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Research paper

A Scientometric Review of Neural Differential Equations: Mapping Research Impact and Collaborative Networks

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Abstract

Neural Differential Equations (NDEs) represent an emerging class of machine learning models that combine the strengths of neural networks and differential equations to model continuous-time dynamics with high interpretability. This study presents a comprehensive bibliometric analysis of NDE research using data extracted from the Scopus database. Analytical tools such as Biblioshiny, VOSviewer, and CiteSpace were employed to uncover patterns, trends, and structural relationships within the field. The annual scientific production shows a significant growth trajectory, with a peak in 2023, indicating rising scholarly interest. Most relevant authors include Rackauckas, Nopens, and Chien, whose contributions have shaped the theoretical and applied dimensions of NDEs. Co-citation networks of both authors and journals revealed well-defined research clusters focused on deep learning techniques, scientific machine learning, and graph-based modeling. Country-wise analysis highlights the dominance of the United States and China, followed by notable contributions from the UK, Canada, and India. Keyword co-occurrence and trend analysis identified emerging themes such as "transformer," "graph neural networks," and "scientific machine learning," reflecting ongoing methodological innovation. Thematic evolution and mapping show a shift from foundational terms to more specialized and interdisciplinary applications. Identified research gaps suggest a need for stronger theoretical integration, benchmark development, and application in real-world domains, offering practical implications for researchers and practitioners in AI, engineering, and applied sciences.

Keywords: *Biblioshiny; Citespace; Neural Differential Equations; Scientometric Analysis; Vosviewer.*

1. Introduction

Neural Differential Equations (NDEs) represent a revolutionary intersection of machine learning and the classical domain of differential equations, offering a hybridized framework that adapts traditional mathematical modeling to data-driven contexts [1], [2]. These equations embed neural networks within the structure of ordinary differential equations (ODEs), enabling models that are both interpretable and flexible [3]. Unlike conventional neural networks that operate in discrete layers, neural differential equations evolve continuously over time, capturing the dynamics of systems more naturally and accurately [4], [5]. The emergence of this approach has significantly influenced areas such as time-series forecasting, physics-informed modeling, and systems biology [6].

The conceptual leap was catalyzed by the introduction of Neural Ordinary Differential Equations (Neural ODEs) by Chen et al. in 2018, where the forward pass of a neural network is treated as a numerical solution to an ODE. This opened avenues to blend deep learning with established numerical solvers, resulting in smoother training dynamics and reduced memory consumption through adjoint sensitivity methods [7]. Since then, the field has expanded into domains like stochastic differential equations, partial differential equations, and control systems, forming a broader class known as Neural Differential Equations [8]. These models demonstrate the capacity to generalize beyond observed data by learning latent dynamics, thus marking a significant shift from black-box models to interpretable frameworks [9].

Compared to traditional machine learning models, Neural Differential Equations offer several distinctive advantages. Unlike conventional neural networks, which are restricted to discrete layers, NDEs evolve continuously over time, enabling them to capture dynamical systems more naturally and with higher fidelity. This continuous formulation allows for adaptive computation, reduced memory use through adjoint sensitivity methods, and greater scalability for long time-series modeling. Furthermore, NDEs enhance interpretability by embedding prior knowledge and physics-informed constraints directly into the learning process. These strengths position NDEs as a powerful alternative to traditional models, bridging the gap between theoretical rigor and practical applicability.

The appeal of Neural Differential Equations lies in their theoretical rigor and practical utility [10], [11]. Theoretical advances in the form of convergence guarantees, stability analysis, and expressivity bounds have enriched the academic understanding of these models [12].

Simultaneously, practical implementations have proliferated through open-source libraries like torchdiffeq, DiffEqFlux, and NeuralPDE, allowing researchers and engineers to deploy these architectures in real-world applications [10]. From modeling chemical reaction kinetics to simulating planetary motion, NDEs have demonstrated their prowess across scientific and engineering domains [11].

Despite promises, there are some open issues in adopting and using neural differential equations [13], [14]. Instability in training, computational cost, and controlling errors in integration are some open areas of research [15]. More importantly, incorporating physics-based constraints and domain knowledge into the neural framework adds a higher level of complexity [16]. As research progresses in the future, it is going to be on hybrid approaches using symbolic and sub-symbolic representations, noise-robustness, and low-energy architectures [17]. As there is an identifiable growth in innovation, there is a need for a systematic as well as a complete scientometric overview of this nascent field [13].

With the development of Neural Differential Equations happening rapidly, it is crucial to chart the scholarship landscape to identify trends in publications, research areas, co-authors, and institutional collaboration [18]. The rationale for this research is driven by an interest in placing development and trends in NDE research within context, especially about new applications in science and engineering [19]. A scientometric perspective provides a systematic framework for assessing growth in the field, a framework for directing future researchers as well as policy-makers through evidence-driven analysis [18], [20].

Unlike prior reviews of Neural Differential Equations that emphasize mathematical formulations, algorithmic innovations, or domain-specific applications, this study adopts a bibliometric and scientometric lens. By focusing on publication trends, collaboration patterns, and thematic evolution, it provides a meta-level synthesis of the research landscape rather than technical derivations or performance benchmarks. This study delimits itself to the scientometric mapping and bibliometric analysis of literature related to Neural Differential Equations from 2018 to 2025. It includes peer-reviewed articles, conference proceedings, and reviews indexed in Scopus databases [21]. The scope further incorporates thematic clustering, co-citation analysis, keyword co-occurrence, and institutional collaborations to reveal the intellectual, conceptual, and social structures of the domain [22], [23]. This analysis does not cover the mathematical derivations or experimental simulations of NDEs, focusing solely on their research trends and academic dissemination.

