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Mapping the Evolution of Neuro-Symbolic Artificial Intelligence : A Bibliometric Analysis (2015-2025)

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Abstract

The field of Neuro-Symbolic Artificial Intelligence has experienced rapid development between 2015 and 2025, as evidenced by a comprehensive bibliometric analysis of 877 peer-reviewed articles sourced from the Scopus database. This study, utilizing the PRISMA framework and advanced tools like VOS viewer and Bibliometric, identifies a notable surge in research productivity and citation impact, with a synchronized acceleration in output observed starting around 2024. Global research activity is heavily concentrated in North America, Europe, and Asia, with Germany, the USA, and China emerging as primary drivers of scholarly influence. Key contributors, such as V. Venkatasubramanian and M.-E. Vidal, have been identified as highly prolific, while the field's intellectual foundation is anchored by seminal works from authors including LeCun Y. (2015), Goodfellow I. (2016), and Kahneman D. (2011). The thematic analysis reveals that core concepts, including "artificial intelligence," "machine learning," and "deep learning," remain central to the research discourse. As these primary themes have evolved, trend topics signify a clear transition toward more advanced architectural approaches, moving from early hybrid expert systems toward modern neuro-symbolic integrations. Furthermore, the study highlights the highly collaborative nature of this specialized community, evidenced by robust international co-authorship networks and a concentrated core of productive experts. By providing a quantitative and visual map of the domain's social and intellectual structure, this research delineates a maturing field characterized by interdisciplinary cooperation. Ultimately, this analysis serves as a foundational resource for understanding the past developments and future trajectories of Neuro-Symbolic AI, confirming its increasing academic significance and central role in the ongoing integration of neural and symbolic methodologies.

Keywords: Neuro-Symbolic Artificial Intelligence; Neural-Symbolic Integration; Hybrid AI Architectures; Machine Learning; Deep Learning; Symbolic Reasoning; Bibliometric Analysis; Systematic Review; PRISMA Framework; Explainable AI (XAI); Knowledge Representation; Scient metrics.

1. INTRODUCTION

The increasing complexity of real-world decision-making problems has further exposed the limitations of relying exclusively on either symbolic reasoning or neural learning. Modern intelligent systems are expected not only to recognize patterns from heterogeneous data but also to explain their decisions, adapt to dynamic environments, incorporate prior knowledge, and reason under uncertainty. These requirements have motivated researchers to explore hybrid computational paradigms that combine the complementary strengths of data-driven learning and symbolic reasoning. Consequently, Neuro-Symbolic Artificial Intelligence (Neuro-Symbolic AI) has emerged as one of the most promising directions in contemporary AI research, seeking to bridge the long-standing divide between statistical learning and symbolic knowledge representation(Besold et al., 2017; de Raedt et al., 2020a; Garcez et al., 2019a).

Unlike conventional deep learning models that primarily learn implicit representations from large volumes of data, Neuro-Symbolic AI incorporates explicit knowledge structures such as ontologies, knowledge graphs, logical rules, semantic networks, and probabilistic reasoning frameworks into neural architectures. This integration enables intelligent systems to perform deductive and inductive reasoning while maintaining the powerful perception capabilities of deep neural networks. As a result, neuro-symbolic systems demonstrate improved interpretability, greater robustness, enhanced generalization, and better performance in knowledge-intensive tasks(Garcez et al., 2019b; Hitzler et al., 2022).

Recent advances in graph neural networks, differentiable logic programming, neural theorem proving, semantic reasoning, probabilistic graphical models, and knowledge graph embeddings have significantly expanded the capabilities of neuro-symbolic systems. These developments have enabled the successful application of hybrid AI across diverse domains, including precision medicine, drug discovery,

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autonomous robotics, cybersecurity, financial fraud detection, scientific discovery, recommendation systems, intelligent tutoring systems, and legal decision support(de Raedt et al., 2020a; Hamilton et al., 2017; Kipf & Welling, 2016).

The emergence of foundation models and large language models (LLMs) has further accelerated interest in neuro-symbolic computing. Although transformer-based models exhibit remarkable capabilities in natural language understanding, text generation, summarization, translation, and question answering, they frequently produce hallucinated information, inconsistent reasoning, and factually incorrect responses. Their inability to consistently perform formal logical reasoning remains a major limitation for applications requiring high reliability. Integrating symbolic reasoning modules, external knowledge bases, ontologies, and rule-based inference mechanisms with LLMs offers a promising solution for improving factual consistency, explainability, and reasoning accuracy(Bommasani et al., 2021; Bubeck et al., 2023; Vaswani et al., 2017).

Another important driver of Neuro-Symbolic AI is the growing emphasis on trustworthy artificial intelligence. Governments, regulatory agencies, and industrial organizations increasingly demand AI systems that satisfy principles of transparency, accountability, fairness, robustness, privacy, and ethical responsibility. Traditional deep learning approaches often struggle to satisfy these requirements because their internal representations are difficult for humans to interpret. Symbolic reasoning complements neural learning by providing explicit reasoning paths, enabling users to understand how decisions are generated and increasing confidence in AI-assisted decision-making. Consequently, Neuro-Symbolic AI is widely regarded as a key enabling technology for the development of responsible and human-centric AI(Doshi-Velez & Kim, 2017; *Ethics Guidelines for Trustworthy AI | Shaping Europe's Digital Future*, n.d.; Modern, 2021).

As the field continues to expand, the volume of scientific publications has grown rapidly across journals, conferences, and interdisciplinary research communities. This rapid expansion makes it increasingly difficult for researchers to identify influential publications, leading authors, productive institutions, emerging research themes, and evolving collaboration networks. Conventional literature reviews provide valuable qualitative insights but often lack the quantitative rigor needed to evaluate large-scale scientific trends. Bibliometric analysis addresses this challenge by applying statistical and network-based methods to publication metadata, enabling researchers to systematically map the intellectual, conceptual, and social structure of a research domain(Aria & Cuccurullo, 2017; Donthu et al., 2021).

