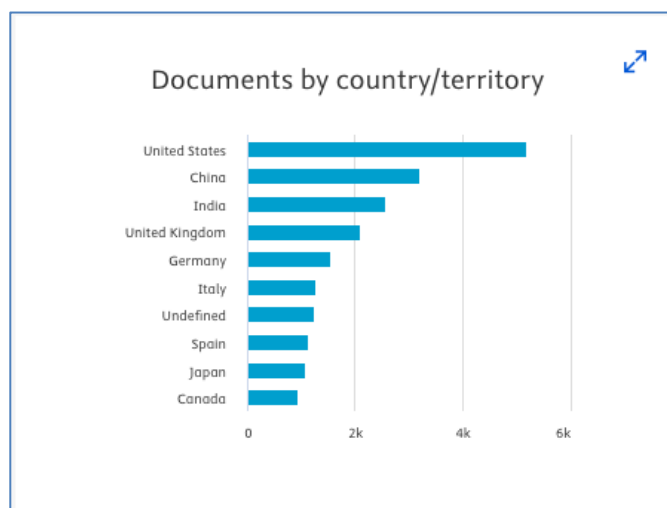


Figure 25. Documents by Country/Territory

Source- Author, 2026

The country distribution places the United States at the highest level, followed by China and India. The United Kingdom, Germany, Italy, an Undefined category, Spain, Japan and Canada form the remaining displayed group. The United States exceeds 5,000 documents in the chart, while China and India follow at lower levels. India's position among the leading displayed contributors is notable within the corpus represented by the analysis. The geographical

distribution demonstrates that AI research is internationally dispersed, with strong contributions from North America, East and South Asia and Europe. Figure 25. should be read as a database-based publication distribution rather than as a measure of national research quality or impact.

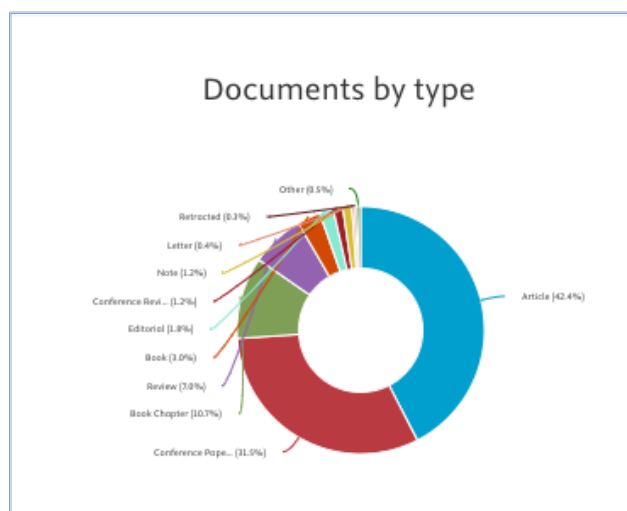


Figure 26. Documents by Type

Source- Author, 2026

Figure 26. as the document-type chart shows articles as the largest category, accounting for approximately 42.4% of the displayed records. Conference papers form another major component at about 31.5%, followed by book chapters at approximately 10.7%. Reviews, editorials, books, conference reviews, notes, letters, retracted documents and other categories make up smaller shares. The substantial conference-paper component is consistent with the computational and technological foundations of AI research, where conference communication has historically played an important role. At the same time, the strong article share indicates extensive journal-based scholarship. The distribution therefore demonstrates that AI–society research is communicated through multiple scholarly formats rather than a single publication channel.

