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Global Research on Learning Transfer: A Bibliometric Perspective Using Scopus Data

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ABSTRACT

This study examines the global development of learning transfer research through a bibliometric analysis of Scopus-indexed publications from 2000 to 2025. Using VOSviewer, the analysis maps keyword co-occurrences, thematic clusters, and intellectual linkages to reveal how learning transfer has evolved into a central paradigm within modern artificial intelligence. The findings show that research is dominated by four interconnected clusters: foundational deep learning concepts, computer vision applications, methodological advancements in transfer learning and domain adaptation, and emerging system-level applications such as reinforcement learning and federated learning. The prominence of terms like contrastive learning, fine tuning, and knowledge transfer highlights a shift toward more sophisticated, data-efficient, and privacy-conscious approaches. The dense interconnections among clusters demonstrate the field's strong interdisciplinary nature, driven by collaborations across machine learning, cognitive science, and engineering. This study provides a comprehensive picture of the intellectual structure and emerging trajectories in learning transfer research, offering valuable insights for scholars, practitioners, and policymakers seeking to advance both theoretical foundations and practical applications.

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1. INTRODUCTION

Learning transfer has long been recognized as a central construct in educational psychology, instructional design, and organizational learning, reflecting the extent to which knowledge, skills, and competencies acquired in one context can be applied effectively in another. Classic perspectives emphasize that the success of learning transfer depends on the similarity of conditions, the relevance of prior knowledge, and the cognitive processes that enable learners to generalize and apply what they have learned. As global challenges increasingly require agile learning, the concept has evolved into a multidimensional construct that spans formal education, workplace training, professional development, and digital learning environments. With the rise of technology-enhanced learning and competency-based education, learning transfer is now seen as a

core measure of instructional effectiveness rather than an optional outcome [1]–[3].

Research on learning transfer has accelerated in the past two decades, highlighting the growing interest of scholars across disciplines such as psychology, management, education, and human resource development. Studies increasingly examine the antecedents and mechanisms that facilitate the transfer process, including learner motivation, instructional design, organizational climate, and supervisor support [4]. Parallel to this, digital learning platforms such as MOOCs, microlearning modules, and simulation-based training environments have introduced new dynamics that influence transfer outcomes. As a result, the literature has become more fragmented, distributed across multiple disciplinary domains, and reliant on different theoretical traditions.

The globalization of education and workforce mobility has further broadened the relevance of learning transfer. Multinational organizations must ensure that training is not only delivered effectively but also results in performance improvement in diverse cultural and organizational contexts. Cross-cultural studies reveal that factors such as learning orientation, cultural norms, and organizational support systems influence transfer effectiveness in different regions [5]. Meanwhile, governments and academic institutions emphasize lifelong learning and upskilling initiatives in response to technological disruption, strengthening the strategic importance of transfer research at the national and international levels.

In addition, the methodological landscape of learning transfer research has expanded. Beyond experimental and survey-based designs, recent work includes mixed-methods, longitudinal tracking, and design-based research focused on understanding how training translates into real-world practice over time. Despite these methodological innovations, the field still exhibits conceptual overlaps and inconsistent definitions, which complicate efforts to synthesize knowledge and assess global research trends. Bibliometric analysis offers a systematic way to map the intellectual structure of the field, reveal thematic concentrations, and identify influential works, authors, and countries contributing to the development of learning transfer theory.

Scopus has emerged as one of the most comprehensive and globally representative databases for mapping scientific knowledge. As learning transfer literature spans multiple domains—education, psychology, organizational science, and training research—Scopus provides wide coverage necessary for identifying the evolution of concepts, publication trajectories, and global collaboration patterns. By using bibliometric tools, scholars can uncover how research clusters have shifted from cognitive perspectives to performance-based models and more recent digital learning contexts [6]–[8]. However, a full global mapping of learning transfer research using Scopus data remains limited, creating a gap in understanding how the field has evolved and how present developments align with future research agendas.