Bibliometric techniques have become an indispensable component of research evaluation because they objectively assess scientific productivity, citation impact, collaboration patterns, thematic evolution, and knowledge diffusion. Methods such as citation analysis, co-citation analysis, bibliographic coupling, keyword co-occurrence analysis, thematic mapping, collaboration network analysis, and science mapping provide complementary perspectives on the development of scientific disciplines. Visualization tools including **VOSviewer** and the **Bibliometrix** R package further facilitate the exploration of complex bibliographic datasets by generating intuitive maps of research clusters, conceptual relationships, and international collaborations(Aria & Cuccurullo, 2017b; van Eck & Waltman, 2010a).

Within the broader artificial intelligence literature, bibliometric investigations have been conducted on machine learning, deep learning, explainable AI, federated learning, reinforcement learning, Internet of Things, digital twins, and healthcare AI. However, dedicated bibliometric analyses focusing exclusively on Neuro-Symbolic Artificial Intelligence remain comparatively scarce despite the field's rapidly increasing scientific importance. Existing review articles predominantly emphasize algorithmic developments, neural-symbolic architectures, or application-specific case studies, while comparatively little attention has been devoted to quantitatively examining publication growth, citation dynamics, institutional performance, international collaboration, keyword evolution, conceptual structures, and the intellectual foundations of Neuro-Symbolic AI research(Besold et al., 2017; Hitzler et al., 2022).

The present study addresses this gap by providing a comprehensive bibliometric assessment of Neuro-Symbolic Artificial Intelligence research published between 2015 and 2025. Using a rigorously screened dataset of 877 peer-reviewed publications retrieved from the Scopus database**,** this study applies the PRISMA framework together with Bibliometric and VOS viewer to investigate the evolution of the field through multiple complementary bibliometric indicators.

Specifically, this research examines annual publication trends, citation performance, influential journals, prolific authors, institutional productivity, geographical distribution of research activities, collaboration networks, highly cited publications, keyword dynamics, conceptual structures, thematic evolution, and intellectual foundations. Through these analyses, the study provides a comprehensive understanding of how Neuro-Symbolic AI has evolved from an emerging interdisciplinary concept into a mature and rapidly expanding research domain(Aria & Cuccurullo, 2017b; Donthu et al., 2021b).

Furthermore, the findings offer practical implications for researchers, practitioners, funding agencies, and policymakers

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by identifying major research hubs, influential contributors, and promising future directions. Understanding these trends is essential for guiding future investments, fostering international collaboration, supporting interdisciplinary research, and accelerating the development of explainable, trustworthy, and human-centric artificial intelligence systems. As Neuro-Symbolic AI continues to evolve alongside advances in foundation models, knowledge graphs, reasoning engines, and explainable AI, comprehensive bibliometric evidence will play an increasingly important role in shaping the future research agenda of this rapidly developing field(Hitzler et al., 2022; Modern, 2021).

2. MATERIALS AND METHODS

2.1 Data Source and Search Strategy

To ensure a comprehensive and reliable overview of the Neuro-Symbolic Artificial Intelligence domain, data was retrieved from the Scopus database, one of the largest and most comprehensive repositories of peer-reviewed scientific literature. Scopus provides extensive coverage of high-quality journals, conference proceedings, and scholarly publications across multiple disciplines, making it a preferred source for bibliometric investigations(Baas et al., 2020; Donthu et al., 2021). A meticulously designed search query was executed on 9 July 2026 to capture the interdisciplinary nature of Neuro-Symbolic Artificial Intelligence by incorporating relevant keywords related to neural-symbolic integration, hybrid artificial intelligence, symbolic reasoning, and knowledge representation. The search strategy was developed following established bibliometric guidelines to maximize both sensitivity and specificity, thereby ensuring comprehensive retrieval of relevant literature while minimizing irrelevant records(Donthu et al., 2021b; Zupic & Čater, 2015a).

2.2 Inclusion and Exclusion Criteria

The retrieved records were subjected to predefined inclusion and exclusion criteria to ensure the quality, consistency, and relevance of the bibliometric dataset. The study considered publications published between 2015 and 2025, reflecting the recent evolution of Neuro-Symbolic Artificial Intelligence research. Only English-language publications indexed in Scopus were included to ensure consistency in bibliographic analysis. Furthermore, the study considered only peer-reviewed journal articles and conference papers while excluding review articles, editorials, book chapters, notes, letters, errata, and other non-research document types. This filtering process ensured that the analysis focused exclusively on original scientific contributions and minimized potential publication bias(Donthu et al., 2021a; Page et al., 2021a).

2.3 PRISMA-Based Literature Screening

The literature selection process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines, which provide a transparent, standardized, and reproducible framework for documenting the study selection process(Page et al., 2021). As illustrated in Figure 1, the screening procedure consisted of four sequential stages: identification, screening, eligibility assessment, and final inclusion. Initially, all records retrieved from the Scopus database were examined based on publication year, document type, and language. Duplicate or irrelevant records were removed through systematic filtering, resulting in a final dataset comprising 877 research articles. The adoption of the PRISMA framework enhances the transparency, reproducibility, and methodological rigor of bibliometric studies(Page et al., 2021).

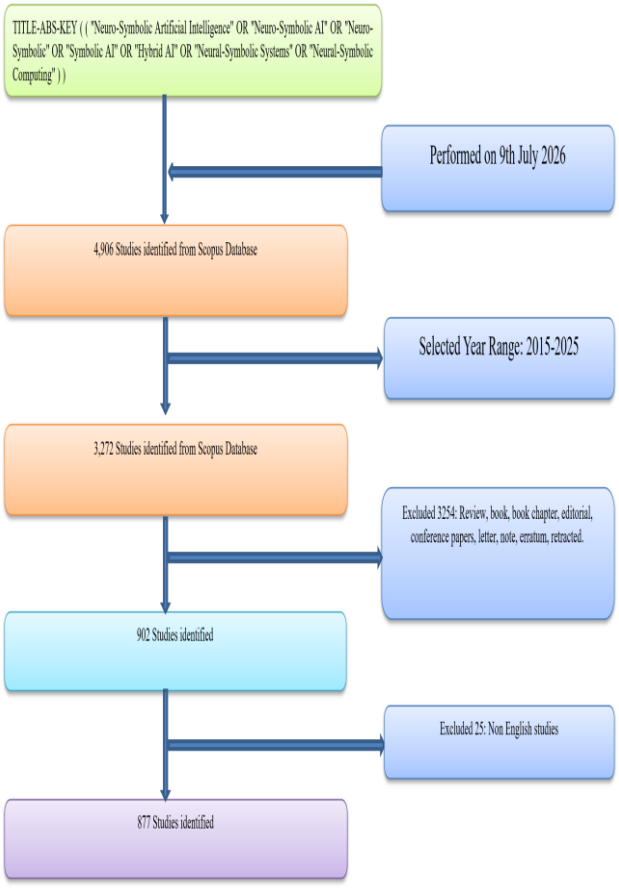


Fig. 1. *PRISMA-based study selection framework for the bibliometric analysis of Neuro-Symbolic Artificial Intelligence research. Records were retrieved from the Scopus database using a predefined search query on 9 July 2026, filtered by publication year (2015–2025), document type, and language. After excluding non-research document types and non-English publications, a final dataset of 877 research articles was retained for subsequent bibliometric analysis.*

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2.4 Bibliometric Workflow

The bibliometric workflow consisted of three major phases: data acquisition, data preprocessing, and bibliometric analysis. During the preprocessing stage, bibliographic records were carefully cleaned and standardized to eliminate inconsistencies in author names, institutional affiliations, country names, and keyword terminology. Data normalization is a critical preprocessing step because inconsistent metadata can significantly influence collaboration networks, citation analyses, and thematic mapping(Aria & Cuccurullo, 2017; Zupic & Čater, 2015). The cleaned dataset was subsequently imported into bibliometric software for quantitative analysis and visualization.

2.5 Bibliometric Indicators

A comprehensive set of bibliometric indicators was employed to evaluate both scientific productivity and research impact. These indicators included annual scientific production, total citations, average citations per publication, local citation analysis, h-index, source productivity, Bradford's Law, author productivity, institutional performance, country productivity, co-authorship networks, keyword co-occurrence analysis, thematic evolution, bibliographic coupling, and co-citation analysis. These bibliometric techniques provide complementary perspectives for understanding the intellectual, conceptual, and social structure of scientific research(Aria & Cuccurullo, 2017; Donthu et al., 2021; Zupic & Čater, 2015).

2.6 Visualization and Statistical Tools

The bibliometric analyses were performed using two widely recognized software packages: Bibliometric and VOS viewer. The Bibliometric R-package was employed for descriptive bibliometric analysis, thematic evolution, scientific production analysis, Bradford's Law analysis, and collaboration network analysis(Aria & Cuccurullo, 2017a) (Aria & Cuccurullo, 2017). VOS viewer was used to construct and visualize bibliometric networks, including keyword co-occurrence networks, co-authorship networks, bibliographic coupling, citation networks, and co-citation maps. VOS viewer applies visualization and clustering techniques that effectively reveal relationships among research themes, authors, institutions, and countries, thereby facilitating the interpretation of complex bibliometric datasets(van Eck & Waltman, 2010a).

3. RESULTS

3.1 Growth of Scientific Publications

Figure 2 illustrates the bibliometric trends of research in Neuro-Symbolic Artificial Intelligence from 2015 to 2025, highlighting both growth in output and citation impact(Aria & Cuccurullo, 2017; Donthu et al., 2021). Panel (a) shows the Annual Scientific Production, which depicts a steady, incremental rise in research activity over the decade, followed by a notable surge in publication volume towards the end of the period. In contrast, panel (b) presents the Average Citations per Year, which reveals a distinct peak around 2018, followed by a fluctuating pattern that suggests varying levels of annual influence as the field has matured. Together, these figures provide a comprehensive overview of the field's rapid expansion and its evolving academic reception within the Scopus database(Aria & Cuccurullo, 2017b; Baas et al., 2020).

3.2 Analysis of Publication Sources

This multifaceted analysis provides a comprehensive assessment of the core sources contributing to Neuro-Symbolic Artificial Intelligence research, illustrating both their quantitative productivity and qualitative impact (Aria & Cuccurullo, 2017b; Donthu et al., 2021b) Panels (a) and (d) establish that IEEE Access is the leading venue in the field, securing the highest number of published documents and the highest *h*-index, thereby positioning it as the central hub for this body of work. Panel (b) further delineates the intellectual landscape by ranking the most locally cited sources, which reveals a clear hierarchy of influence among researchers and journals that form the foundational pillars of current studies. Complementing this, panel (c) applies Bradford's Law to mathematically categorize the literature into "Core," "Zone 2," and "Zone 3" segments; this statistical distribution demonstrates that a small, highly focused set of journals accounts for the majority of core research, a finding that reinforces the field's structural maturity(Donthu et al., 2021b; Zupic & Čater, 2015b)**.** Finally, panel (e) offers a temporal perspective by tracking "Sources' Production over Time," which visually confirms a synchronized and sharp acceleration in research output across these top-tier journals starting around 2024, providing compelling evidence of the field's rapid expansion and increasing academic significance in the most recent years(Baas et al., 2020).

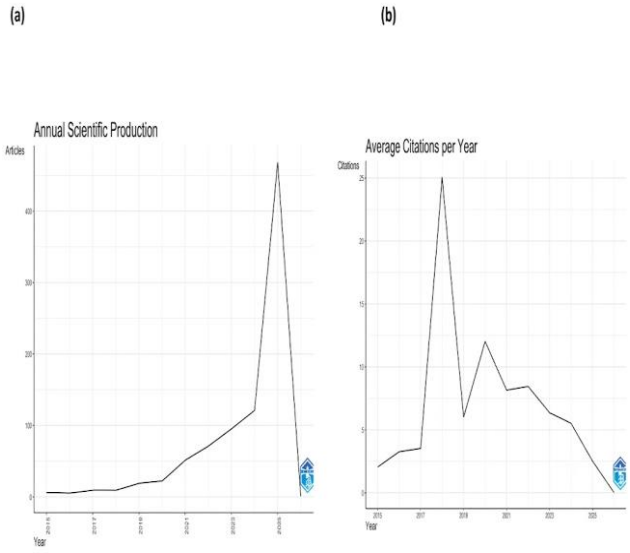


Figure 2. Annual scientific production and citation trends in the research field. (a) Annual scientific publications showing the growth of research output over the study period. **(b)** Average citations received per publication per year, illustrating the temporal evolution of research impact.

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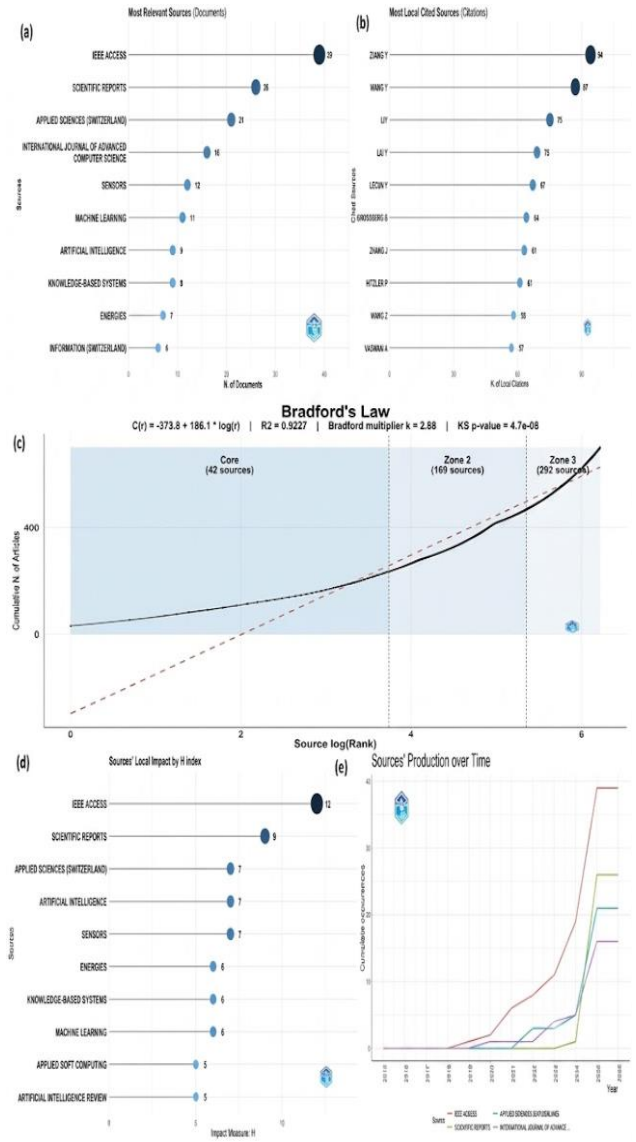


Figure 3. Bibliometric analysis of publication sources. (a) Most relevant sources ranked by the number of published articles. **(b)** Most locally cited sources within the dataset. **(c)** Bradford's Law identifying the core journals of the research field. **(d)** Local impact of publication sources based on citation performance. **(e)** Source production over time, illustrating the annual publication trends of the leading journals.

3.3 Analysis of Author Productivity

This comprehensive bibliometric evaluation details the contributions and academic impact of key authors within the Neuro-Symbolic Artificial Intelligence research domain over the 2015–2025 period(Aria & Cuccurullo, 2017; Donthu et al., 2021) Panel (a) ranks the most relevant authors by their total document output, with V. Venkatasubramanian and M.-E. Vidal emerging as the most prolific contributors to the field. Panel (b) illustrates the depth of foundational influence through local citation analysis, highlighting authors , whose work serves as a cornerstone for current research(Hitzler et al., 2022b; Sarker et al., 2021c). Complementing these productivity and influence metrics, panel (c) provides a longitudinal timeline of "Authors' Production over Time," which visually maps the acceleration and persistence of individual research efforts throughout the decade. Finally, panel (d) evaluates scholarly impact using the *h*-index, which corroborates the high level of sustained influence maintained by researchers within this highly specialized interdisciplinary community(Donthu et al., 2021b). Together, these figures underscore the emergence of a concentrated, highly productive core of experts whose work is central to the ongoing evolution and integration of neural and symbolic AI methodologies(Hitzler et al., 2017)

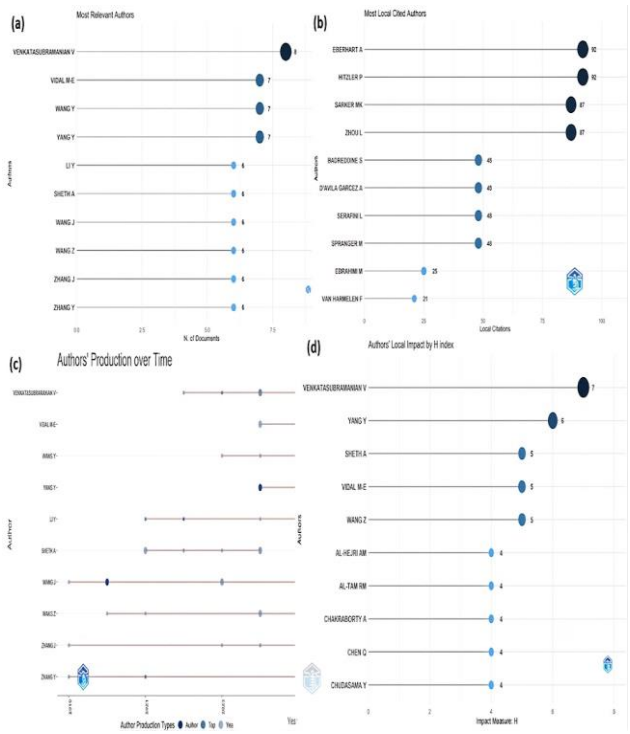


Figure 4. Bibliometric analysis of author productivity and impact. (a) Most relevant authors ranked by publication output. **(b)** Most locally cited authors within the research field. **(c)** Authors' production over time showing the evolution of publication activity. **(d)** Top authors based on scientific impact (e.g., H-index, total citations, or fractionalized publications, depending on the analysis).

3.4 Institutional Performance Analysis

This figure examines the institutional landscape of Neuro-Symbolic Artificial Intelligence research, highlighting both the most active affiliations and their growth trajectories from 2015 to 2025(Aria & Cuccurullo, 2017b; Donthu et al., 2021b) Panel (a) identifies the University of Florida as the most productive institution, leading with 15 published articles, followed by Columbia University and the University of California. Panel (b) provides a longitudinal analysis through the "Affiliations' Production over Time," which reveals a synchronized trend of rapid research acceleration across these leading institutions, particularly showing a sharp increase in output initiated between 2023 and 2025. Together, these visualizations underscore the concentration of high-impact research within a select group of globally recognized universities, demonstrating their pivotal role in driving the recent expansion of the field(Aria & Cuccurullo, 2017b; Baas et al., 2020).

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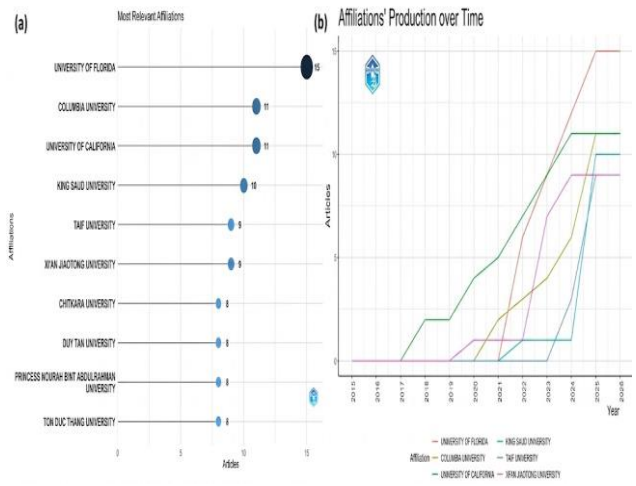


Figure 5. Institutional research productivity. (a) Most relevant affiliations ranked according to scientific publications. **(b)** Affiliations' production over time showing the evolution of institutional research output.

3.5 Country-Level Scientific Performance

This multi-panel analysis provides a comprehensive overview of the global scientific landscape for Neuro-Symbolic Artificial Intelligence, illustrating both geographical productivity and scholarly impact(Aria & Cuccurullo, 2017b; Donthu et al., 2021b) . Panel (a) presents the global distribution of scientific production, while panel (b) highlights a pronounced acceleration in publication trends across leading nations, particularly noting a sharp upward trajectory beginning around 2024. Panel (c) ranks the "Most Cited Countries," identifying Germany, the USA, and China as the primary drivers of influence based on total citation counts. Furthermore, panel (d) differentiates between Single Country Publications (SCP) and Multiple Country Publications (MCP), revealing that countries such as China and India maintain substantial research output through a robust mix of domestic and international collaborations(Baas et al., 2020) Collectively, these visualizations underscore the concentration of high-impact, collaborative research within a few key global hubs, which are critical to the ongoing evolution of the field (Donthu et al., 2021b; Zupic & Čater, 2015b).

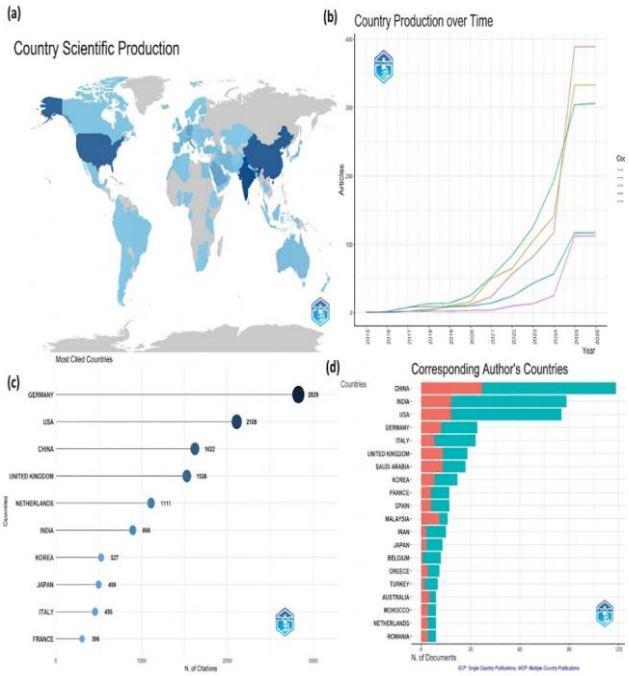
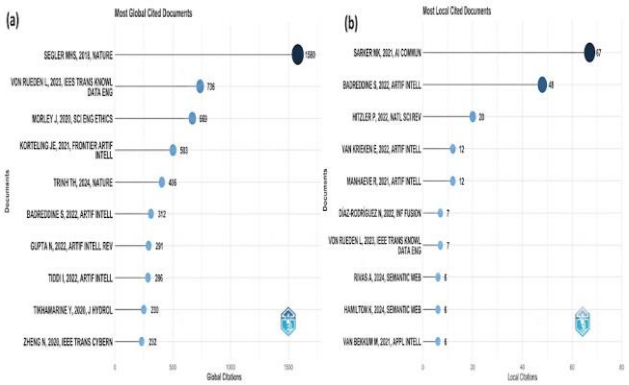


Figure 6. Country-level scientific production and impact. (a) Scientific production by country. **(b)** Country-wise publication trends over time. **(c)** Most cited countries based on total citation counts. **(d)** Geographical distribution of corresponding authors by country.

3.6 Analysis of Highly Influential Articles

This figure presents a comparative analysis of document influence within the Neuro-Symbolic Artificial Intelligence field, distinguishing between broader academic recognition and specific community impact(Donthu et al., 2021b). Panel (a) highlights the "Most Global Cited Documents," showcasing works, which have achieved high citation counts across the scientific literature(Segler et al., 2018) In contrast, panel (b) displays the "Most Local Cited Documents," which identifies foundational research highly utilized within this specific research domain,(Sarker et al., 2021)**.** Together, these metrics illustrate the dual nature of scholarly influence, where certain documents gain widespread recognition while others serve as critical, highly cited references specifically within the Neuro-Symbolic AI community(Hitzler et al., 2017, 2022)



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Figure 7. Citation analysis of highly influential articles. (a) Most globally cited articles ranked by total citations in the Scopus database. **(b)** Most locally cited articles based on citations within the analyzed dataset.

3.7 Reference Analysis

This visualization provides a concise overview of the "Most Local Cited References" within the Neuro-Symbolic Artificial Intelligence research community, mapping the foundational texts that underpin the field's ongoing discourse(Goodfellow et al., 2016; Lecun et al., 2015a) The chart ranks these influential references based on their local citation frequency, leading the list. further represent the importance of explainability in AI research(Goodfellow et al., 2016; Lecun et al., 2015)Together, these references reflect a robust intellectual lineage, demonstrating how core concepts in deep learning, neural network architectures, optimization, probabilistic reasoning, and explainable AI are synthesized to drive current research developments within this specialized domain(Besold et al., 2017; de Raedt et al., 2020; Garcez et al., 2019).

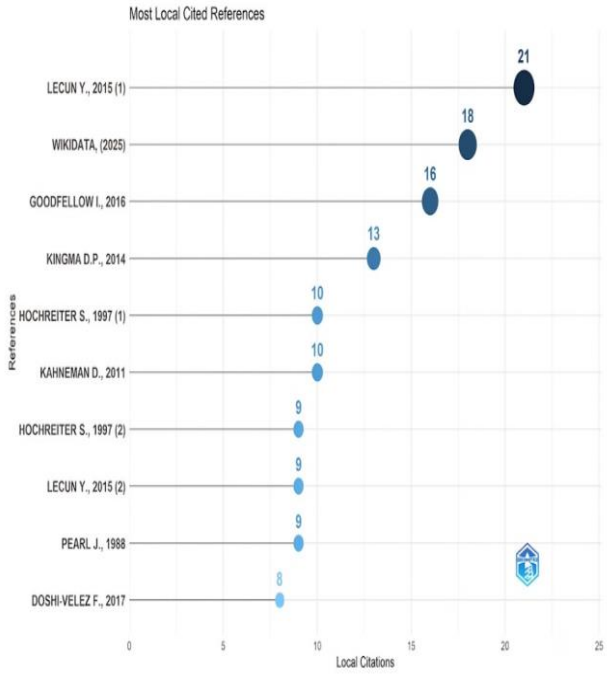


Figure 8. Analysis of influential references. Most locally cited references representing the intellectual foundation of the research field.

3.8 Keyword Analysis and Research Trends

This multi-panel figure provides a detailed bibliometric analysis of terminology within the field of Neuro-Symbolic Artificial Intelligence (Aria & Cuccurullo, 2017; van Eck & Waltman, 2010) **.** Panel (a) highlights the most relevant keywords, with "artificial intelligence," "machine learning," and "deep learning" emerging as the most frequently occurring terms(Goodfellow et al., 2016; Modern, 2021). Panel (b) illustrates these research themes through a word cloud, emphasizing the prominence of core concepts alongside specialized topics like "learning systems" and "forecasting." Panel (c) charts the cumulative "Words' Frequency over Time," showcasing a significant, synchronized acceleration in the usage of these primary keywords, particularly trending upward around 2024. Finally, panel (d) maps "Trend Topics," tracking the chronological emergence of various research subjects—from early focus on "hybrid expert systems" to more recent advancements in "artificial intelligence" and "deep learning"—which reflects the evolving technical landscape of the domain(Garcez et al., 2019a; Hitzler et al., 2022a; Sarker et al., 2021d)

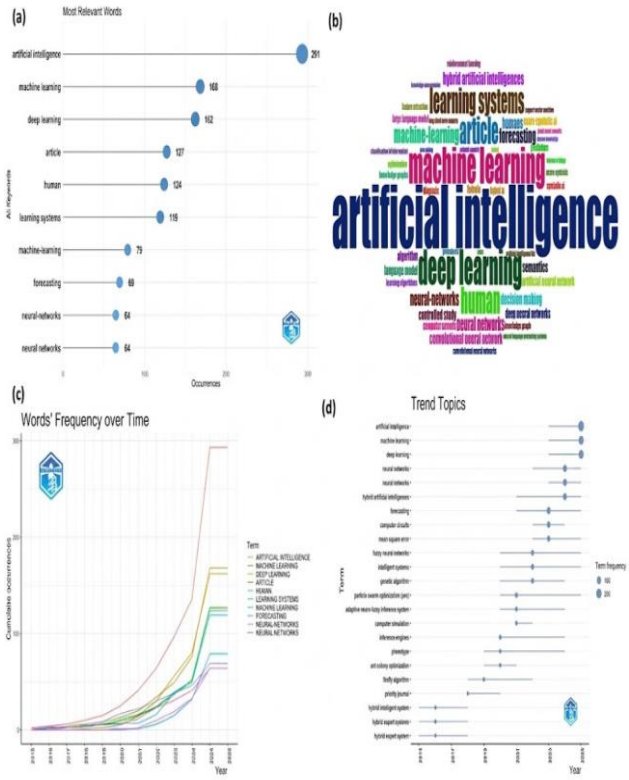


Figure 9. Keyword analysis and research evolution. (a) Most frequently occurring author keywords. **(b)** Word cloud illustrating the prominence of major research themes. **(c)** Temporal evolution of keyword frequency over the study period. **(d)** Trend topics highlighting emerging and declining research themes.

3.9 Conceptual Structure of the Research Field

This figure provides a bibliometric visualization of key thematic structures within the field of Neuro-Symbolic Artificial Intelligence(Aria & Cuccurullo, 2017; van Eck & Waltman, 2010). Panel (a) displays a co-occurrence network, illustrating the complex relationships and clusters between major research concepts, where terms like "artificial intelligence," "machine learning," and "deep learning" act as central nodes(Goodfellow et al., 2016; Modern, 2021). Complementing this, panel (b) presents a thematic map that plots these topics based on their relevance (centrality) and development degree (density), distinguishing between emerging or niche themes, established motor themes, and declining areas of interest(Donthu et al., 2021). Together, these visualizations offer a comprehensive look at how research topics are interconnected and their current standing within the scholarly discourse of this

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domain(Zupic & Čater, 2015).

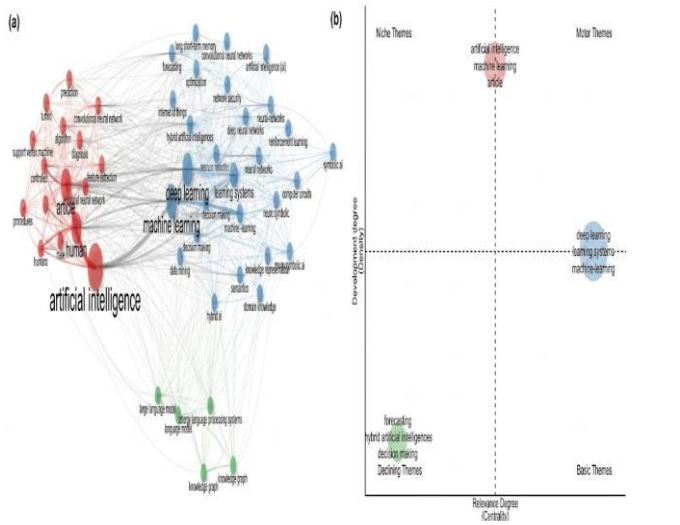


Figure 10. Conceptual structure of the research field. (a) Keyword co-occurrence network illustrating relationships among major research themes. **(b)** Thematic map showing the development, relevance, and maturity of research topics.

3.10 Social and Intellectual Structure of the Research Field

This figure presents a comprehensive bibliometric overview of the research landscape in Neuro-Symbolic Artificial Intelligence, highlighting both intellectual influence and global collaboration(Aria & Cuccurullo, 2017a; van Eck & Waltman, 2010)**.** Panel (a) features a co-citation network that identifies foundational scholarly works, which serve as critical nodes connecting different research clusters(Goodfellow et al., 2016; Lecun et al., 2015a; *Thinking, Fast and Slow.*, n.d.-a)**.** Panel (b) illustrates a global collaboration map, demonstrating the widespread international cooperation in the field, with high-intensity research activity and connectivity centered in regions like North America, Europe, and parts of Asia(Baas et al., 2020; Donthu et al., 2021). Finally, panel (c) displays a co-authorship network that maps the relationships between individual researchers, revealing collaborative groups and prominent figures within the community(Aria & Cuccurullo, 2017) **.** Together, these visualizations detail how intellectual knowledge is structured and how the scientific community is geographically and socially integrated(Besold et al., 2017; Garcez et al., 2019a)

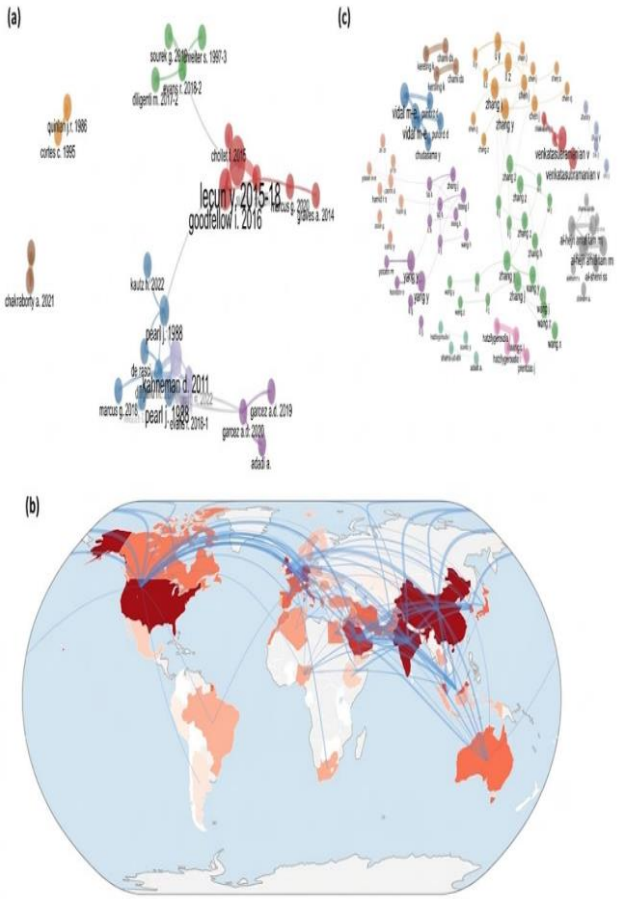


Figure 11. Social and intellectual structure of the research field. (a) Co-citation network revealing the intellectual foundations of the research domain. **(b)** International collaboration world map illustrating research partnerships among countries. **(c)** Author collaboration network showing scientific cooperation among leading researchers.

4. DISCUSSION

The findings of this bibliometric analysis demonstrate that Neuro-Symbolic Artificial Intelligence has transitioned from a theoretical intersection of disciplines into a rapidly maturing, high-impact field of research(Besold et al., 2017; de Raedt et al., 2020b; Garcez et al., 2019a). The observed surge in publication volume, particularly post-2024, indicates that the scientific community has increasingly recognized the limitations of isolated connectionist and symbolic models, driving a collective pivot toward hybrid architectures that prioritize both high-dimensional pattern recognition and formal logical reasoning(Hitzler et al., 2022) This shift is corroborated by the thematic evolution highlighted in our analysis, where early explorations of "hybrid expert systems" have been progressively replaced by sophisticated, integrated frameworks capable of addressing complex, real-world problems(de Raedt et al., 2020c; Garcez et al., 2019a).

Our institutional and country-level performance analysis underscores a global convergence of expertise, with North America, Europe, and Asia serving as the primary engines of this technological progression(Baas et al., 2020; Donthu et al., 2021). The high frequency of international co-authorship suggests that the complexity of Neuro-Symbolic AI inherently necessitates interdisciplinary and cross-border cooperation(Aria & Cuccurullo, 2017a). Furthermore,

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the prominence of leading journals, as identified by our Bradford's Law analysis, reflects a concentration of core research that provides a stable, high-quality foundation for future inquiry(Donthu et al., 2021b; Zupic & Čater, 2015. This structural maturity is essential for the field to maintain scientific rigor as it integrates deeper into mainstream computational research.

The intellectual foundation of the domain, characterized by highly cited seminal works, reveals a robust lineage that bridges cognitive science and machine learning(Goodfellow et al., 2016; Lecun et al., 2015). The enduring influence of foundational references suggests that while the field embraces cutting-edge deep learning, it remains deeply rooted in established principles of probabilistic reasoning and knowledge representation(Hochreiter & Schmidhuber, 1997; Kingma & Ba, 2014). As researchers continue to build upon these pillars, the challenge of explainability—a hallmark of symbolic AI—emerges as a critical success factor for the widespread adoption of modern Neuro-Symbolic systems(Doshi-Velez & Kim, 2017; *High-Level Expert Group on Artificial Intelligence | Shaping Europe's Digital Future*, n.d.)

Looking forward, the bibliometric evidence points toward a sustained trajectory of growth, fueled by both academic necessity and practical application. As deep learning models face increasing scrutiny regarding their "black-box" nature, the integration of symbolic components provides a viable pathway to achieving transparency without sacrificing performance(Bommasani et al., 2021; Bubeck et al., 2023; Doshi-Velez & Kim, 2017). evolution is mirrored in our trend topic mapping, which shows a gradual shift from generalized machine learning terminologies toward more specific, architecturally complex keywords that reflect the field's increasing technical depth(Garcez et al., 2019; Hitzler et al., 2022)**.**

In summary, this research clarifies that the trajectory of Neuro-Symbolic AI is defined by a move toward robustness and interpretability(Besold et al., 2017; Hitzler et al., 2022). As the community continues to refine these hybrid models, the concentration of research within high-impact hubs and the ongoing synthesis of diverse methodologies will likely yield the next generation of intelligent, human-centric systems(Bommasani et al., 2021; de Raedt et al., 2020) **.**This study provides a vital empirical snapshot of this growth, offering a roadmap for stakeholders to anticipate and contribute to the continued advancement of this interdisciplinary domain.

5. CONCLUSION

This bibliometric study has provided a rigorous and comprehensive assessment of the Neuro-Symbolic Artificial Intelligence landscape over the 2015–2025 period(Aria & Cuccurullo, 2017b; Donthu et al., 2021). By synthesizing data from 877 peer-reviewed articles retrieved from the Scopus database, the research identifies a significant, synchronized acceleration in scholarly output and citation impact, particularly beginning around 2024(Baas et al., 2020). The findings highlight that the research community is increasingly prioritizing the development of sophisticated hybrid architectures that bridge the gap between connectionist pattern recognition and formal logical reasoning, a shift clearly evidenced by the evolution of trend topics from early hybrid expert systems toward modern, interpretability-focused methodologies(Besold et al., 2017; Garcez et al., 2019; Hitzler et al., 2022). Furthermore, the study delineates a global intellectual and social structure, where key institutions and countries—specifically Germany, the USA, and China—serve as primary engines of innovation, supported by robust international co-authorship networks(Aria & Cuccurullo, 2017; Donthu et al., 2021). The enduring influence of seminal works by authors confirms that the field remains anchored in a strong intellectual lineage while simultaneously branching into specialized, architecturally complex research(Goodfellow et al., 2016; Lecun et al., 2015). Ultimately, this analysis establishes that the future of intelligent, human-centric systems is inextricably linked to the successful integration of neural and symbolic methodologies, providing a foundational roadmap for practitioners and policymakers to navigate the ongoing maturation and interdisciplinary expansion of this vital research domain(Bubeck et al., 2023; de Raedt et al., 2020).

6. LIMITATIONS

Despite the comprehensive insights provided by this bibliometric analysis, several inherent limitations must be acknowledged to ensure a balanced interpretation of the findings(Donthu et al., 2021b; Zupic & Čater, 2015). First, the study relies exclusively on data retrieved from the Scopus database; while Scopus is a high-quality repository for peer-reviewed literature, it may exclude relevant research indexed in other databases like Web of Science or Google Scholar, as well as grey literature, books, and non-English publications that could offer additional perspectives on Neuro-Symbolic AI(Baas et al., 2020). Second, the reliance on keyword-based retrieval inherently depends on the consistency and accuracy of terminology used by authors and indexers; since interdisciplinary fields often experience semantic drift or terminology variation, there is a potential risk that some relevant studies were omitted or that tangential research was inadvertently included(Page et al., 2021a). Third, citation-based metrics, such as the h-index and total citation counts, are subject to time-lag effects and disciplinary biases, meaning they may not fully capture the qualitative significance of very recent contributions, particularly those published in the latter part of the study period(Donthu et al., 2021). Finally, bibliometric analysis is inherently quantitative and does not account for the intrinsic quality or content-level merit of individual publications, nor does it mitigate the potential for self-citation or collaborative biases within research clusters(Aria & Cuccurullo, 2017b; Zupic & Čater, 2015). Consequently, while this work provides a robust statistical map of the field's intellectual and social evolution, the findings should be viewed as a complementary lens alongside qualitative expert reviews rather than an exhaustive representation of all knowledge production within the Neuro-Symbolic AI domain(Donthu et al., 2021).

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