While the existing literature on NDEs has primarily emphasized methodological advances and domain-specific applications, there remains a clear gap in systematic bibliometric syntheses of the field. Previous works have charted important milestones—most notably the introduction of Neural ODEs in 2018—which laid the foundation for subsequent developments such as physics-informed NDEs, stochastic formulations, and graph-based models. However, despite the rapid growth of research output, no comprehensive scientometric study has yet mapped the intellectual structure, collaboration patterns, and thematic evolution of NDEs. This study addresses that unmet need by providing the first consolidated bibliometric analysis of the domain.

Recent works have also introduced several noteworthy advances in Neural Differential Equations and related operator learning frameworks. For example, PINNsFormer (2023) integrates transformer architectures into physics-informed neural networks to better capture temporal dependencies in PDEs, demonstrating superior generalization compared to classical PINNs [24]. The GITO model (2025) proposes a Graph-Informed Transformer Operator that combines graph neural networks with transformer neural operators to handle PDE systems on irregular geometries, achieving mesh-agnostic predictions [25]. ODEFormer (2023) infers symbolic forms of multidimensional ODE systems from observed trajectories, showing robustness to noisy and irregularly sampled data [26]. Moreover, Transformers as Neural Operators for Solutions of PDEs establishes that transformer-based models possess the universal approximation property as solution operators, with applications to the Izhikevich neuron model and fractional-order Leaky Integrate-and-Fire systems. These studies not only highlight methodological innovations (transformers, symbolic regression, operator learning) but also illustrate expanding interdisciplinary applications in neuroscience, computational biology, and control theory, underscoring the relevance of incorporating recent trends into the reviewed literature.

Scientometric analysis is a valuable tool for tracking the development and organization of scientific knowledge [22], [27], [28]. In the context of Neural Differential Equations, it allows one to identify leading research themes, key authors and journals, and knowledge production geographies. By using citation, keyword trends, and co-authorship networks, this research explains how the research community has structured itself across this new paradigm [29], [30]. Academic scholarship as well as research policy are informed by what can be gleaned from such an analysis in terms of gaps, trends, and potential opportunities [31], [32].

Biblioshiny, an R-based web interface for the Bibliometrix package, facilitates interactive bibliometric analysis with a focus on visualization and customization [33 - 35]. It supports comprehensive descriptive and inferential statistics such as author productivity, annual growth rates, and Bradford's Law distribution [36], [37]. Biblioshiny's intuitive interface allows researchers to perform analyses without extensive coding, making it an ideal tool for interdisciplinary investigations. In this study, Biblioshiny is used for trend analysis, keyword growth, and source impact metrics, offering an overarching narrative of the field's development [35].

VOSviewer and CiteSpace specialize in mapping and visualizing bibliographic networks [38], [39]. VOSviewer excels in generating clustered visual maps of co-authorship, keyword co-occurrence, and citation networks. Its strength lies in handling large-scale data and producing high-resolution knowledge maps [40], [41]. CiteSpace complements this by focusing on temporal patterns, burst detection, and turning points in research evolution. It identifies pivotal articles and emerging themes through timeline visualizations and citation bursts [42 - 44]. The synergy of these tools enables a multidimensional view of the Neural Differential Equations landscape, offering both breadth and depth in scientometric insights.

The primary objective of this study is to conduct a comprehensive scientometric analysis of the literature on Neural Differential Equations using the tools Biblioshiny, VOSviewer, and CiteSpace. This analysis seeks to uncover key publication trends, influential sources, and prominent contributors shaping the field. Additionally, it aims to map the conceptual and intellectual structure through keyword co-occurrence and co-citation networks, analyze collaboration patterns among authors, institutions, and countries, and detect emerging research fronts and thematic evolutions. Through these objectives, the study intends to generate actionable insights for researchers, educators, and policy-makers, thereby offering a meta-level understanding of the growth, direction, and interdisciplinary impact of Neural Differential Equations within the scientific community.

2. Materials and Methods

The bibliometric data for this study were sourced from Scopus, a widely recognized database that offers a broad collection of peer-reviewed scientific literature, ensuring high-quality research inclusion [45 - 47]. The search query used was TITLE-ABS-KEY ("Neural Differential Equations"), ensuring a comprehensive retrieval of relevant publications. The search was not restricted by language, and the dataset included records from peer-reviewed journal articles, book chapters, and conference papers. To enhance the reliability of the dataset, a meticulous screening process was undertaken to remove duplicate entries and irrelevant document types, such as reviews, editorials, books, short notes, letters, data papers, and short surveys. Figure 1 illustrates the PRISMA framework used for inclusion and exclusion. Out of 118 initial records retrieved from Scopus, 5 records were excluded due to being categorized as conference reviews, books, and Data papers. The remaining 113 records (59 journal articles, 51 conference papers, and 3 book chapters) were assessed for eligibility and subsequently included in the bibliometric review. This systematic process ensures that only relevant and high-quality research studies contribute to the scientometric analysis. The final dataset was saved in both CSV and RIS formats and analyzed using CiteSpace (version 6.2.R3 Advanced), VOSviewer, and Biblioshiny (Bibliometrix R package). These tools facilitated network visualization, co-authorship mapping, citation analysis, and keyword co-occurrence analysis, offering insights into the research trends, influential authors, and emerging themes in customer journey research.

To further enhance reproducibility, we specified the key parameters used in the analysis. In VOSviewer (v1.6.20), co-occurrence analysis was performed with a minimum keyword threshold of 2, using fractional counting and LinLog/modularity clustering. CiteSpace (v6.2.R3 Advanced) employed annual time slices (2016–2025), the g-index with k = 25 for citation selection, cosine similarity for network normalization, and pruning through the pathfinder option. These settings provide a transparent basis for replicating the bibliometric mapping process.

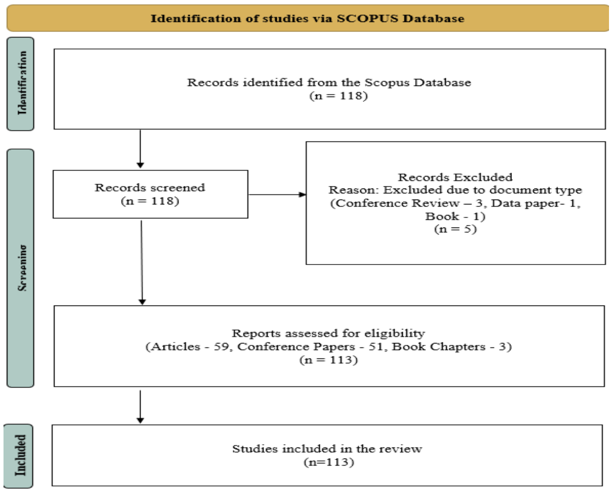

Fig. 1: PRISMA Flow Diagram Used to Identify, Screen, and Include Papers in the Bibliometric Analysis.

3. Findings

3.1. Main information of the investigation

The main information derived from the scientometric investigation of Neural Differential Equations from 2016 to 2025 highlights the rapid and growing interest in this emerging field. With 113 documents published across 82 sources, the study exhibits a remarkable annual growth rate of 38.7%, signaling a vibrant and expanding research domain. The average document age of 2.12 years confirms the recency and novelty of contributions, while an average citation rate of 8.885 per document reflects substantial academic engagement. The dataset includes 4,598 references, indicating a strong foundation in interdisciplinary research. Overall, the metrics suggest that Neural Differential Equations have quickly become a focal point of scholarly attention, driven by their applicability across scientific and engineering disciplines.

3.2. Annual scientific productions

Figure 2 illustrates the annual scientific production on Neural Differential Equations from 2016 to May 2025, revealing a clear upward trend in publication activity. The field began with minimal contributions in its early years—only one article each in 2016 and 2019, and none in 2017 and 2018. However, starting in 2020, there is a notable surge in research output, increasing from 5 publications in 2020 to 14 in 2021, peaking at 30 articles in 2023. This rapid growth reflects the field's rising academic relevance and research momentum. Although there is a slight decline in 2024 (23 articles) and a total of 19 articles by May 2025, the cumulative trend underscores sustained scholarly interest and the establishment of Neural Differential Equations as a vibrant and evolving research area.

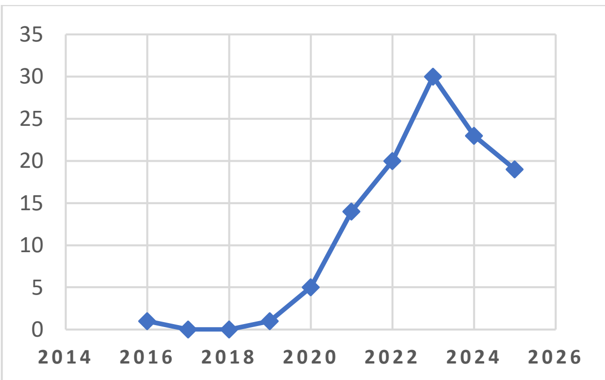

Fig. 2: Significant Growth Trajectory from 2016 to 2025.

3.3. Most relevant authors

Figure 3 presents the most relevant authors in the domain of Neural Differential Equations based on the number of publications. The leading contributors are Ingmar Nopens and Christopher Rackauckas, each with four articles, indicating their prominent and sustained engagement in the field. Following closely are a group of researchers—Yi-Hsiang Chen, Jen-Tzung Chien, Mark Girolami, Min Han, Qiyu Kang, Wee Peng Tay, and Qipeng Wang—each with three publications, highlighting a core group of active scholars contributing to the foundational and applied research on Neural Differential Equations. Wenjun Cui, with two publications, also appears among the top contributors. The relatively close distribution of publication counts among these authors reflects a collaborative and rapidly growing research community, with multiple thought leaders shaping the field's evolution.

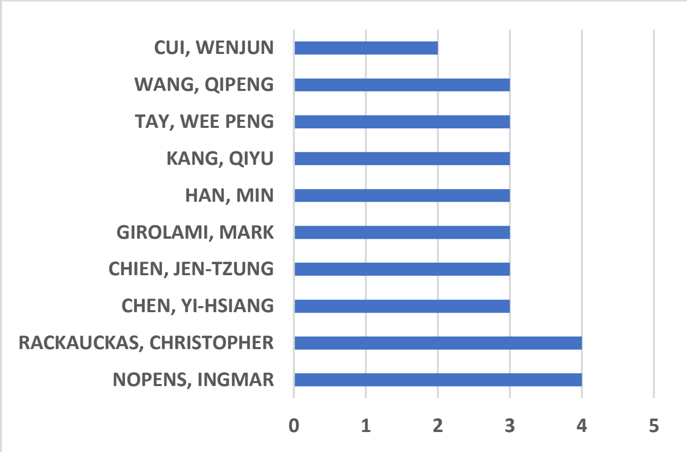

Fig. 3: Most Relevant Authors.

3.4. Network visualization of co-citation of cited authors

The network visualization in Figure 4 reveals nine distinct clusters of co-cited authors, each representing a thematic focus in the field of Neural Differential Equations (NDEs). Cluster #0, titled “Deep Learning Technique,” is the largest, comprising 62 members with a silhouette value of 0.695. This cluster anchors the theoretical foundations of NDEs, with highly cited contributors such as Rubanova Y (24 citations), Kingma DP (23), Rackauckas C (23), and Raissi M (21). These authors are pivotal in establishing the early frameworks that combine differential equation modeling with deep learning, particularly in the context of Neural ODEs and Physics-Informed Neural Networks (PINNs). The major citing works in this cluster explore solver heuristics, black-box modeling, and time-series analysis using deep learning techniques.

Cluster #1 (“Inductive Spatio-Temporal GraphODE”) and Cluster #2 (“Sequential Learning”) reflect more specialized applications of NDEs. Cluster #1, with 29 members and a high silhouette value of 0.843, focuses on integrating graph neural networks with differential equations to model dynamic spatio-temporal systems like traffic flow. Key contributors include Kidger P (30 citations) and He K (19). Cluster #2 (25 members; silhouette: 0.887) is centered around attention-based models and sequence learning, citing Vaswani A (18 citations) and Liu X (11). This cluster connects continuous-time modeling with Transformer architectures and self-attention mechanisms, underlining NDEs' growing relevance in time-series and long-sequence tasks.

Further technical sophistication is evident in Cluster #3 (“ODE Adjoint”) and Cluster #4 (“Adaptive Graph Convolution”), which have 23 and 20 members, respectively. Cluster #3 (silhouette: 0.94) includes authors like Dormand Jr. and Grathwohl, W, and focuses on optimization, stability, and efficient training of NDEs using adjoint methods. Cluster #4 (silhouette: 0.869) brings together research in adaptive and causal graph convolutional networks within the NDE framework. Influential authors such as Hochreiter S (11 citations) and Lechner M (5) demonstrate how spatial learning is being redefined through neural-differential modeling for structured and temporal data.

The remaining clusters reflect niche or emerging applications of NDEs. Cluster #5 (“Continuous Depth Recurrent”) highlights innovations in recurrent neural architectures and includes the most cited individual in the network, Chen RT (40 citations). Cluster #6 (“Demand Response Program”) explores energy systems and control, while Cluster #7 (“Face Recognition”) focuses on vision-based applications of NDEs. The smallest yet most coherent cluster, Cluster #8 (“Colloidal Fouling”), centers on the application of NDEs in physical systems such as fluid dynamics. Together, these clusters illustrate both the diverse methodological advancements and the wide-ranging applicability of NDEs, with significant cross-disciplinary relevance emerging in engineering, physics, and artificial intelligence.

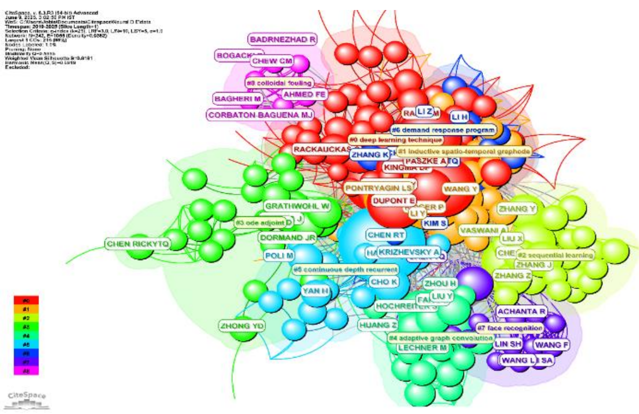

Fig. 4: Network Visualization of Co-Citation of Cited Authors.

3.5. Most relevant sources

Table 1 highlights the most relevant publication sources contributing to the field of Neural Differential Equations. Leading the list is "Advances in Neural Information Processing Systems" (NeurIPS) with 9 articles, reflecting its central role in disseminating cutting-edge research in machine learning and deep learning. This is followed by the "Proceedings of Machine Learning Research" with 7 publications, and "Lecture Notes in Computer Science" with 5, indicating the academic community's preference for venues that emphasize theoretical frameworks and algorithmic innovations. Other significant sources include "Information Sciences" and the "AAAI Conference on Artificial Intelligence", each contributing 3 articles, showcasing interdisciplinary interest from both computer science and applied mathematics domains. Additionally, specialized venues such as "Applied Intelligence", "Computers and Chemical Engineering", and "ICASSP", each with 2 articles, demonstrate the field's application across engineering, signal processing, and domain-specific problem-solving. Overall, the distribution of sources confirms that Neural Differential Equations are gaining recognition across both foundational AI conferences and application-oriented journals.

