

Explainable Decision Support Systems (2010–2024): A Bibliometric Review of Intellectual Structure

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ABSTRACT

This study provides a comprehensive bibliometric analysis of Explainable Decision Support Systems (EDSS) research published between 2010 and 2024, with the objective of mapping its intellectual structure, thematic evolution, and emerging trends. Data were collected from the Scopus database and analyzed using quantitative bibliometric techniques, including performance analysis and science mapping, supported by visualization through VOSviewer. The results indicate a significant growth in EDSS publications, particularly after 2019, driven by the increasing demand for transparency and accountability in artificial intelligence-based decision-making. The network and density analyses reveal that core research themes are centered on machine learning, decision support systems, and artificial intelligence, while emerging topics include interpretability, trust, and human-centered design. Co-authorship and co-citation analyses highlight the interdisciplinary nature of the field, with strong contributions from domains such as healthcare, industry, and data science. