Journal of Scientometric Research, 2026; 15(2):347-355.
https://www.jscires.org

Research Article

From Equations to Algorithms: A Bibliometric Analysis and Visualization of Physics-Informed Machine Learning Research

Haulath K[1], Mohamed Jamshad K[1], Beenamole T[2], Jobin Varghese P[3], Annu Paul[4], Seenamol K Stephen[5], Jeena Joseph[6,*]

[1]Department of Computer Science, E.M.E.A. College of Arts and Science, Kondotty, Kerala, INDIA.
[2]Mar Ivanios College (Autonomous), Thiruvananthapuram, Kerala, INDIA.
[3]Department of Computer Applications, K E College, Mannanam, Kerala, INDIA.
[4]Department of Computer Science, Alphonsa College, Pala, Kerala, INDIA.
[5]Department of Physics, Government Polytechnic College, Kaduthuruthy, Kerala, INDIA.
[6]Department of Computer Applications, Marian College, Kuttikkanam, Kerala, INDIA.

ABSTRACT

Physics-Informed Machine Learning (PIML) is a highly promising hybrid model, with a combination of physical principles and machine learning methods, to improve predictive performance, interpretability, and computationally efficiency in the simulation of complex real-world systems. PIML enhances the trustworthiness of forecasting by incorporating physics-based restrictions into data-driven models, retaining causal consistency. This bibliometric work was done via Biblioshiny, VOSviewer and CiteSpace on the publications indexed on the Scopus database and gives a complete picture of the intellectual and structural development of the field. The analysis will demonstrate that the number of scientific publications is growing rapidly each year, with the most prominent authors, journals, and sources of publications. Co-citation networks are used to discover significant thematic clusters, whereas the analysis of international collaboration reveals the key contribution of China and the United States to the field development. The thematic shift of the foundational issues of machine learning and neural networks to the new fields of digital twins, parameter estimation, and anomaly detection is evidenced by keyword co-occurrence and citation burst analysis. Regardless of the rapid growth, uncertainty quantification, real-time data integration, and interdisciplinary standardization have research gaps. Overall, the findings provide a current overview of the evolving PIML research landscape and highlight emerging directions for future investigation.

Keywords: Bibliometric Analysis, Biblioshiny, Citespace, Physics-Informed Machine Learning, VOSviewer.

Correspondence:
Jeena Joseph
Department of Computer Applications, Marian College Kuttikkanam, Kerala, INDIA.
Email: jeenajoseph005@gmail.com
ORCID: 0000-0003-4070-5868

Received: 13-03-2026;
Revised: 04-05-2026;
Accepted: 28-07-2026.

INTRODUCTION

Physics-Informed Machine Learning has been a revolutionary framework in recent years that inserts physical laws into machine learning models (Hao *et al.*, 2023; Muther *et al.*, 2023; Nghiem *et al.*, 2023). Machine learning models have hitherto been based only on data and are therefore limited in generalizability and accuracy in modeling intricate scientific systems (Tan and Luo, 2023). PIML addresses these limitations by embedding governing equations, conservation laws, and physical constraints into machine learning models, thereby improving prediction accuracy and interpretability. Its adoption has accelerated in domains where data are limited and prior scientific knowledge is essential for model development (Doumèche *et al.*, 2024).

Increased applicability of PIML can be interpreted in light of its use in different fields ranging from fluid dynamics and climate modeling through materials science and structural engineering (Ghidalia *et al.*, 2023; Zhang *et al.*, 2024). These are nonlinear high-dimensional problems involving limited or expensive direct measurements. Through incorporating physics-based constraints in the context of machine-learning methods within it, PIML enhances solution accuracy, regularization, and avoidance of overfitting (Marian and Tremmel, 2023). Additionally, it also enhances models' extrapolation capability outside training data and hence serves as a principal tool for scientific discovery and design in engineering (Karniadakis *et al.*, 2021).

PIML's interdisciplinary nature has attracted researchers from both domain-specific sciences and machine learning. Numerous

DOI: 10.5530/jscires.20262121

approaches-including neural networks constrained by PDEs (e.g., Physics-Informed Neural Networks or PINNs), Gaussian processes, and hybrid data-physics models-have been proposed and applied (Cuomo *et al*., 2022; Meng *et al*., 2025). These methods leverage advances in algorithms and computational hardware to solve problems that were previously intractable (Chew *et al*., 2025; Sharma *et al*., 2023). Over the past decade, the volume of scholarly publications on PIML has grown substantially, making a systematic evaluation of research trends, influential studies, and emerging thematic areas increasingly necessary.

Despite the rapid growth of Physics-Informed Machine Learning (PIML), its intellectual, collaborative, and thematic structure remains insufficiently explored through bibliometric analysis. To address this gap, this study employs quantitative bibliometric techniques to examine publication trends, collaboration networks, co-citation patterns, and thematic evolution. The analysis provides insights into the field's development, emerging research hotspots, and future directions, offering an objective assessment of PIML's growth at the intersection of artificial intelligence and physical sciences (Al Rousan and Khasawneh, 2024).

This study aims to perform a comprehensive bibliometric analysis of the scientific literature on PIML using three widely recognized tools-Biblioshiny, VOSviewer, and CiteSpace. The study aims to (i) examine publication and citation trends, (ii) identify leading authors, journals, institutions, and countries, (iii) analyze research collaboration patterns, and (iv) detect major themes and intellectual shifts in PIML research. It covers Scopus-indexed publications up to 2025 using relevant PIML keywords.

The study employs bibliometric analysis to examine publication trends, co-authorship and co-citation networks, and keyword co-occurrence patterns, revealing influential works, collaboration structures, and emerging themes. The analysis is conducted using tools such as Biblioshiny, VOSviewer, and CiteSpace for visualization and scientific mapping (Cherian *et al*., n.d.; Joseph and Kartheeban, 2024). Biblioshiny, an interface for Bibliometrix, provides a user-friendly platform for performing quantitative research evaluation, focusing on citation analysis, trend analysis, and network visualization (Ghorbani, 2024). VOSviewer specializes in creating visualizations of bibliometric networks, such as citation, co-authorship, and keyword co-occurrence maps, helping researchers identify relationships and clusters within the data (John *et al*., 2024). Citespace, on the other hand, is designed to visualize the structure and dynamics of scientific research through network analysis, detecting emerging trends, key authors, and evolving research themes (Xie and Li, 2020; Yang *et al*., 2017). Together, these tools offer a multi-dimensional perspective of the PIML research domain, facilitating a deeper understanding of its structure, evolution, and future trajectories.

METHODOLOGY

Bibliometric data were retrieved from the Scopus database using a TITLE-ABS-KEY search strategy without language restrictions to maximize coverage of publications related to Physics-Informed Machine Learning (PIML). The initial search yielded 1,016 records. Following a PRISMA-based screening process, non-research document types, including reviews, conference reviews, editorials, errata, data papers, short surveys, notes, and books, were excluded. The final dataset comprised 949 publications, including 673 journal articles, 261 conference papers, and 15 book chapters. The dataset was exported in CSV and RIS formats and analyzed using CiteSpace (v6.2.R3 Advanced), VOSviewer, and Biblioshiny (Bibliometrix R package). Citation analysis, co-authorship mapping, co-citation analysis, network visualization, and keyword co-occurrence analysis were performed to identify publication trends, collaboration patterns, influential contributors, and emerging thematic areas within the evolving PIML research landscape.

RESULTS

Main information of the investigation

PIML research has experienced dynamic and rapid growth during the period 2017-2025. The dataset comprises 949 publications distributed across 529 sources, with an annual growth rate of 59.71%, demonstrating the remarkable expansion of the field. The average age of publications is 1.75 years, reflecting the emerging nature of the domain, while the average citation rate of 13.98 citations per document indicates a moderate but growing scholarly impact. The field exhibits considerable thematic diversity, represented by 6,715 Keywords Plus and 2,207 Author Keywords. A total of 2,843 authors contributed to the literature, with an average of 4.34 co-authors per publication and 23.08% of studies involving international collaboration, highlighting the highly collaborative and interdisciplinary character of PIML research.

Annual Scientific Productions

The annual publication trend shows a rapid increase in PIML research output over the study period. Publications grew from 58 in 2021 to 132 in 2022, 223 in 2023, and peaked at 371 in 2024. The lower count in 2025 is likely due to incomplete indexing rather than reduced research activity. This growth reflects the increasing adoption of Physics-Informed Neural Networks (PINNs), advances in automatic differentiation, and greater access to high-performance computing resources. Overall, the trend suggests an ongoing shift in scientific computing toward the integration of data-driven learning and physical modeling to develop accurate, interpretable, and computationally efficient predictive models.

Most Relevant Authors

Analysis of author productivity reveals the presence of a core group of influential contributors driving the development of PIML. Wang Y. emerged as the most productive author with 23 publications, followed closely by Li Y. with 22 publications. Other notable contributors include Chen Y. (18 publications), Wang H. (17 publications), Liu Y. (15 publications), and Wang P. (12 publications). Additional active contributors such as Hu Y., Zhang X., Wang L., and Wang Z. each produced approximately 10-11 publications. The relatively balanced distribution among leading authors suggests that knowledge generation in PIML is supported by multiple research groups rather than being concentrated within a single dominant cluster. This pattern reflects the interdisciplinary nature of the field and highlights the collaborative contributions of researchers from machine learning, computational science, applied mathematics, physics, and engineering disciplines.

Network visualization of co-citation of cited authors

Figure 1 presents a dense and strongly connected co-citation network, highlighting the foundational literature and interdisciplinary nature of PIML. Major clusters span reliability engineering, transfer learning, hydrology, geosciences, environmental modeling, surrogate modeling, and energy systems. Cluster #0 (Remaining Useful Life Prediction) and Cluster #1 (Transfer Learning) demonstrate the integration of predictive maintenance and domain adaptation in data-scarce industrial settings. Foundational authors such as Raissi and Karniadakis occupy central positions, reflecting the influence of Physics-Informed Neural Networks (PINNs), while researchers including Wang and Li contribute to domain-specific applications. Clusters focused on ungauged regions, surrogate modeling, discrete fracture networks, and system-level physics-informed detection indicate growing applications in climate science, geophysics, smart grids, and engineering. The coexistence of a stable methodological core with expanding application-oriented clusters suggests both intellectual consolidation and thematic diversification. Overall, the network structure indicates that PIML is evolving from foundational innovation toward broader practical adoption while maintaining a cohesive theoretical foundation.

Most Relevant Sources

The leading publication sources in PIML research (2017-2025) reflect its interdisciplinary nature and broad application scope. Computer Methods in Applied Mechanics and Engineering leads with 24 publications, followed by the Journal of Computational Physics (22) and Philosophical Transactions of the Royal Society A (20), highlighting the field's strong computational and theoretical foundations. Application-oriented contributions are prominent in Reliability Engineering and System Safety (12) and Mechanical Systems and Signal Processing (11), while Scientific Reports published 10 articles. Additional contributions from Physics of Fluids, Water Resources Research, Proceedings of Machine Learning Research, and SPIE Proceedings (9 publications each) further demonstrate the diverse theoretical, computational, and applied research interests within the evolving PIML domain.

Network visualization of Co-citation of Cited Journals

Figure 2 presents the co-citation network of journals, revealing the interdisciplinary foundations of PIML research through eight major clusters. Clusters such as Heterogeneous Micromechanical Properties Identification (#0) and Fatigue Life Prediction (#2) highlight strong connections between materials science and structural engineering, supported by influential journals including Applied Mathematical Modelling and Journal of the Mechanics and Physics of Solids. Computational and AI-focused clusters, including Breaking Boundaries (#1) and Data-Driven Model (#3), are anchored by journals such as Journal of Computational Physics and Advances in Neural Information Processing Systems, reflecting the growing integration of physics-based and data-driven approaches. Emerging clusters such as Discrete Fracture Network and System-Level Physics-Informed Detection further demonstrate the expanding application of PIML across diverse scientific and engineering domains. Overall, the network highlights the interdisciplinary nature of the field and its increasing opportunities for cross-domain innovation.

Countries Scientific Production

The global distribution of PIML research highlights both established and emerging research hubs. The United States leads with 470 publications, supported by a strong AI ecosystem, followed by China with 205 publications, reflecting its rapidly expanding AI research landscape. The United Kingdom (70), Germany (62), and France (39) demonstrate the strength of international collaboration initiatives such as Horizon Europe. India also contributed 39 publications, indicating growing research momentum. Additional contributions from Canada (34), Italy (29), Singapore (26), and South Korea (23) further underscore the increasing global engagement and interdisciplinary interest in PIML research.

Network Visualization of Countries Collaborations

The global collaboration network in Figure 3 identifies the United States as the central research hub, with strong partnerships involving China, the United Kingdom, Germany, Canada, and Italy. The prominent U.S.-China connection reflects extensive cross-continental collaboration, while European countries such as Germany, Switzerland, Austria, and Italy form active regional networks. China has also strengthened collaborations with Singapore, Hong Kong, India, and Germany, demonstrating its growing global engagement. Emerging contributions from Portugal, Brazil, and the United Arab Emirates indicate the geographical expansion of PIML research. However, the network remains uneven, with developing regions comparatively underrepresented, highlighting disparities in research infrastructure and access to scientific resources.

Network Visualization of Bibliographic Coupling between Authors

The bibliographic coupling network in Figure 4 generated using VOSviewer illustrates intellectual relationships among authors based on shared references. Stronger links indicate greater overlap in cited literature and closer alignment of research themes. The central cluster, comprising authors such as Bagheri A., Dubey M. A., and Ghaffar A., reflects a high degree of shared scholarly foundations and thematic similarity. Another notable cluster includes Geneva N. and Gabarros N., suggesting common research interests and intellectual proximity. In contrast, authors such as Stephanie P. and Earls C. occupy more peripheral positions, indicating specialized or emerging research contributions. Overall, the network demonstrates how diverse

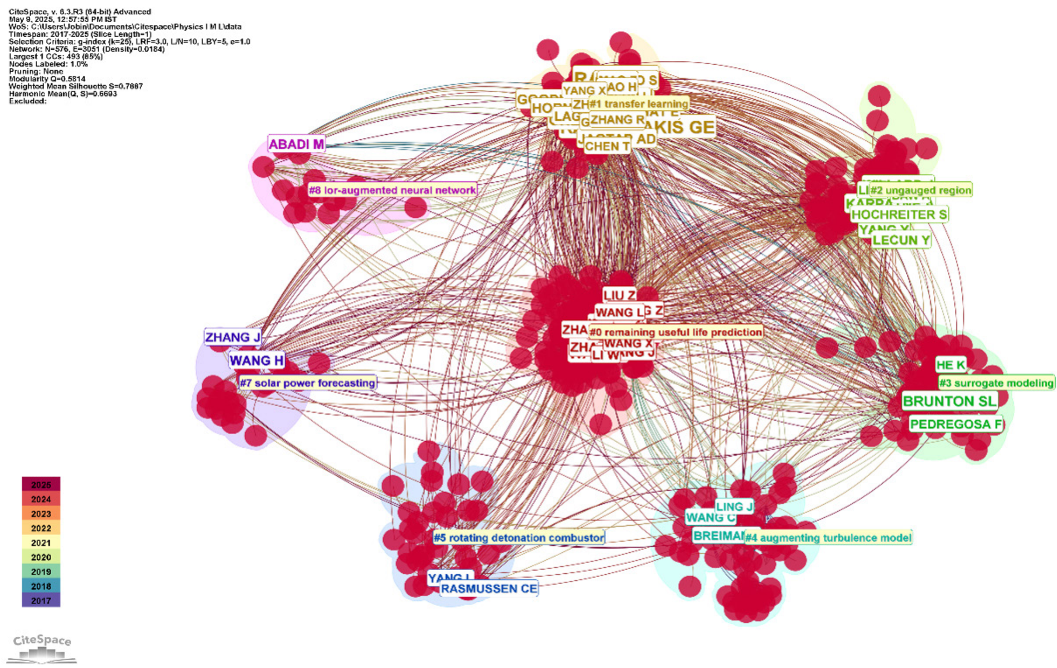

Figure 1: Network visualization of co-citation of cited authors.

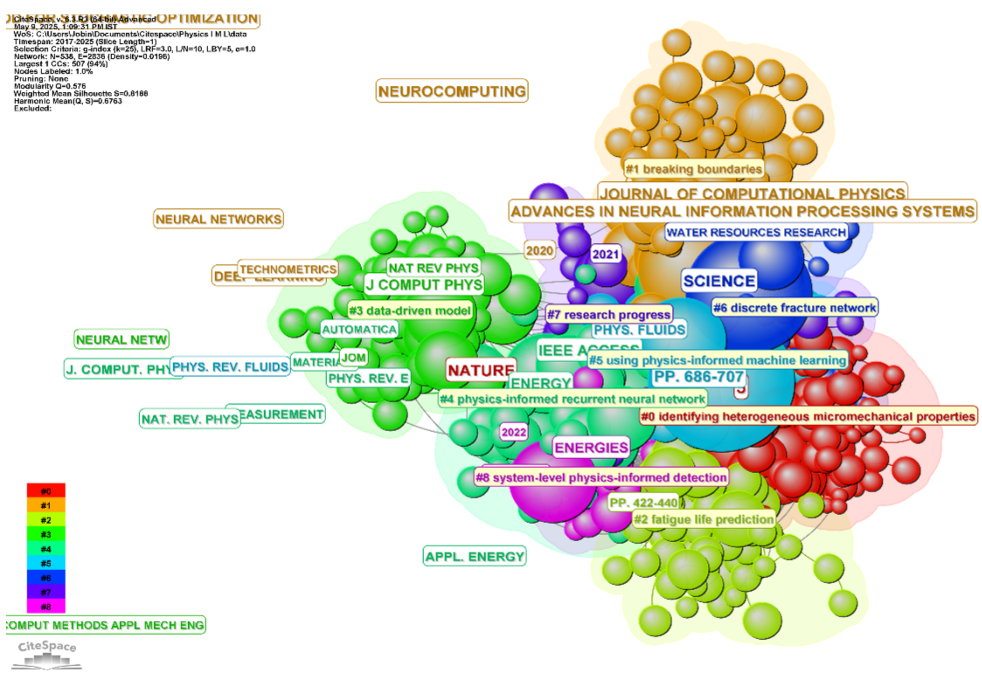

Figure 2: Network visualization of co-citation of cited journals.

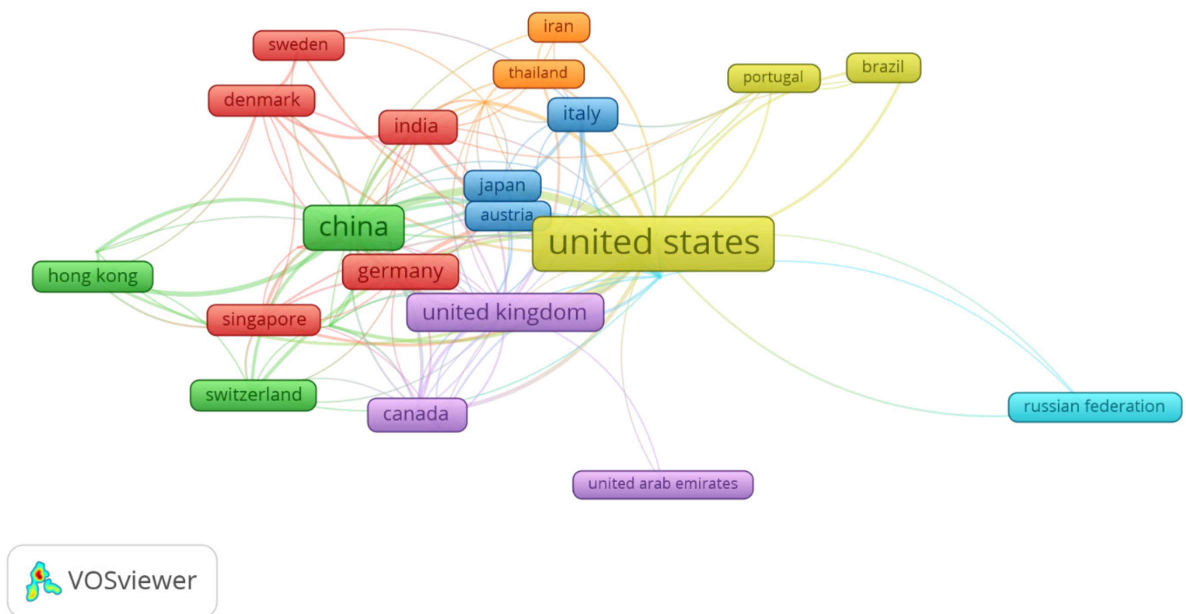

Figure 3: Timeline Network visualization of countries collaborations.

research communities within PIML remain interconnected through shared theoretical foundations and mutual scholarly influence.

Co-occurrence of all keywords

Figure 5 presents the co-occurrence network of author keywords, highlighting the major themes in PIML research. Machine learning is the dominant keyword, reflecting its central role in the field. Closely associated terms such as physics-informed, neural networks, inverse problems, and partial differential equations demonstrate the integration of artificial intelligence with physical modeling. Distinct clusters represent theoretical, computational, and application-oriented research. Keywords including turbulence, fatigue, and hydrological modeling indicate applications in engineering and environmental sciences, while lithium-ion batteries and state of health highlight growing interest in predictive maintenance and energy systems. Emerging topics such as graph neural networks and domain decomposition further reflect methodological innovation. Overall, the network underscores the interdisciplinary growth and expanding application scope of PIML.

Keywords with the Strongest Citation Bursts

Figure 6 presents the keywords with the strongest citation bursts in PIML research, highlighting shifts in thematic priorities over time. During 2017-2021, keywords such as Navier-Stokes equations (5.66), machine learning methodologies (4.68), and learning systems (4.67) reflected efforts to integrate physical equations with data-driven approaches. Interest in artificial intelligence and decision trees further underscored the convergence of traditional physics-based modeling and AI techniques. Since 2019, increased attention to topics such as turbulence, Reynolds number, and wind power has indicated growing applications in fluid dynamics and renewable energy. More recent bursts (2020-2025), including uncertainty quantification, lithium-ion batteries, and recurrent neural networks, suggest a shift toward scalable, real-time, and energy-focused applications. Overall, the burst analysis reflects the evolution of PIML from foundational methodological research to practical and sustainability-oriented applications.

Trend Topics

Figure 7 illustrates trending topics in PIML research between 2020 and 2024, highlighting the field's evolving focus. Core terms such as physics-informed machine learning, machine learning, and deep learning remained dominant throughout the period, reflecting their foundational role. Topics including neural networks, additive manufacturing, and parameter estimation indicate growing application-oriented integration. Since 2022, advanced architectures such as deep neural networks and recurrent neural networks have gained prominence for modeling complex physical systems. Emerging themes such as turbulence modeling and reduced-order modeling further suggest increasing specialization in computational fluid dynamics and simulation efficiency. Overall, the figure shows that while foundational concepts remain central, domain-specific innovations are increasingly shaping the evolution of PIML research.

Thematic Map

Figure 8 presents a thematic map of PIML research based on keyword centrality and density, classifying themes into Motor, Basic, Niche, and Emerging/Declining categories. Digital twin, physics-informed machine learning, and anomaly detection emerge as influential motor themes driving the field's development. Basic themes, including machine learning, deep learning, neural networks, physics-informed approaches, and partial differential equations, form the conceptual foundation of PIML. Niche themes such as Gaussian processes, computational fluid dynamics, porous media, and recurrent neural networks are technically mature but relatively specialized. Emerging or declining themes, including reduced-order modeling, surrogate modeling, and uncertainty, represent potential future research directions. Overall, the thematic map highlights the interdisciplinary maturity of PIML and identifies key areas for continued theoretical and application-oriented development.

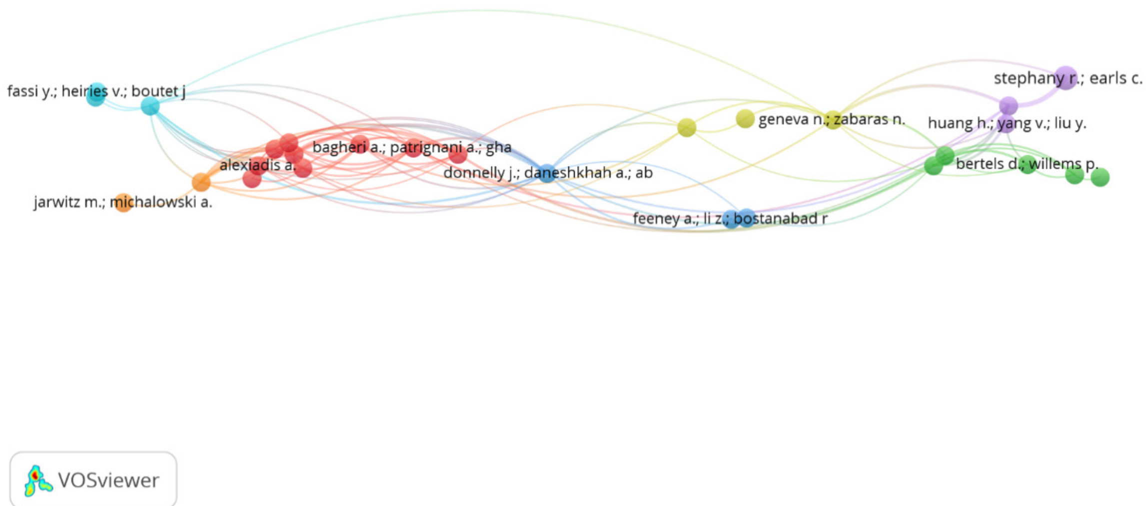

Figure 4: Network visualization of Bibliographic Coupling between Authors.

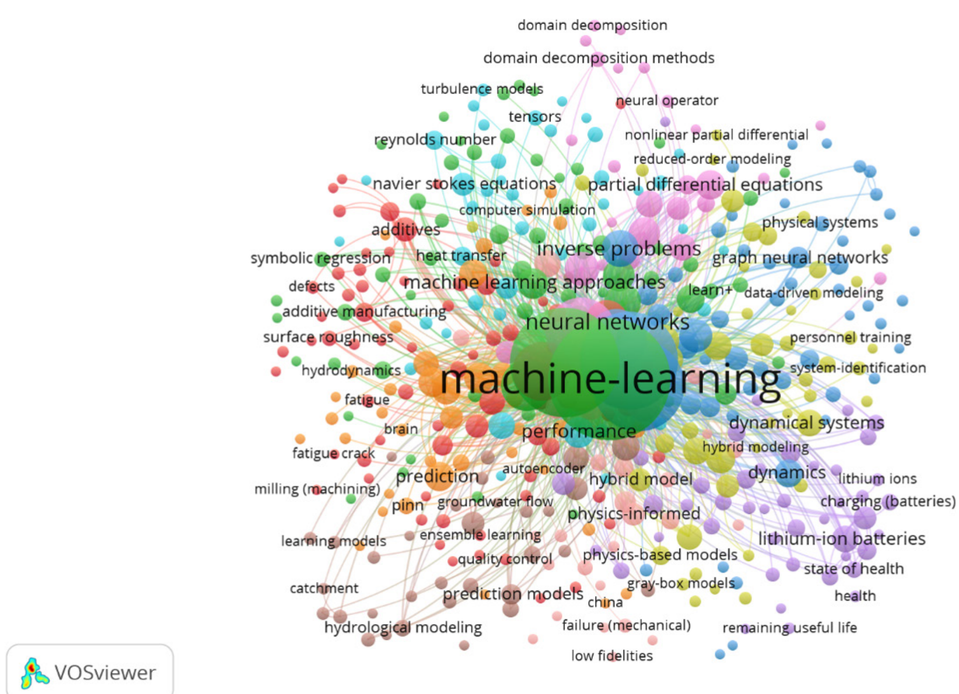

Figure 5: Co-occurrence of author keywords.

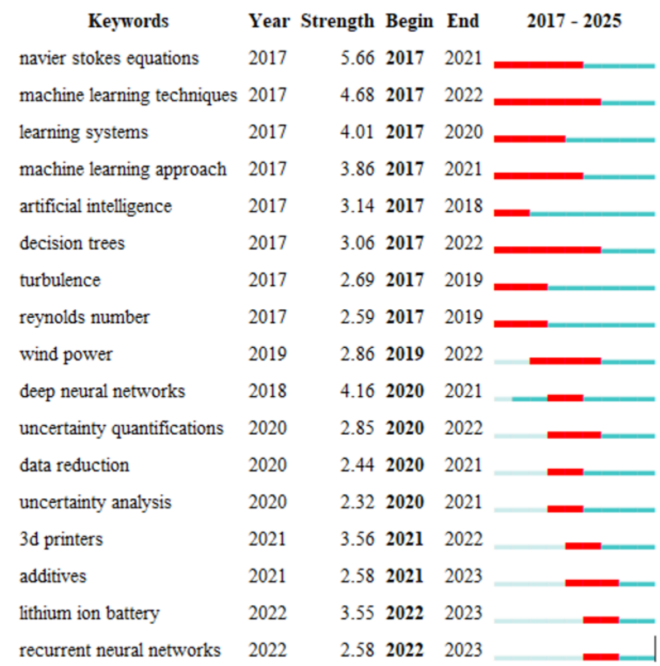

Figure 6: Keywords with the Strongest Citation Bursts.

Thematic Evolution

Figure 9 illustrates the thematic evolution of PIML research between 2017-2021 and 2022-2025. Early themes such as physics-informed machine learning, deep learning, data-driven methods, and big data reflected the integration of data-centric and physics-based modeling approaches. Over time, these themes evolved and diversified, with deep learning and big data converging toward more specialized PIML frameworks. Similarly, data-driven approaches expanded into areas such as machine learning and uncertainty quantification, indicating increased emphasis on model reliability and practical applicability. The evolution of physics-informed machine learning into physics-informed neural networks further highlights growing methodological sophistication. Overall, the thematic evolution reveals a transition from foundational concepts toward more specialized and application-oriented research, reflecting the maturation and diversification of PIML as an interdisciplinary field.

DISCUSSION

The bibliometric analysis provides valuable insights into the evolving landscape of Physics-Informed Machine Learning (PIML). The significant increase in publications since 2020 reflects growing interest in integrating physical principles with machine learning to develop more reliable and interpretable models for scientific and engineering applications. The publication peak observed in 2024 indicates intensified research activity, driven by advances in deep learning, computational physics, and hybrid modeling approaches.

The presence of influential authors and strong collaboration networks highlights the interdisciplinary nature of PIML, bringing together expertise from computational science, mathematics, engineering, and applied domains. However, the concentration of research output among a limited number of institutions suggests opportunities for broader participation and intellectual diversity.

Thematic analysis reveals a shift from foundational topics such as neural networks and partial differential equations toward application-oriented areas including digital twins, anomaly detection, parameter estimation, and uncertainty quantification. This transition demonstrates the increasing practical relevance of PIML in addressing complex real-world problems. While the United States and China remain dominant contributors, greater involvement from emerging economies could promote more balanced global development. As the field continues to evolve, these findings should be viewed as indicators of current trends rather than definitive conclusions regarding its future trajectory.

Research Gaps and Practical Implications

Despite rapid methodological advances, uncertainty quantification and surrogate modeling remain underrepresented in PIML research, highlighting gaps in robustness, validation, and benchmarking standards. Although many models achieve high predictive accuracy, the absence of standardized cross-domain evaluation frameworks may limit scalability and reproducibility. The fragmentation of specialized areas such as porous media, Gaussian processes, and computational fluid dynamics further suggests incomplete integration between theory and application. These challenges also present important opportunities. Greater integration of PIML with digital twins, anomaly detection, and parameter estimation could enhance predictive maintenance and improve the reliability of energy, healthcare, and climate systems. Future research on uncertainty quantification and surrogate modeling will be critical for improving model trustworthiness, scalability, and interdisciplinary adoption, thereby supporting the continued maturation of the PIML paradigm.

Structural Evolution of PIML as a Hybrid Scientific Paradigm

The bibliometric evidence suggests that PIML is evolving from a specialized machine learning approach into a broader interdisciplinary framework. While early research focused on embedding physical constraints into neural networks, recent studies emphasize methodological diversification and applications in digital twins, energy systems, manufacturing, and predictive maintenance. Core themes such as neural networks and partial differential equations remain central, indicating that PIML complements traditional physics-based modeling. However, comparatively limited attention to uncertainty quantification and interpretability highlights important methodological challenges. Overall, the field appears to be entering a consolidation phase in which standardization, reproducibility, and theoretical rigor

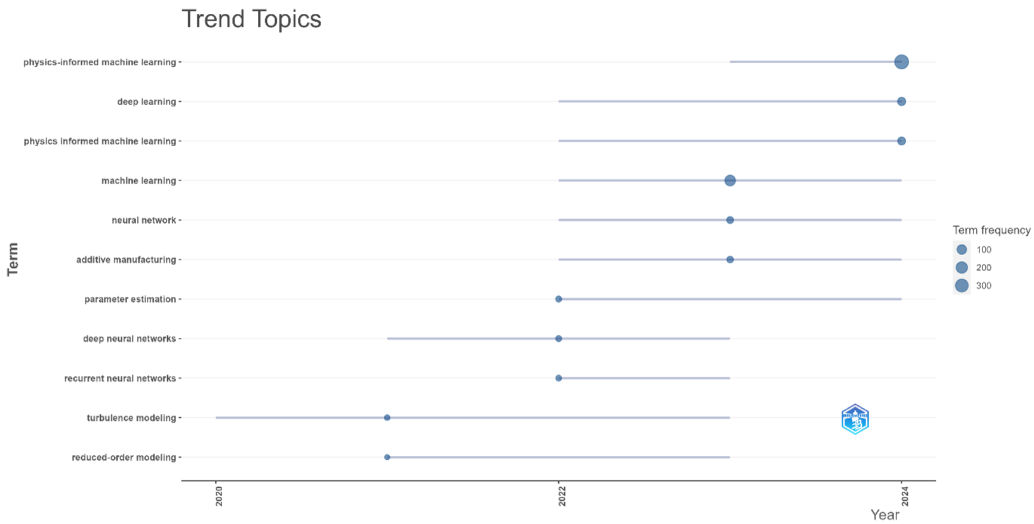

Figure 7: Visualization of trending topics.

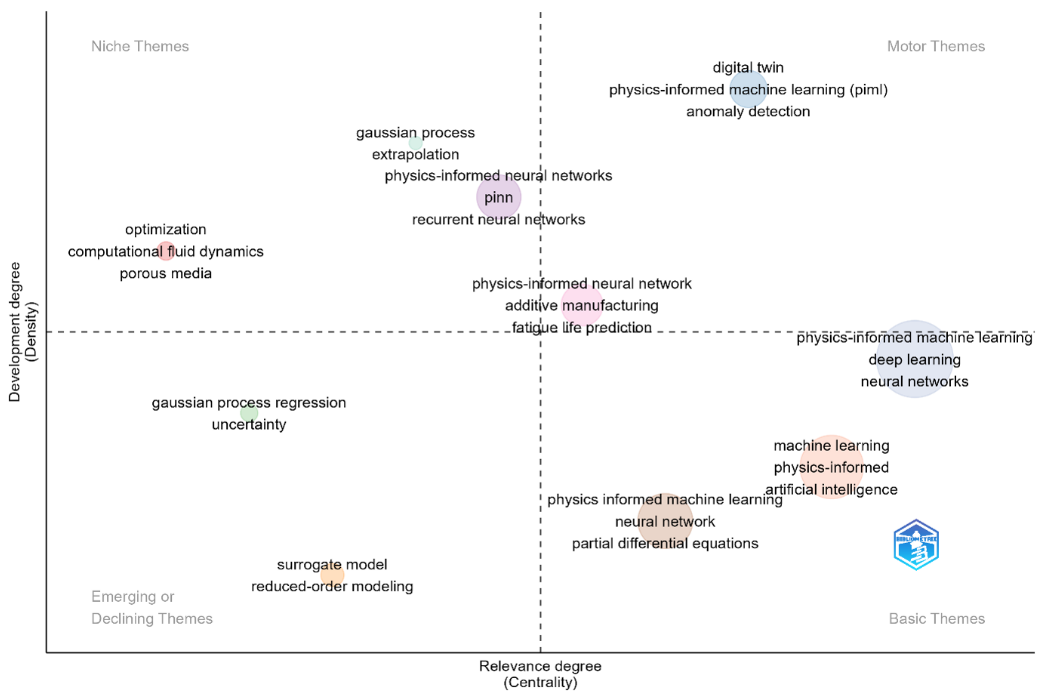

Figure 8: Thematic visualization of keywords.

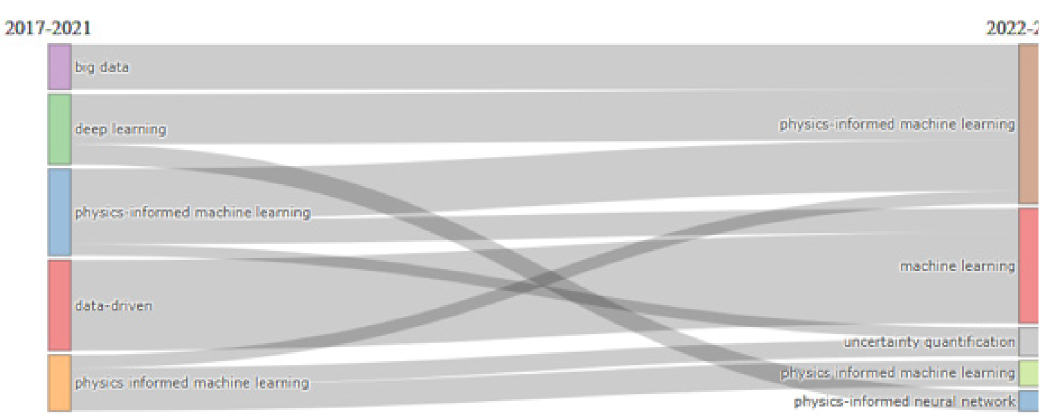

Figure 9: Thematic evolution of keywords.

will be critical for continued advancement. The findings also demonstrate the value of bibliometric analysis in tracking the evolution of emerging research domains.

CONCLUSION

This bibliometric review indicates that Physics-Informed Machine Learning (PIML) is emerging as an important paradigm in scientific computation by integrating physical knowledge with data-driven learning. The rapid growth of publications since 2020, along with stable co-citation networks and expanding thematic clusters, reflects the increasing maturity and diversification of the field. PIML has progressed beyond foundational methodological studies and is now applied across domains such as energy systems, manufacturing, hydrology, and reliability engineering. While neural networks and partial differential equations remain central research themes, emerging topics including digital twins, parameter estimation, anomaly detection, and uncertainty quantification are driving new directions. Nevertheless, the comparatively limited focus on uncertainty quantification and surrogate modeling suggests opportunities for future methodological development. Although research activity is currently concentrated in the United States and China, broader international collaboration may further accelerate innovation. Overall, this study provides a valuable overview of current trends and highlights promising directions for future PIML research.

ABBREVIATIONS

AI: Artificial Intelligence; **CFD:** Computational Fluid Dynamics; **CSV:** Comma-Separated Values; **PDE:** Partial Differential Equation; **PDEs:** Partial Differential Equations; **PIML:** Physics-Informed Machine Learning; **PINN:** Physics-Informed Neural Network; **PINNs:** Physics-Informed Neural Networks; **PRISMA:** Preferred Reporting Items for Systematic Reviews and Meta-Analyses; **RIS:** Research Information Systems.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

REFERENCES

Al Rousan, R., and Khasawneh, N. (2024). Mapping 30 years of tourism and hospitality research in the Arab world: A review based on bibliometric analysis. *Tourism Review*, *79*(6), 1280-1298. Scopus. https://doi.org/10.1108/TR-04-2023-0201

Cherian, S., Joseph, J., Thomas, B., and Jose, J. (n.d.). *Navigating the New Normal: A Bibliometric Analysis of Masked Face Recognition Research Using VOSviewer and Biblioshiny*.