Table 1: Most Relevant Sources

Sources	Articles
Advances in Neural Information Processing Systems	9
Proceedings of Machine Learning Research	7
Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	5
Information Sciences	3
Proceedings of The AAAI Conference on Artificial Intelligence	3
11th International Conference on Learning Representations, ICLR 2023	2
Applied Intelligence	2
Computer Methods in Applied Mechanics and Engineering	2
Computers and Chemical Engineering	2
ICASSP, IEEE International Conference on Acoustics, Speech and Signal Processing - Proceedings	2

3.6. Timezone network visualization of co-citation of cited journals

The co-citation network in Figure 5 comprises 9 major clusters, each indicating a distinct scholarly community based on shared citation patterns among journals. Cluster #0, labeled Physics-Informed Deep Learning, is the largest with 45 members and a strong silhouette value of 0.878, signaling cohesive thematic alignment. This cluster is anchored by journals like Computer Methods in Applied Mechanics and Engineering, Journal of Computational Physics, and Chemical Engineering Journal, all heavily cited in research applying neural differential equations (NDEs) to physics-constrained and mechanistic modeling. Articles in this cluster focus on integrating deep learning with domain knowledge, especially in fields like biomechanics, materials modeling, and energy systems. The co-citation strength suggests this domain plays a foundational role in bridging engineering applications with AI techniques.

Cluster #1, Aware Neural Differential Equation, with 32 members (silhouette: 0.707), showcases journals like IEEE Access, Neural Ordinary Differential Equations, and prominently the International Conference on Machine Learning (ICML). The thematic orientation here lies in awareness-driven modeling, including human-trajectory prediction, neural reaction-diffusion systems, and high-order differentiable networks. This cluster highlights emerging developments in biologically and socially aware NDE frameworks. Similarly, Cluster #2, Preserving Invariant Quantities (30 members; silhouette: 0.897), is methodologically focused, emphasizing models that incorporate physical or mathematical constraints. Core publications like ICLR and Advances in Neural Information Processing Systems (NeurIPS) dominate this space, reflecting the push toward interpretability and model stability in neural dynamical systems.

Cluster #3, named Neural Net, has 29 members with a silhouette value of 0.841 and includes sources such as Neural Computation, Neurocomputing, and International Conference on Artificial Intelligence and Statistics (AISTATS). Its focus is mainly on neural architectures, as well as algorithmic innovation in NDE frameworks, including fractional-order networks as well as variable-depth networks. Cluster #4 (Face Recognition, 25 members; silhouette: 0.858) and Cluster #5 (Behavioural Change, 25 members; silhouette: 0.886) capture specific application areas. Cluster #4 has a close association with areas such as computer vision, as well as with pattern recognition, referring to conferences such as AAAI and CVPR, whereas Cluster #5 connects health dynamics with multi-agent modeling, referring to high-impact multidisciplinary sources such as Nature as well as Science. These two clusters show how NDEs pervade technical as well as application areas.

The remaining clusters—Cluster #6 (Sequential Learning, 18 members), Cluster #7 (Deep Learning Framework, 13 members), and Cluster #8 (Learning Visual Feature, 7 members)—although smaller in size, show high silhouette values (above 0.9), indicating specialized yet internally consistent citation behaviors. For instance, Cluster #6 integrates NDEs with attention-based models in time-series learning, citing sources like Scientific Reports and Machine Learning for Signal Processing. Cluster #7 and #8 concentrate on physics-based modeling and visual learning, citing niche journals such as Chaos, Phys. Fluids and Neural Networks. Overall, Figure 5 highlights a diverse and multidisciplinary ecosystem in which NDEs are applied, with distinct communities evolving around core methodological innovations, theoretical modeling, and practical applications in science, healthcare, and vision.

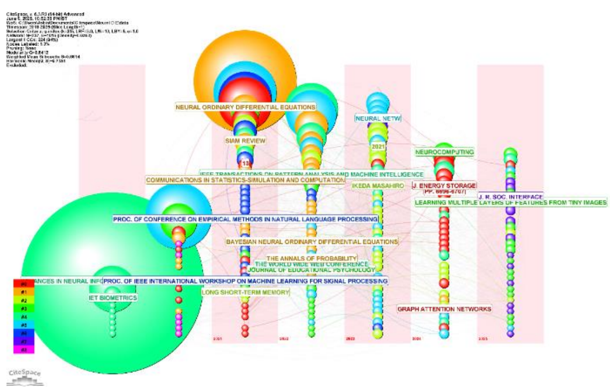

Fig. 5: Timezone Network Visualization of Co-Citation of Cited Journals.

3.7. Countries' scientific productions

Table 2 presents the country-wise scientific production in the field of Neural Differential Equations, revealing a globally distributed yet concentrated pattern of research contributions. The United States leads with 32 documents, reflecting its dominant role in advancing computational modeling and AI research. Closely following is China with 30 publications, highlighting its rapid growth and investment in emerging technologies. The United Kingdom ranks third with 12 contributions, maintaining a strong presence in theoretical and applied AI research. Canada and India each contributed 8 documents, demonstrating active participation from both North American and South Asian academic communities. Belgium and Germany, with 6 publications each, reflect Europe's continued engagement in interdisciplinary research. Meanwhile, countries like Italy, Singapore, and South Korea each contributed 4 documents, underscoring the global relevance and collaborative nature of the field. This geographical distribution indicates that Neural Differential Equations are of international interest, with leading contributions stemming from countries with established AI research ecosystems.

Table 2: Countries' Scientific Productions

Country/Territory	Documents
United States	32
China	30
United Kingdom	12
Canada	8
India	8
Belgium	6
Germany	6
Italy	4
Singapore	4
South Korea	4

3.8. Network visualization of citation of documents

Figure 6 presents a visual and tabular depiction of the most cited publications in Neural Differential Equations, demonstrating impact through citation count. Leading is Gu (2021) with an astonishing 308 citations, undoubtedly leading all other citations and highlighting foundational significance or a commonly applied method within the field. Close behind come Yue (2022) with 70 citations, then Quaghebeur (2022) with 51, both contributing seminal pieces that have profoundly influenced current research trajectories. Other influential works include Ma (2021) and Yuan (2022) with 43 and 40 citations, respectively, while a steady cluster of documents like Kim (2021), De Jaegher (2020), and Rehman (2024) show moderate but impactful citation counts ranging from 26 to 30. The bubble size and placement in the VOSviewer map visually reflect the relative impact of each document, where larger circles and central positions indicate higher citation impact and interconnection with other works. Collectively, this figure highlights the core literature driving the Neural Differential Equations research community and provides insight into the scholarly works that form the theoretical and methodological backbone of the field.

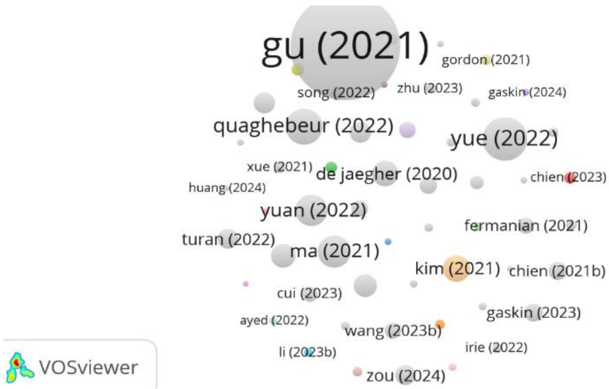

Fig. 6: Network Visualization of Citation of Documents.

3.9. Co-occurrence of all keywords

Figure 7 illustrates the co-occurrence network of author keywords related to Neural Differential Equations, generated using VOSviewer with a minimum occurrence threshold of 2. From 264 keywords, 29 met this criterion, resulting in a network of 28 nodes distributed across five distinct clusters. Each cluster, differentiated by color, represents a thematic grouping within the research landscape. Cluster 1 (Red) includes keywords like "neural ODEs," "differential equations," and "neural networks," focusing on foundational mathematical constructs and computational structures. Cluster 2 (Green) comprises terms such as "graph neural networks," "neural differential equations," and "mechanism modeling," reflecting specialized architectures and the integration of structured data into dynamic modeling tasks. These clusters suggest that the core theoretical and structural aspects of Neural Differential Equations are deeply interlinked with evolving model architectures and problem-solving strategies.

Cluster 3 (Blue), the most extensive, centers around "neural differential equations," "machine learning," and "model calibration," indicating the dominant role of general-purpose AI and optimization within the field. Cluster 4 (Yellow) features emerging interdisciplinary terms such as "scientific machine learning," "physics-informed machine learning," and "data assimilation," reflecting increasing penetration of discipline-specific knowledge integration and uncertainty quantification. Finally, Cluster 5 (Purple) is centered on "neural ordinary differential equations," synthesizing theoretical developments with practical tools. The network structure reflects both core theme maturity as well as specialized areas' growth, highlighting Neural Differential Equations as a rich, interdisciplinary community influenced by seminal theory, recent machine learning, and scientific computation.

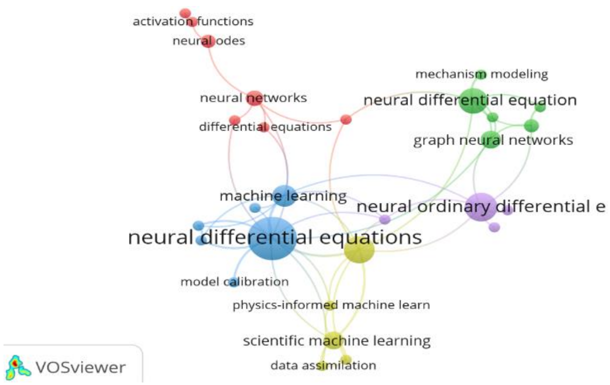

Fig. 7: Co-Occurrence of Author Keywords.

3.9. Trend topics

Figure 9 illustrates the trend topics in the field of Neural Differential Equations between 2022 and 2025, highlighting the evolution of research themes based on term frequency. The most prominent topic is "neural differential equations", peaking in 2023 with the highest term frequency, signifying its centrality in recent discourse. Closely related terms such as "neural ordinary differential equations," "deep learning," and "neural differential equation" appeared strongly in 2024, reflecting the maturation of foundational concepts and models. Other emerging themes include "scientific machine learning" and "graph neural networks," indicating growing interdisciplinary applications and methodological expansions within the field.

Additionally, earlier trends in 2022, such as "machine learning" and "neural networks," provided a broader context before the community focused on more specialized terms. Newer concepts like "transformer" and "neural ODEs" also began to surface, suggesting the integration of cutting-edge deep learning architectures into differential equation modeling. The timeline and frequency patterns suggest a progressive deepening of focus—from general AI and machine learning principles toward domain-specific hybrid models like Neural Differential Equations and their variants. This trend reflects a natural trajectory in scientific inquiry as researchers refine broad ideas into more precise, high-impact applications.

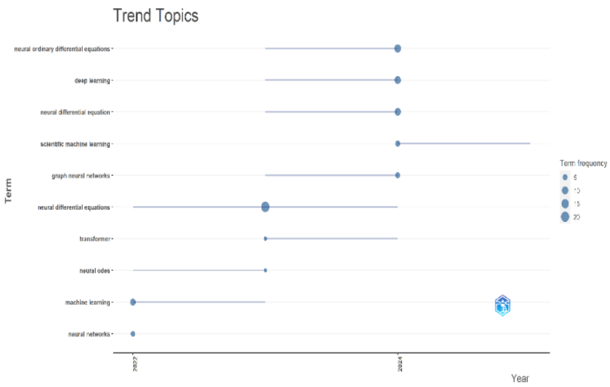

Fig. 8: Visualization of Trending Topics in the Realm of Research.

3.11. Thematic map

Figure 10 presents a thematic map that categorizes research themes in the field of Neural Differential Equations based on two dimensions: centrality (relevance) and density (development). The quadrants represent four thematic categories: motor themes (top-right), niche themes (top-left), emerging or declining themes (bottom-left), and basic themes (bottom-right). The motor themes quadrant includes terms such as "scientific machine learning," "data assimilation," and "uncertainty quantification", which are both highly developed and central to the field. These themes are driving the intellectual structure of the domain and are well-integrated with other research areas, indicating that they are mature, influential, and of continuing importance.

In the niche themes quadrant (top-left), we find topics like "transformer" and "position encoding." These themes are well-developed internally but show lower levels of connection to the broader field, indicating specialization and depth within smaller sub-communities. They represent cutting-edge, high-potential areas that may become more central in the future as integration increases, especially with the growing popularity of transformers in time-series modeling and scientific computing.

The basic themes quadrant (bottom-right) includes "neural differential equations," "deep learning," "neural ODEs," "graph neural networks," and "autonomous driving." These themes are highly relevant but still under development, suggesting that they are foundational to the field's growth and are likely to attract increasing scholarly attention. The emerging or declining themes (bottom-left quadrant) house tightly packed terms like "neural differential equation" and its variants, which appear to be at an early developmental stage despite their high relevance. This indicates that while these terms are central to the field, their research structures are still maturing. Overall, the thematic map illustrates a vibrant research landscape with promising foundational areas, emerging interdisciplinary links, and several well-developed themes pushing the field forward.

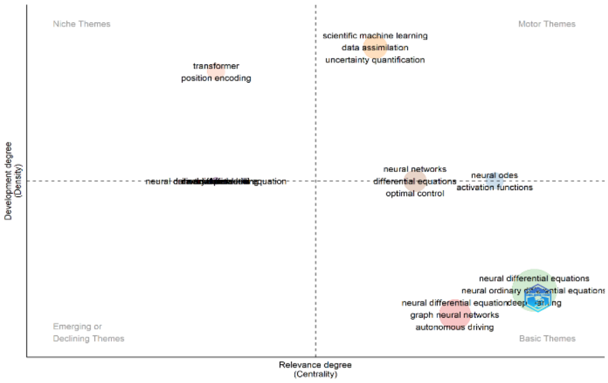

Fig. 9: Thematic Visualization of Keywords.

3.12. Thematic evolution

Figure 11 illustrates the thematic evolution of research topics in Neural Differential Equations from 2016 to 2025. Initially, between 2016 and 2022, the field was primarily rooted in "deep learning" and "neural differential equations." By 2023, the theme "neural differential equations" became central and further split into "neural ordinary differential equations" and variants of itself, indicating increasing specialization. In 2024, the themes expanded to include "graph neural networks" and continued emphasis on both "neural differential equations" and "deep learning," reflecting a broader interdisciplinary focus. By 2025, the evolution culminated in the consolidation of topics like "neural ordinary differential equations" and "neural differential equations," showcasing the field's thematic refinement and ongoing maturation. This evolution underscores a transition from broad foundational themes to more complex, domain-specific constructs.

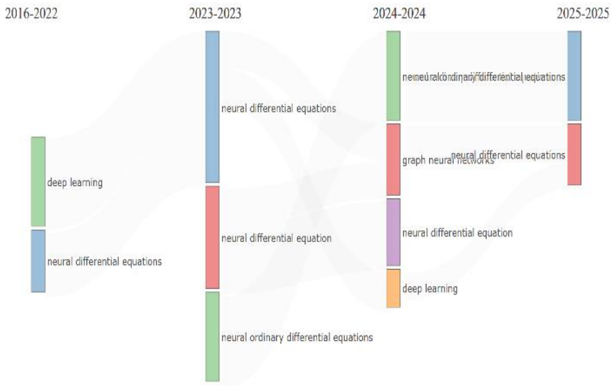

Fig. 10: Thematic Evolution of Research Topics.

4. Discussions

The scientometric analysis documented a strong and consistent growth in research on Neural Differential Equations, particularly post-2020. Annual scientific output trended upward with a sharp incline, peaking in 2023, suggesting increasing academic as well as interdisciplinary demand. Top authors such as Rackauckas, Nopens, and Chien have dominated mainstream discourse, with publishing activity dispersed over a mix of core computer science conferences as well as field-specific journals. These findings are supported further by a high average citation count per document coupled with a young document age, testifying to a dynamic and nascent scholarly environment for NDEs.

The network visualization of co-cited authors and journals provided a window into the intellectual structure of the field. Nine author clusters centered around major themes such as deep learning techniques, graph neural networks, and ODE adjoint methods. Highly cited authors like Rubanova, Raissi, Kingma, and Chen RT are critical to the field's development. Similarly, the journal co-citation analysis revealed that NeurIPS, ICML, AAAI, and Journal of Computational Physics are the intellectual hubs shaping research discourse. These clusters highlight how the field bridges theory and application, with communities forming around both algorithmic innovations and domain-specific implementations.

Geographic analysis showed that the United States and China lead global contributions, with strong representation from the UK, Canada, India, and several European and Asian countries, confirming the international and collaborative nature of the field. Influential documents by Gu (2021), Yue (2022), and Quaghebeur (2022) dominate citation networks, suggesting methodological breakthroughs or comprehensive frameworks. Keyword co-occurrence and burst analyses identified "neural differential equations," "graph neural networks," and "scientific machine learning" as central and growing topics, while thematic mapping and evolution confirmed the progression from foundational ideas to more sophisticated, interdisciplinary, and specialized themes.

Overall, the findings suggest a maturing but dynamic research landscape, with well-developed motor themes and emerging niches such as transformer-based models and uncertainty quantification. Practical implications include the need for standardization in architectural design, interdisciplinary collaboration, and computational efficiency improvements. The study also revealed a research gap in benchmarking, interpretability, and real-world deployment of NDEs. These insights not only guide future research directions but also provide a roadmap for educators, developers, and policymakers to harness the full potential of Neural Differential Equations in scientific, engineering, and AI-driven applications.

5. Research Gaps and Practical Implications

Based on the Trend Topics and Thematic Map analyses, two key research gaps emerge in the domain of Neural Differential Equations (NDEs). First, while foundational terms like "neural differential equations" and "deep learning" are central and frequently occurring, their placement in the basic themes quadrant suggests that these areas, despite their popularity, remain underdeveloped in terms of conceptual clarity, standardization, and practical deployment. Additionally, although themes like "graph neural networks" and "transformers" are beginning to gain traction, their classification as niche or emerging highlights a lack of integration with the broader research framework. This indicates a gap in unifying advanced architectures with domain-specific applications, such as uncertainty modeling, real-time control systems, and physics-informed scenarios. Moreover, the presence of themes like "neural ODEs" and "autonomous driving" in low-density regions underscores the need for deeper theoretical grounding and empirical validation.

The practical implications of these findings are twofold. First, there is a critical opportunity to bridge mature research themes—such as "scientific machine learning" and "data assimilation"—with still-developing but highly relevant concepts like "transformers" and "position encoding," especially for sequential and time-series data modeling. This could foster the design of hybrid models that better capture temporal dependencies and dynamical systems behavior. Second, researchers and practitioners should prioritize the translation of foundational NDE concepts into applied domains, addressing the current underdevelopment of core ideas. Developing robust benchmarks, open-source tools, and interdisciplinary collaborations will be essential to propel NDEs from conceptual frameworks to widely adopted, real-world solutions in fields such as healthcare, climate modeling, and autonomous systems.

6. Limitations

While this study provides a comprehensive scientometric overview of Neural Differential Equations (NDEs), certain limitations should be noted. The analysis relies exclusively on the Scopus database, which, although extensive, may introduce coverage bias by excluding works indexed in other repositories such as Web of Science. This may result in the omission of relevant contributions, particularly in fast-emerging or niche domains. Additionally, the temporal lag in citation accumulation may underrepresent the influence of recent studies, especially those published in 2023–2025, which have not yet had time to accrue significant citations. As a bibliometric review, this study also does not assess the mathematical rigor, theoretical depth, or empirical performance of individual NDE models. These limitations highlight the need for future research that integrates multiple databases, accounts for citation dynamics, and complements scientometric mapping with detailed technical evaluations.

7. Conclusion

This bibliometric analysis of Neural Differential Equations (NDEs) reveals a rapidly evolving research landscape characterized by increasing publication trends, diverse thematic development, and strong interdisciplinary engagement. The co-citation networks and keyword analyses highlight the centrality of deep learning, graph neural networks, and scientific machine learning in shaping the intellectual structure of the field. While foundational themes are gaining maturity, several emerging areas, such as transformers and uncertainty quantification, remain underexplored. Notably, the field exhibits strong international collaboration, with the United States and China leading global contributions. Based on these findings, three key recommendations are proposed: (1) researchers should focus on integrating niche innovations like attention mechanisms into the broader NDE framework; (2) the community should work towards developing standardized benchmarks and datasets to support empirical comparisons; and (3) increased emphasis should be placed on real-world applications in domains such as healthcare, physics, and autonomous systems. These strategies will help accelerate the practical impact and theoretical advancement of NDEs. In conclusion, the rise of graph-based NDEs reflects their strength in modeling complex spatio-temporal systems, underscoring why this trend is gaining momentum. Future research should prioritize interdisciplinary collaborations—particularly in areas like climate modeling and computational biology—alongside the creation of standardized benchmark datasets to enable robust validation and broader adoption of NDEs.

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