Despite the increasing volume of publications on learning transfer, the field lacks a comprehensive and up-to-date bibliometric synthesis that maps its global research patterns, thematic evolution, collaborative networks, and intellectual foundations. Prior reviews tend to be narrative, limited to specific subfields, or focused on particular training contexts, leaving researchers without a holistic understanding of how learning transfer knowledge has developed worldwide over time. This gap hinders the ability of scholars and practitioners to identify emerging trends, influential works, key authors, and research directions that could strengthen theory development and practical application of learning transfer in diverse educational and organizational settings. This study aims to conduct a global bibliometric analysis of learning transfer research using Scopus data to systematically map publication trends, influential authors and documents, collaborative networks, and thematic clusters from 2000 to 2025.

2. METHOD

This study employed a bibliometric research design to map the global landscape of learning transfer studies indexed in the Scopus database. Scopus was selected due to its comprehensive coverage of peer-reviewed journals, conference proceedings, and multidisciplinary research outputs relevant to education, psychology, training, and organizational learning. The search strategy used the keywords "learning transfer" OR "transfer of learning" applied to titles, abstracts, and keywords, covering the publication period from 2000 to 2025. The search was refined to include only journal articles, conference papers, and reviews, while excluding editorials, book chapters, and non-scholarly outputs. All retrieved metadata—including authors, affiliations, publication years, sources, citations, abstracts, and keywords—were exported in RIS/CSV format for further analysis.

The exported dataset was then processed using VOSviewer, a specialized bibliometric visualization software widely used to analyze and map scientific knowledge structures. VOSviewer was utilized to perform (1) co-authorship analysis to identify collaboration patterns among authors, institutions, and countries; (2) co-occurrence analysis of keywords to map the conceptual structure and dominant themes in learning transfer research; (3) citation and co-citation analysis to identify influential documents and intellectual foundations; and (4) bibliographic coupling to detect thematic linkages among recent publications. The software's threshold settings were adjusted to refine the networks—such as minimum number of documents per author, minimum keyword occurrences, and minimum citations per reference—to ensure the visualizations represented robust patterns rather than noise.

All network maps generated by VOSviewer—such as network visualization, overlay visualization, and density visualization—were analyzed qualitatively to interpret thematic clusters, temporal trends, and areas of emerging interest. The network structures, cluster colors, node sizes, and link strengths were examined to derive insights into how the field has developed over time and how different research themes are interconnected. No manual coding or subjective thematic categorization was imposed; instead, the interpretation relied fully on the patterns revealed by VOSviewer's algorithms. The combination of Scopus data extraction and VOSviewer visual analytics enabled a systematic, reproducible, and comprehensive mapping of global learning transfer research.

3. RESULT AND DISCUSSION

3.1 Network Visualization

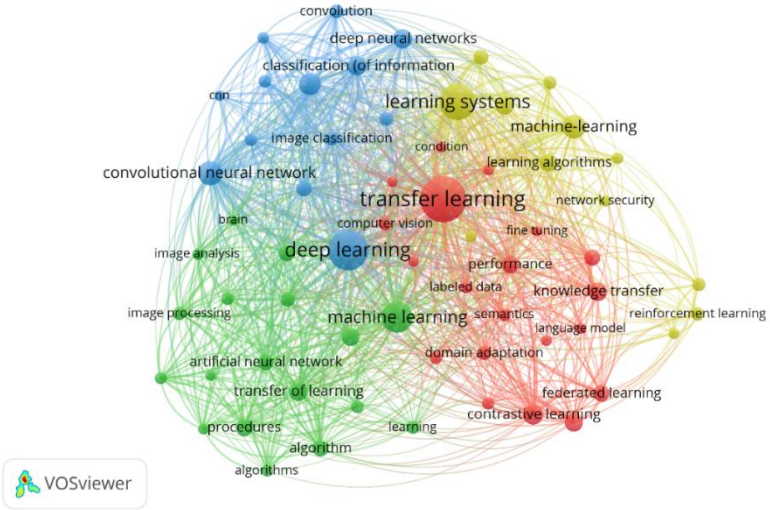

Figure 1. Network Visualization
Source: Data Analysis Result, 2025

The VOSviewer keyword co-occurrence map illustrates the intellectual structure of global research on learning transfer, revealing four major thematic clusters that are closely interconnected. At the center of the visualization, "transfer learning" emerges as the most dominant and highly linked keyword, showing its pivotal role across domains. Surrounding it, the red cluster represents advanced methodological developments such as domain adaptation, knowledge transfer, contrastive learning, and federated learning, indicating growing interest in enhancing model generalization and privacy-preserving learning. The blue cluster highlights the strong foundation of computer vision research, featuring terms like convolutional neural network, image classification, and deep neural networks, demonstrating that many transfer learning applications rely heavily on CNN-based architectures. The green cluster reflects the broader backbone of machine learning and deep learning, with keywords such as deep learning, machine learning, artificial neural network, and image processing, showing that transfer learning is deeply rooted in fundamental AI techniques. Meanwhile, the yellow cluster captures emerging system-level applications, including learning systems, reinforcement learning, and network security, signaling the expansion of transfer learning into adaptive decision-making and high-stakes computational environments. Overall, the dense connections and cluster integrations illustrate a rapidly evolving, multidisciplinary field where advancements in deep learning and neural models continue to drive innovation in transfer learning research.

3.2 *Overlay Visualization*

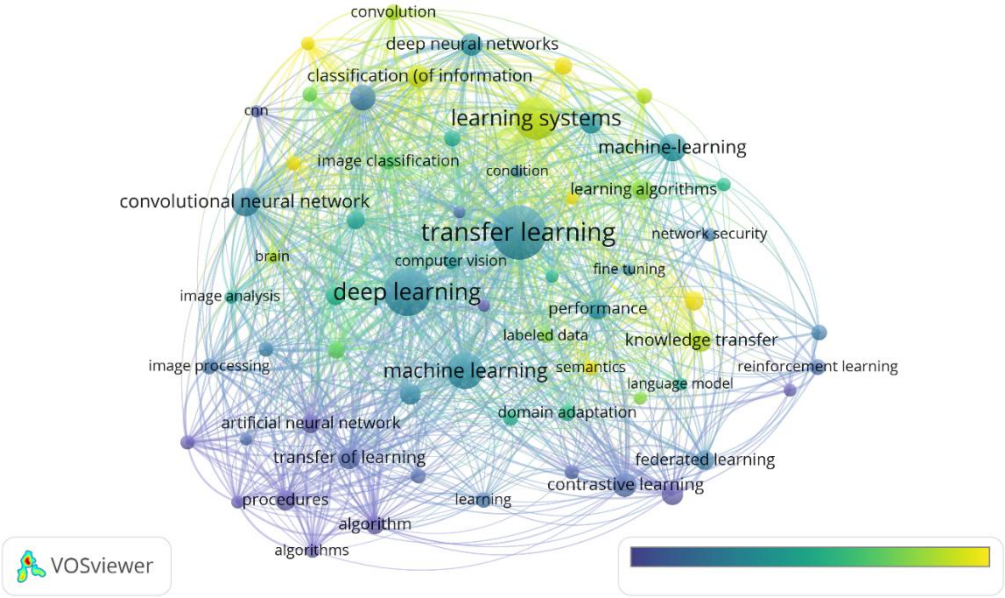

Figure 2. Overlay Visualization
Source: Data Analysis Result, 2025

The overlay visualization map generated by VOSviewer illustrates the temporal evolution of research themes within the field of transfer learning by using a color gradient from dark blue (older publications) to bright yellow (more recent studies). The figure shows that foundational concepts such as "artificial neural network," "image processing," "procedures," and "algorithms" appear in darker shades, indicating that these topics represent the earliest phases of research in the field. As the colors shift toward green and yellow, the map highlights newer and emerging topics—especially around "learning

systems," "learning algorithms," "domain adaptation," "knowledge transfer," "contrastive learning," and "federated learning." The bright yellow nodes, such as "deep neural networks," "transfer learning," and "machine-learning," show that these areas have gained significant traction in the most recent years. Meanwhile, cutting-edge terms like "reinforcement learning," "network security," and "language model" appear in lighter green and yellow, signaling their increasing relevance in contemporary applications. Overall, the figure demonstrates a clear progression from foundational deep learning and neural network techniques toward more sophisticated, specialized, and system-oriented research directions, illustrating how the field of transfer learning is evolving toward complex, data-efficient, and real-world adaptive AI systems.

3.3 Citation Analysis

Table 1. Most Cited Article

Citations	Author and Year	Title
393	[9]	The PRIDE database at 20 years: 2025 update
118	[10]	The STRING database in 2025: protein networks with directionality of regulation
95	[11]	Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance
87	[12]	Nucleotide Transformer: building and evaluating robust foundation models for human genomics
84	[13]	Adaptive Intermediate Class-Wise Distribution Alignment: A Universal Domain Adaptation and Generalization Method for Machine Fault Diagnosis
77	[14]	CapMatch: Semi-Supervised Contrastive Transformer Capsule with Feature-Based Knowledge Distillation for Human Activity Recognition
73	[15]	Multidimensional Engineering of Nanoconfined Catalysis: Frontiers in Carbon-Based Energy Conversion and Utilization
71	[16]	Domain generalization for rotating machinery fault diagnosis: A survey
64	[17]	CTBViT: A novel ViT for tuberculosis classification with efficient block and randomized classifier
63	[18]	Less Data, More Knowledge: Building Next-Generation Semantic Communication Networks

Source: Scopus, 2025

The table of most cited articles highlights the dominant research directions shaping scientific output in 2025, showcasing a blend of foundational data infrastructures, advanced artificial intelligence models, and cutting-edge applications across multiple disciplines. Leading the list is [9] database 20-year update (393 citations), underscoring the central role of large-scale proteomics repositories in supporting global bioinformatics research. This is followed by the STRING database 2025 update (118 citations), which continues to serve as a critical resource for mapping protein-protein interaction networks with enhanced regulatory features. [11] influential study on metacognitive laziness in the age of generative AI (95 citations) reflects growing academic concern over how AI tools affect learners' motivation and cognitive engagement. In the field of genomics, [12] Nucleotide Transformer foundation model (87 citations) demonstrates the rapid integration of transformer architectures into biological sequence modeling. Several highly cited engineering and AI papers focus on domain adaptation, fault diagnosis, and feature-efficient learning,

such as [13] universal domain adaptation method (84 citations) and [14] CapMatch contrastive transformer capsule model for human activity recognition (77 citations). Additional impactful works include [15] article on nanoconfined catalysis for energy conversion (73 citations), [14] survey on domain generalization for machinery diagnosis (71 citations), and [17] CTBViT Vision Transformer for tuberculosis detection (64 citations). Rounding out the list, [18] study on semantic communication networks (63 citations) highlights emerging efforts to reduce data requirements while enhancing communication efficiency. Altogether, the table illustrates a research landscape driven by data-rich biological resources, generative and transfer learning models, and practical AI innovations addressing challenges in health, engineering, and communication systems.

3.4 Density Visualization

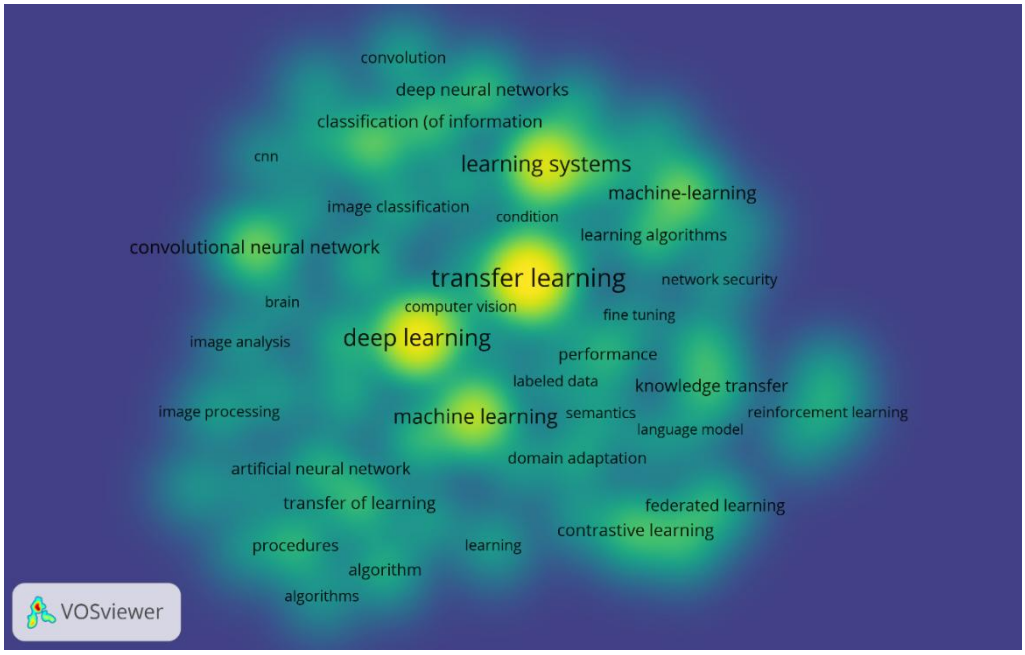

Figure 3. Density Visualization
Source: Data Analysis Result, 2025

The density visualization map highlights the concentration and intensity of research activity within the field of transfer learning, with brighter yellow areas indicating high-frequency and high-impact keywords. At the center of the map, "transfer learning," "deep learning," and "machine learning" appear in the most luminous regions, showing that these concepts dominate the scientific landscape and form the core foundation of current research. Surrounding these central themes, moderately bright areas cluster around terms like "learning systems," "convolutional neural network," "deep neural networks," "knowledge transfer," and "domain adaptation," reflecting their strong but slightly more specialized roles in scholarly publications. Meanwhile, keywords positioned in greener or darker zones—such as "algorithms," "procedures," "image processing," and "reinforcement learning"—indicate areas of steady yet comparatively lower density, representing supportive or emerging components of the field. Overall, the figure illustrates a research ecosystem heavily concentrated on deep learning and transfer learning methodologies, while also showing a diverse spread of related topics that collectively enrich and expand the field's theoretical and practical development.

3.5 Co-Authorship Network

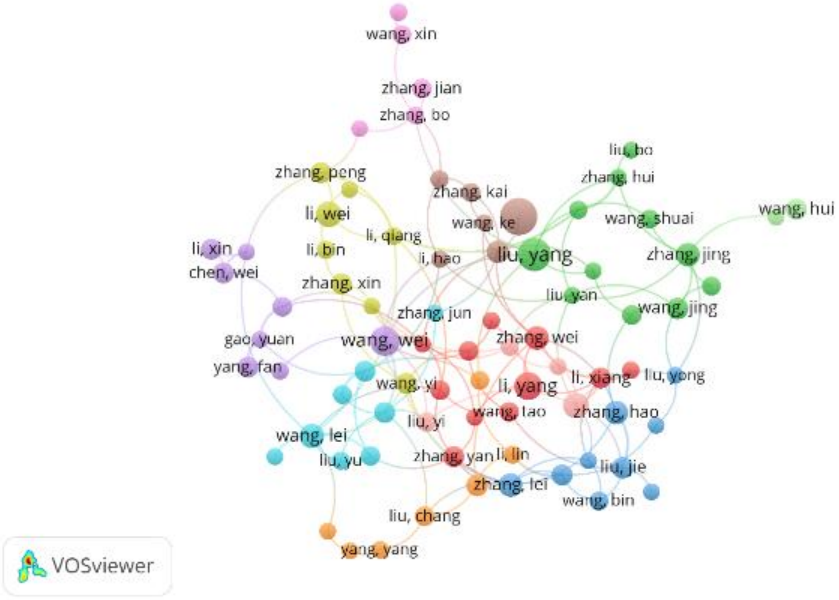

Figure 4. Author Visualization
Source: Data Analysis Result, 2025

The author collaboration network visualized in the VOSviewer map reveals a highly interconnected yet cluster-based structure, indicating that research on transfer learning is driven by several distinct but overlapping groups of scholars. Larger nodes such as liu yang, wang wei, wang lei, li yang, and zhang lei represent the most active and influential authors, reflecting their high publication output and strong connectivity within the co-authorship network. The different colored clusters illustrate collaborative sub-communities, where groups of authors frequently publish together, suggesting shared institutional affiliations, joint research projects, or thematic specialization. For example, the green cluster comprises authors like wang hui, zhang jing, and liu bo, forming a tightly connected group with strong internal collaboration. Similarly, the blue and yellow clusters show dense interaction patterns, indicating cohesive research teams. The network also highlights cross-cluster linkages connecting central authors, suggesting the presence of knowledge bridges that facilitate the exchange of ideas across research groups. Overall, the figure demonstrates that the field is dominated by collaborative teamwork centered around key authors, with moderately strong inter-group connections contributing to the diffusion and advancement of transfer learning research.

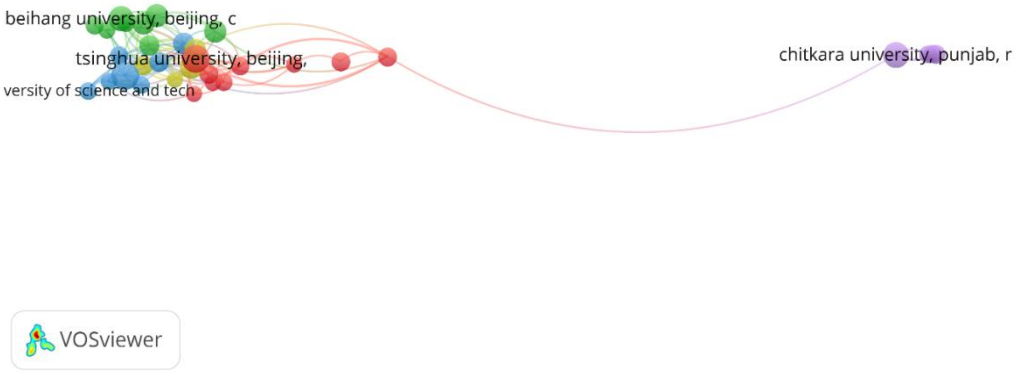

Figure 5. Affiliation Visualization
Source: Data Analysis Result, 2025

The Affiliation collaboration map shows a highly centralized and regionally concentrated research network, dominated by leading Chinese universities. Institutions such as Beihang University (Beijing), Tsinghua University (Beijing), and the University of Science and Technology form dense, tightly connected clusters, indicating strong internal collaboration and frequent joint publications in the field of transfer learning. The close proximity of these nodes demonstrates that these institutions work closely together, sharing research themes, resources, and authorship networks. In contrast, the figure also highlights a small but noticeable external connection leading to Chitkara University in Punjab, India, which appears isolated from the main Chinese cluster. This long-distance link suggests occasional but limited international collaboration between Indian and Chinese institutions, with Chitkara University functioning on the periphery of the global research network. Overall, the visualization reflects that organizational research in transfer learning is largely driven by Chinese academic hubs, with only minimal and emerging cross-border institutional partnerships.

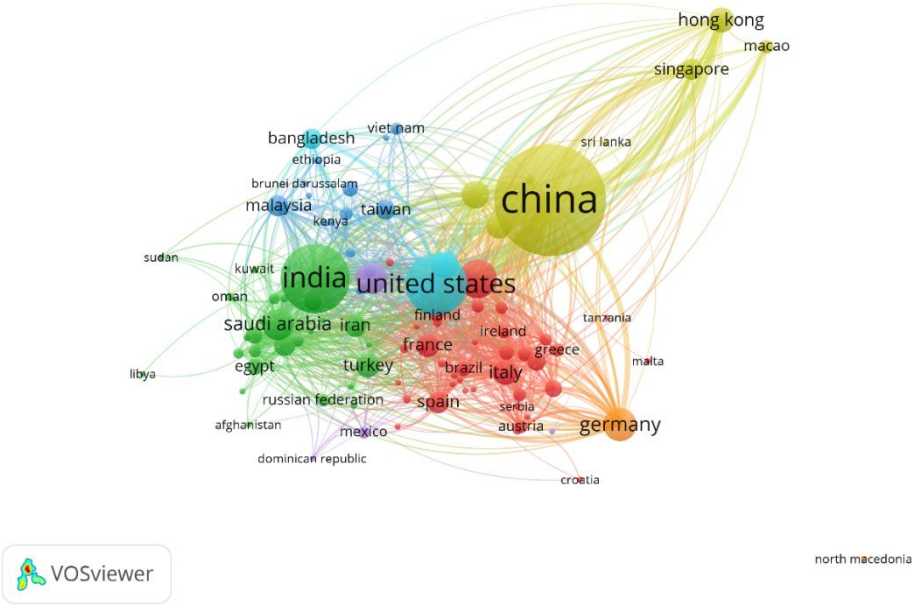

Figure 6. Country Visualization
Source: Data Analysis Result, 2025

The country collaboration map reveals a highly globalized yet uneven research landscape, where a few nations act as central hubs of scientific activity in transfer learning. China, shown as the largest and most interconnected node, dominates the field with extensive collaborative links across Asia, Europe, and North America. Surrounding China, strong partnerships are visible with Hong Kong, Singapore, Taiwan, and Macao, forming a dense regional research network. The United States and India also emerge as major contributors, each forming large clusters with wide-ranging connections to countries across the Middle East, Europe, and Southeast Asia. European countries—such as Germany, France, Spain, Italy, Finland, and Greece—form a cohesive collaborative community, marked by frequent cross-border research interactions. Meanwhile, Middle Eastern and South Asian countries including Saudi Arabia, Iran, Egypt, Kuwait, and Bangladesh appear as active but regionally centered contributors. The presence of long-distance connection lines demonstrates that transfer learning research is shaped by strong transnational collaboration, though participation is highly concentrated among a few leading countries. Overall, the map illustrates a vibrant and interconnected global research ecosystem, with China, the United States, India, and Germany acting as key anchors driving international knowledge exchange and scholarly partnerships.

3.6 Discussion

a. Practical Implications

The findings of this study have several important practical implications for industries, policymakers, educators, and AI practitioners. First, the dominance of keywords such as "fine tuning," "knowledge transfer," and "domain adaptation" suggests that transfer learning has become a preferred strategy for solving real-world problems where labeled data is limited or expensive. Organizations working in healthcare imaging, agriculture, finance, cybersecurity, and smart systems can benefit from adopting transfer learning models to reduce development time and improve performance in specialized domains. Second, the presence of federated learning and other privacy-preserving techniques indicates a growing trend toward decentralized AI solutions. This has implications for sectors handling sensitive data—such as healthcare, banking, and public administration—because these techniques enable model development without exposing raw data. Decision makers seeking to modernize digital infrastructure should therefore prioritize investments in AI models that incorporate secure and distributed learning mechanisms.

Third, the strong connection between transfer learning and image classification, convolutional neural networks, and deep neural networks suggests that practitioners in computer vision can apply pre-trained models to domain-specific tasks with relatively low computational barriers. This democratizes access to advanced AI capabilities, enabling smaller organizations and developing regions to leverage high-performing models without extensive training resources. Fourth, the emergence of reinforcement learning, learning systems, and network security within the yellow cluster shows that AI applications are expanding into safety-critical domains. Policymakers must ensure that these technologies are implemented responsibly, emphasizing fairness, transparency, and robustness. The findings suggest a need for regulatory frameworks that address both the ethical and practical dimensions of transfer

learning deployment. Finally, for educators and trainers, the evolution of transfer learning underscores the importance of teaching not only foundational machine learning theory but also hands-on skills in fine-tuning, model adaptation, and neural architecture optimization. Curricula in computer science, data science, and engineering programs should integrate these topics to prepare students for emerging industry demands.

b. Theoritical Implications

This study contributes to the theoretical understanding of learning transfer in several meaningful ways. First, the bibliometric mapping demonstrates that transfer learning is no longer confined to cognitive or behavioral interpretations; instead, it is embedded within a computational paradigm driven by neural networks and deep learning. This shift suggests a broadening of the theoretical lens through which learning transfer is conceptualized. Traditional theories, such as generalization and conditioned learning, now intersect with algorithmic adaptations that replicate human-like transfer mechanisms in artificial systems. Second, the strong clustering around domain adaptation and knowledge transfer highlights the emergence of a hybrid theoretical space where cognitive ideas about applying prior knowledge merge with technical strategies for adjusting neural weights across domains. This convergence supports a more comprehensive theory of transfer that bridges human cognition and machine intelligence.

Third, the integration of federated learning and contrastive learning into the transfer learning landscape suggests new theoretical pathways. Federated learning, for example, extends the concept of transfer by enabling decentralized model improvement without direct data sharing—introducing a sociotechnical dimension to transfer theory. Contrastive learning, on the other hand, expands theoretical discussions by emphasizing representation learning and similarity-based reasoning, aligning with contemporary cognitive theories of pattern recognition. Fourth, the multidisciplinary nature of the clusters indicates that learning transfer theory is evolving into a cross-domain framework. The fact that clusters span computer vision, general deep learning, reinforcement learning, and cybersecurity demonstrates that transfer learning provides a unifying construct across multiple fields. This broad applicability strengthens the conceptual coherence of transfer learning as a foundational principle in modern AI research. By mapping these developments, this study contributes theoretically by clarifying the intellectual structure of the field, identifying emerging research fronts, and revealing conceptual linkages that shape the ongoing evolution of transfer learning theory.

c. Limitations

Although this study offers meaningful insights, several limitations must be acknowledged. First, the analysis relies exclusively on Scopus data, which, while comprehensive, excludes publications indexed in other databases such as Web of Science, IEEE Xplore, and arXiv. These sources contain highly influential AI research that may not appear in Scopus due to indexing differences. As a result, the representation of emerging topics—especially those in preprint form—may be incomplete. Second, the study uses only VOSviewer for analysis. While VOSviewer is a powerful tool for generating networks and visualizing

co-occurrences, it does not offer advanced techniques such as topic modeling, bibliometric coupling strength quantification, or machine-assisted cluster validation. Other tools like Bibliometrix R or CiteSpace could have provided complementary insights into thematic evolution, burst detection, and citation trajectories. Third, the interpretation of clusters remains partly subjective. Although the software identifies groups based on co-occurrence strength, the assignment of conceptual meaning to these clusters depends on human judgment. Different analysts might categorize or interpret the clusters differently. Fourth, this study focuses specifically on keyword co-occurrence, which reflects thematic relationships but does not capture conceptual depth or methodological nuances. For example, two keywords may co-occur frequently without indicating a substantive theoretical relationship. Similarly, emerging or niche topics may not appear prominently due to lower publication volume, despite their conceptual importance. Finally, the bibliometric approach cannot evaluate the quality, rigor, or validity of the individual studies included in the dataset. Citation frequency and keyword strength do not always correspond to theoretical significance or practical impact. Future studies could integrate qualitative systematic reviews to complement the quantitative findings presented here.

4. CONCLUSION

This bibliometric analysis provides a comprehensive overview of the global landscape of learning transfer research, revealing a field that has rapidly evolved from its theoretical roots in education and psychology into a central component of modern artificial intelligence. The VOSviewer keyword network demonstrates that transfer learning now functions as a bridging paradigm that connects foundational deep learning methods, computer vision applications, advanced algorithmic innovations, and emerging system-level domains such as reinforcement learning and cybersecurity. The strong interlinkages among clusters highlight the field's multidisciplinarity and the growing sophistication of its methodological foundations. Moreover, the emergence of recent concepts such as federated learning and contrastive learning indicates that research on learning transfer is shifting toward more complex, data-efficient, and privacy-aware frameworks. Overall, the findings affirm that learning transfer has become a core engine for innovation across global scientific communities, and future research will benefit from deeper theoretical integration, stronger interdisciplinary collaboration, and a focus on developing more generalizable, interpretable, and human-aligned models.

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