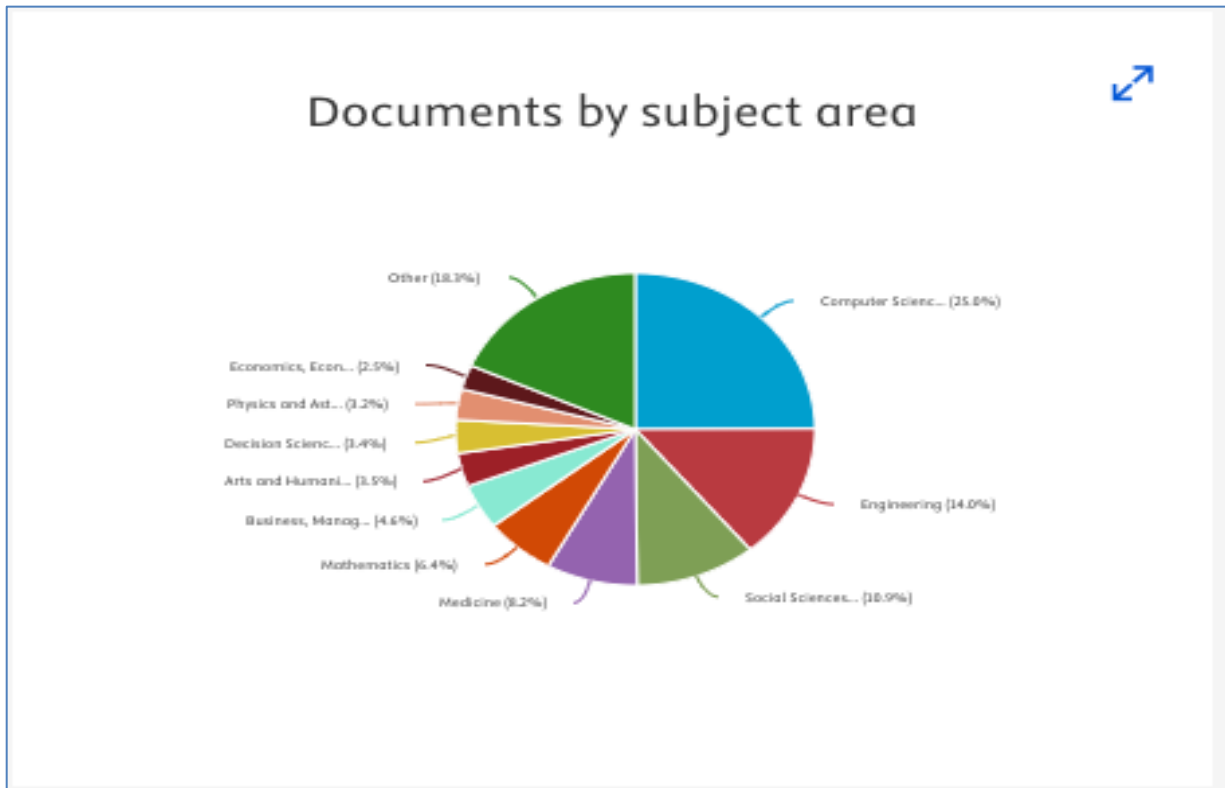


Figure 27. Documents by Subject Area

Source- Author, 2026

The subject-area distribution is led by Computer Science at approximately 25%, followed by Engineering at around 14%. Social Sciences and Medicine also represent substantial components, while Mathematics, Business and Management, Arts and Humanities, Decision Sciences, Physics and Economics contribute smaller shares. The Other category forms a considerable additional component. This distribution provides direct evidence of interdisciplinarity: although Computer Science remains central, the corpus extends into social sciences, medicine, management, humanities and quantitative fields. The result is important for the study because it demonstrates that societal AI scholarship is not confined to technical disciplines. Instead, it connects computational knowledge with fields concerned with people, institutions, health, economics and social systems in Figure 27.

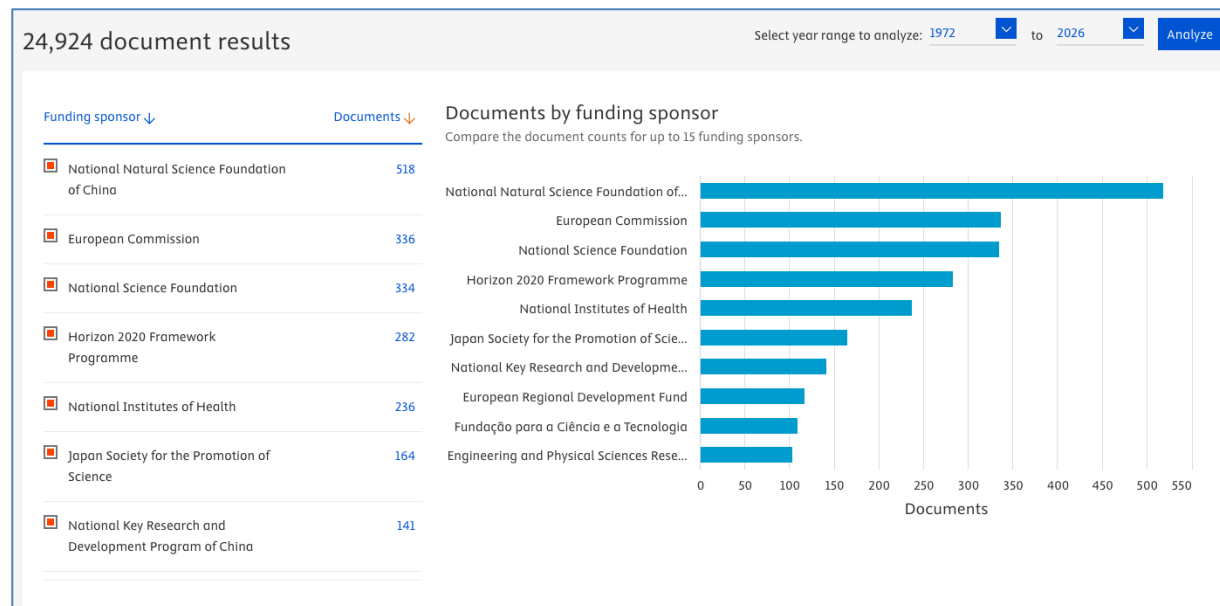


Figure 28. Documents by Funding Sponsor

Source- Author, 2026

The funding-sponsor panel reports 24,924 document results for the selected period and identifies the National Natural Science Foundation of China as the largest displayed sponsor, with 518 documents. The European Commission and National Science Foundation follow with 336 and 334 documents respectively, while the Horizon 2020 Framework Programme accounts for 282 and the National Institutes of Health for 236. Other visible sponsors include the Japan Society for the Promotion of Science and the National Key Research and Development Program of China. Figure 28. demonstrates the role of major national and international funding agencies in supporting the research corpus and shows that AI scholarship has a substantial institutional funding infrastructure.

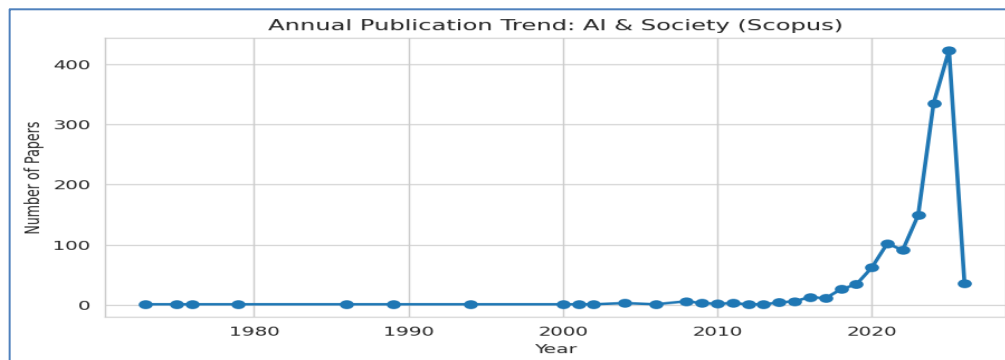


Figure 29. Annual Publication Trend: AI & Society — Scopus

Source- Author, 2026

The annual publication trend in Figure 29. shows a long period of very limited output followed by rapid expansion in the late 2010s and especially the 2020s. Publication counts begin rising noticeably around the late 2010s, increase sharply after 2020 and reach a peak of approximately 425 papers near the end of the displayed period. The final year shows a strong decline. Because the dataset extends to 2026, the last observation may represent an incomplete publication year and should not be interpreted as a completed annual total. The overall trajectory nevertheless demonstrates a major recent expansion of AI–society publications within the Scopus-based corpus.

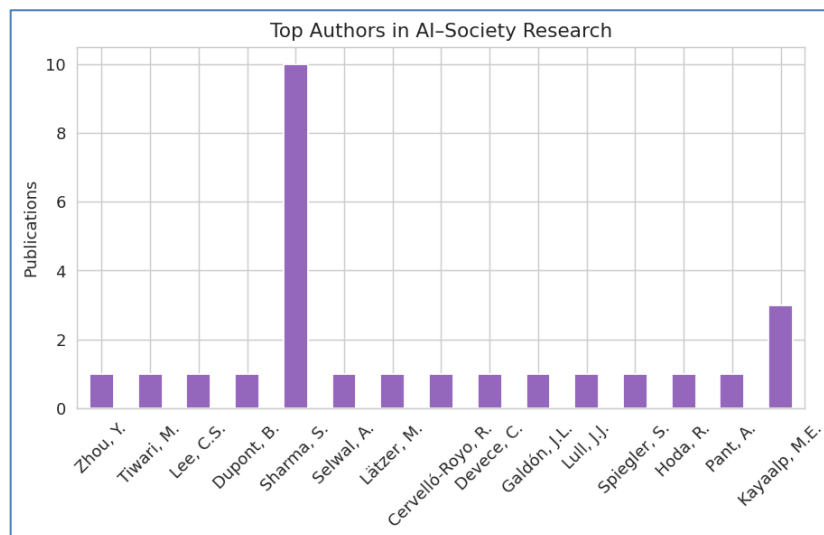


Figure 30. Top Authors in AI-Society Research — Scopus

Source- Author, 2026

The author graph in Figure 30. shows one particularly prominent contributor with approximately 10 publications, while most of the other displayed authors have around one publication and one contributor has approximately three. This produces a highly uneven author-output distribution in the displayed Scopus subset. The pattern indicates that the field includes a broad contributor base but comparatively few authors with repeated publication presence. The graph should be understood as a productivity profile within the selected records rather than as a measure of

scholarly quality or influence. The relatively small counts for most authors also suggest that AI–society research remains distributed across many research teams and disciplinary communities.

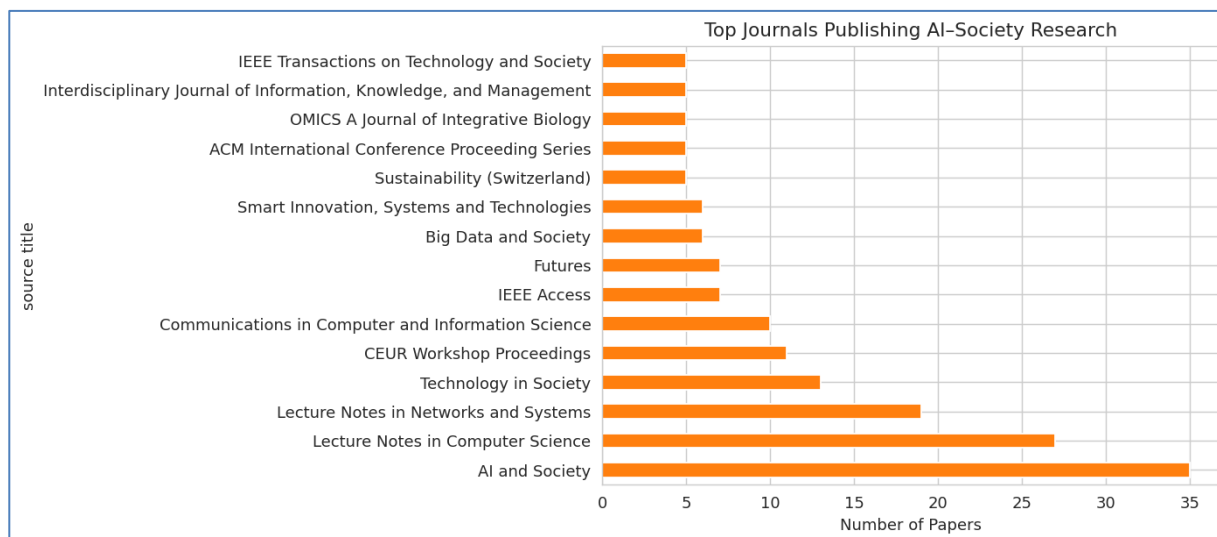


Figure 31. Top Journals Publishing AI–Society Research — Scopus

Source- Author, 2026

In Figure 31., the journal distribution again places AI and Society at the highest displayed level, with approximately 35 papers. Lecture Notes in Computer Science follows with about 27, while Lecture Notes in Networks and Systems contributes approximately 19. Technology in Society and CEUR Workshop Proceedings also occupy visible positions, followed by Communications in Computer and Information Science, IEEE Access, Futures, Big Data and Society, Smart Innovation, Systems and Technologies and Sustainability. The recurrence of these outlets across the presentation reinforces the interdisciplinary publication structure of AI–society research. Dedicated society journals coexist with computing and technology channels, demonstrating the interaction between technical AI scholarship and research on societal implications.

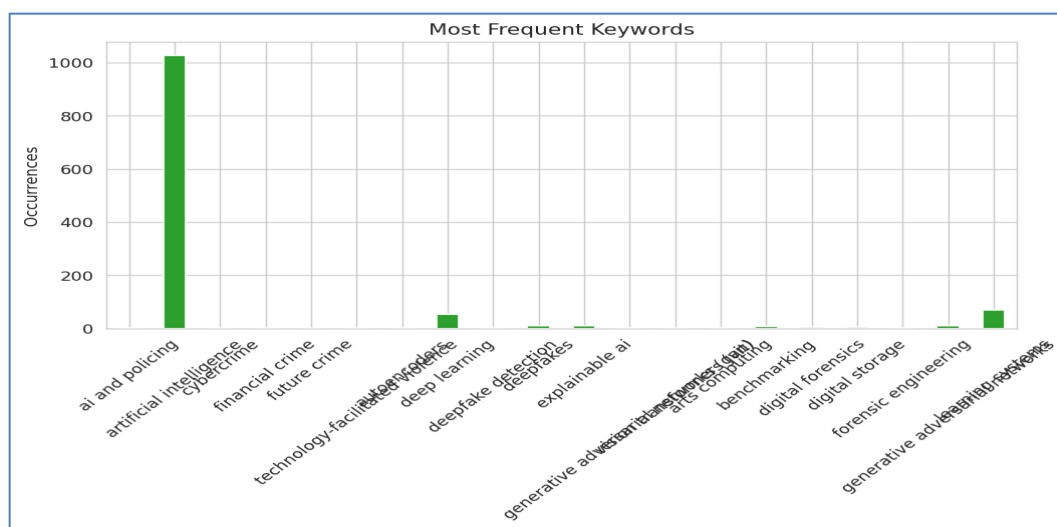


Figure 32. Most Frequent Keywords — Scopus

Source- Author, 2026

The keyword-frequency graph is dominated by “AI and policing”, which exceeds 1,000 occurrences in the displayed chart. Other visible terms occur at much lower frequencies and include artificial intelligence, financial crime, future crime, technology-facilitated crime, deep learning, explainable AI and generative AI. The distribution therefore reveals a strong application-oriented component in the displayed Scopus keyword set, particularly around policing and crime-related contexts. At the same time, the presence of deep learning, explainable AI and generative AI demonstrates continued connection with technical developments. Figure 32. illustrates how computational concepts and socially consequential applications coexist within the selected AI–society literature.

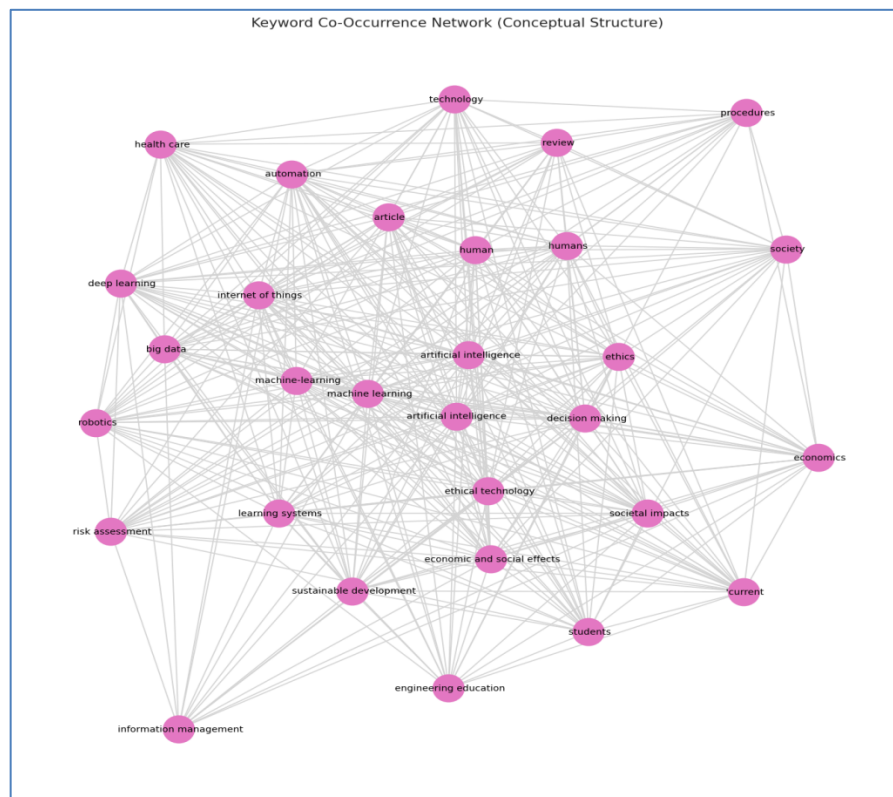


Figure 33. Keyword Co-Occurrence Network — Scopus

Source- Author, 2026

The final network visualisation presents a dense set of keyword relationships, with multiple central nodes linked to surrounding concepts. The network structure indicates that the principal terms do not occur independently but are repeatedly associated across the literature. Technical AI concepts are connected with themes involving society, ethics, human impacts, applications and governance-related concerns. The density of the network reflects conceptual overlap and supports the interpretation of an integrated research field. Peripheral nodes represent more specialised topics, while central nodes connect several thematic areas. Figure 33. therefore provides a network-level summary of the intellectual structure identified in the Scopus corpus and complements the frequency-based keyword analysis.

6. Results Synthesis

Taken together, the results demonstrate a pronounced transformation in the intellectual structure of AI–society research. The bibliographic evidence shows that societal engagement represents a relatively small component of the overall AI literature, yet this component has expanded rapidly, particularly after the late 2010s. Both OpenAlex and Scopus show strong concentrations of recent publications, with the most substantial growth occurring during the 2020s. The thematic results demonstrate that social, society, public and ethics constitute important dimensions, while governance, policy, sustainability, inequality, trust, bias and justice form additional thematic extensions.

The conceptual and network analyses reveal increasing interconnection among computer science, artificial intelligence, psychology, political science, sociology, law, engineering, business, medicine and social sciences. The intellectual-space maps similarly indicate a shared conceptual core accompanied by expanding interdisciplinary components. The five paradigm clusters further indicate that AI–society research contains multiple intellectual configurations rather than one homogeneous research stream. Generative AI is represented in the temporal framework as an important recent inflection point and as a bridge linking AI with wider societal and interdisciplinary concerns.

7. Discussion and Conclusions

The scientometric evidence presented in this study indicates that the relationship between Artificial Intelligence and society has undergone substantial intellectual expansion, particularly during the recent phase of AI development. Although societal terminology represents only a fraction of the much larger AI publication universe, the temporal patterns in both Scopus and OpenAlex demonstrate a strong increase in AI–society research during the late 2010s and especially the 2020s. This expansion corresponds with the increasing incorporation of questions concerning social systems, ethics, governance, policy, public applications and human well-being into AI scholarship.

The thematic results show that social constitutes the dominant societal dimension, while society, public concerns and ethics form additional major components. Governance, policy, trust, sustainability, inequality, bias and justice occupy smaller but analytically important spaces. This suggests that societal engagement is not restricted to a single concern but encompasses multiple dimensions ranging from broad social relationships to institutional and normative questions. The disciplinary evidence further demonstrates that AI–society research remains rooted in Computer Science and Artificial Intelligence while simultaneously incorporating Psychology, Political Science, Sociology, Law, Engineering, Social Sciences, Business, Medicine and other fields. The co-word networks and intellectual-space maps reinforce this interdisciplinary structure by showing extensive connections among technical and societal concepts. The five paradigm clusters further indicate that the field contains multiple intellectual configurations rather than one dominant structure.

Generative AI emerges in the temporal analysis as an important recent inflection point, coinciding with a pronounced acceleration in societal AI publications. Its representation as a structural bridge in the conceptual framework reflects the increasing interaction between AI technologies and wider societal systems.

Overall, the study demonstrates a transition from predominantly technical AI scholarship toward a more interdisciplinary and societally engaged intellectual landscape. The findings provide an empirical basis for understanding thematic and conceptual transitions in AI research and support continued attention to responsible AI, governance, public policy and societal well-being. The results should nevertheless be interpreted in relation to database coverage, keyword-based societal filtering and the possibility of incomplete records for the latest publication years.

REFERENCES:

1. Alperin, J. P., Portenoy, J., Demes, K., Larivière, V., & Haustein, S. (2024). *An analysis of the suitability of OpenAlex for bibliometric analyses*. arXiv. <https://doi.org/10.48550/arXiv.2404.17663>
2. Aman, V., & Gläser, J. (2025). Investigating knowledge flows in scientific communities: The potential of bibliometric methods. *Minerva*, 63, 155–182. <https://doi.org/10.1007/s11024-024-09542-2>
3. Aria, M., Cuccurullo, C., D’Aniello, L., Misuraca, M., & Spano, M. (2024). Comparative science mapping: A novel conceptual structure analysis with metadata. *Scientometrics*, 129, 7055–7081. <https://doi.org/10.1007/s11192-024-05161-6>
4. Culbert, J. H., Hobert, A., Jahn, N., Haupka, N., Schmidt, M., Donner, P., & Mayr, P. (2025). Reference coverage analysis of OpenAlex compared to Web of Science and Scopus. *Scientometrics*, 130, 2475–2492. <https://doi.org/10.1007/s11192-025-05293-3>
5. Delgado-Quirós, L., & Ortega, J. L. (2025). Research entity information and coverage in eight free access scholarly databases. *Online Information Review*, 49(6), 1135–1153. <https://doi.org/10.1108/OIR-03-2024-0131>
6. 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>
7. Forchino, M. V., & Torres-Salinas, D. (2026). The OpenAlex database in review: Evaluating its applications, capabilities, and limitations. *Journal of Informetrics*, 20(2), 101800. <https://doi.org/10.1016/j.joi.2026.101800>
8. Harder, R. (2024). Using Scopus and OpenAlex APIs to retrieve bibliographic data for evidence synthesis: A procedure based on Bash and SQL. *MethodsX*, 12, 102601. <https://doi.org/10.1016/j.mex.2024.102601>
9. Haunschild, R., & Bornmann, L. (2024). The use of OpenAlex to produce meaningful bibliometric global overlay maps of science on the individual, institutional, and national levels. *PLOS ONE*, 19(12), e0308041. <https://doi.org/10.1371/journal.pone.0308041>
10. Ishii, K., et al. (2024). Defining intelligence: Bridging the gap between human and artificial perspectives. *Intelligence*, 104, 101832. <https://doi.org/10.1016/j.intell.2024.101832>
11. Lim, W. M., Kumar, S., & Donthu, N. (2024). How to combine and clean bibliometric data and use bibliometric tools synergistically: Guidelines using metaverse research. *Journal of Business Research*, 182, 114760. <https://doi.org/10.1016/j.jbusres.2024.114760>

12. McCarthy, J., Minsky, M. L., Rochester, N., & Shannon, C. E. (1955). *A proposal for the Dartmouth Summer Research Project on Artificial Intelligence*. <https://doi.org/10.1609/aimag.v27i4.1904>
 13. National Institute of Standards and Technology. (2023). *Artificial intelligence risk management framework (AI RMF 1.0)* (NIST AI 100-1). U.S. Department of Commerce. <https://doi.org/10.6028/NIST.AI.100-1>
 14. OECD. (2019). *Artificial Intelligence in Society*. OECD Publishing.
 15. OECD. (2024). *Explanatory memorandum on the updated OECD definition of an AI system*. OECD Artificial Intelligence Papers, No. 8. <https://doi.org/10.1787/623da898-en>
 16. OpenAlex. (n.d.). *OpenAlex: The open catalog to the global research system*. Retrieved January 20, 2026, from <https://openalex.org/>
 17. Öztürk, O., Kocaman, R., & Kanbach, D. K. (2024). How to design bibliometric research: An overview and a framework proposal. *Review of Managerial Science*, 18, 3333–3361. <https://doi.org/10.1007/s11846-024-00738-0>
 18. Priem, J., Piwowar, H., & Orr, R. (2022). *OpenAlex: A fully-open index of scholarly works, authors, venues, institutions, and concepts*. arXiv. <https://doi.org/10.48550/arXiv.2205.01833>
 19. Pritchard, A. (1969). Statistical bibliography or bibliometrics. *Journal of Documentation*, 25(4), 348–349.
 20. Russell, S., & Norvig, P. (2021). *Artificial Intelligence: A Modern Approach* (4th ed.). Pearson.
 21. Salton, G., & Buckley, C. (1988). Term-weighting approaches in automatic text retrieval. *Information Processing & Management*, 24(5), 513–523. [https://doi.org/10.1016/0306-4573\(88\)90021-0](https://doi.org/10.1016/0306-4573(88)90021-0)
 22. Tomczyk, P., Brüggemann, P., & Paul, J. (2024). Variable science mapping as literature review method. *Journal of Marketing Analytics*, 12, 829–841. <https://doi.org/10.1057/s41270-024-00336-9>
 23. Triguero, I., Molina, D., Poyatos, J., Del Ser, J., & Herrera, F. (2024). General purpose artificial intelligence systems (GPAIS): Properties, definition, taxonomy, societal implications and responsible governance. *Information Fusion*, 103, 102135. <https://doi.org/10.1016/j.inffus.2023.102135>
 24. UNESCO. (2021). *Recommendation on the Ethics of Artificial Intelligence*. UNESCO.
 25. Wu, H. C., Luk, R. W. P., Wong, K. F., & Kwok, K. L. (2008). Interpreting TF-IDF term weights as making relevance decisions. *ACM Transactions on Information Systems*, 26(3), 1–37. <https://doi.org/10.1145/1361684.1361686>
 26. Zupic, I., & Čater, T. (2015). Bibliometric methods in management and organization. *Organizational Research Methods*, 18(3), 429–472. <https://doi.org/10.1177/1094428114562629>
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