Chew, A. W. Z., He, R., and Zhang, L. (2025). Physics Informed Machine Learning (PIML) for Design, Management and Resilience-Development of Urban Infrastructures: A Review. *Archives of Computational Methods in Engineering*, *32*(1), 399-439. https://doi.org/10.1007/s11831-024-10145-z

Cuomo, S., Di Cola, V. S., Giampaolo, F., Rozza, G., Raissi, M., and Piccialli, F. (2022). Scientific Machine Learning Through Physics-Informed Neural Networks: Where we are and What's Next. *Journal of Scientific Computing*, *92*(3), 88. https://doi.org/10.1007/s10915-022-01939-z

Doumèche, N., Bach, F., Biau, G., and Boyer, C. (2024). *Physics-informed kernel learning*. https://arxiv.org/abs/2409.13786

Ghorbani, B. D. (2024). Bibliometrix: Science Mapping Analysis with R Biblioshiny Based on Web of Science in Applied Linguistics. In H. Meihami and R. Esfandiari (Eds.),*A Scientometrics Research Perspective in Applied Linguistics* (pp. 197-234). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-51726-6_8

Hao, Z., Liu, S., Zhang, Y., Ying, C., Feng, Y., Su, H., and Zhu, J. (2023). *Physics-Informed Machine Learning: A Survey on Problems, Methods and Applications*. https://arxiv.org/abs/2211.08064

John, J., Joseph, J., Mathew, L., James, S., and Jose, J. (2024). Exploring the Predictive Analytics Frontier in Business: A Bibliometric Journey. *Journal of Scientometric Research*, *13*(2), 365-381. Scopus. https://doi.org/10.5530/jscires.13.2.29

Joseph, J., and Kartheeban, K. (2024). Visualizing the Impact of Machine Learning on Cardiovascular Disease Prediction: A Comprehensive Analysis of Research Trends. *Scientific Visualization*, *16*(5), 1-21. https://doi.org/10.26583/sv.16.5.01

Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., and Yang, L. (2021). Physics-informed machine learning. *Nature Reviews Physics*, *3*(6), 422-440. https://doi.org/10.1038/s42254-021-00314-5

Marian, M., and Tremmel, S. (2023). Physics-Informed Machine Learning—An Emerging Trend in Tribology. *Lubricants*, *11*(11). https://doi.org/10.3390/lubricants11110463

Meng, C., Griesemer, S., Cao, D., Seo, S., and Liu, Y. (2025). When physics meets machine learning: A survey of physics-informed machine learning. *Machine Learning for Computational Science and Engineering*, *1*(1), 20. https://doi.org/10.1007/s44379-025-00016-0

Muther, T., Dahaghi, A. K., Syed, F. I., and Van Pham, V. (2023). Physical laws meet machine intelligence: Current developments and future directions. *Artificial Intelligence Review*, *56*(7), 6947-7013. https://doi.org/10.1007/s10462-022-10329-8

S. Ghidalia, O. L. Narsis, A. Bertaux, and C. Nicolle. (2023). Automating Physical Knowledge Integration in Machine Learning. *2023 17th International Conference on Signal-Image Technology and Internet-Based Systems (SITIS)*, 14-21. https://doi.org/10.1109/SITIS61268.2023.00013

Sharma, P., Chung, W. T., Akoush, B., and Ihme, M. (2023). A Review of Physics-Informed Machine Learning in Fluid Mechanics. *Energies*, *16*(5). https://doi.org/10.3390/en16052343

T. X. Nghiem, J. Drgoňa, C. Jones, Z. Nagy, R. Schwan, B. Dey, A. Chakrabarty, S. Di Cairano, J. A. Paulson, A. Carron, M. N. Zeilinger, W. Shaw Cortez, and D. L. Vrabie. (2023). Physics-Informed Machine Learning for Modeling and Control of Dynamical Systems. *2023 American Control Conference (ACC)*, 3735-3750. https://doi.org/10.23919/ACC55779.2023.10155901

Tan, R., and Luo, W. (2023). Physics-Informed Machine Learning Model Generalization in AIoT: Opportunites and Challenges. *Proceedings of Cyber-Physical Systems and Internet of Things Week 2023*, CPS-IoT Week *'23*, 170-176. https://doi.org/10.1145/3576914.3588751

Xie, M., and Li, S. (2020). Bibliometric and Visualized Analysis of Visual Brand Identity of Sports Team Based on Web of Science and CiteSpace. In *Advances in Intelligent Systems and Computing: 1190 AISC* (pp. 171-181). https://doi.org/10.1007/978-3-030-49829-0_13

Yang, J., Cheng, C., Shen, S., and Yang, S. (2017). Comparison of complex network analysis software: Citespace, SCI 2 and Gephi. *2017 IEEE 2nd International Conference on Big Data Analysis (ICBDA)*, 169-172.

Zhang, Y., Chen, N., Vialard, J., and Fang, X. (2024). A Physics-Informed Auto-Learning Framework for Developing Stochastic Conceptual Models for ENSO Diversity. *Journal of Climate*, *37*(23), 6323-6347. https://doi.org/10.1175/JCLI-D-24-0092.1

Cite this article: Haulath K, Jamshad KM, Beenamole T, Varghese PJ, Paul A, *et al*. From Equations to Algorithms: A Bibliometric Analysis and Visualization of Physics-Informed Machine Learning Research. J Scientometric Res. 2026;15(2):347-55.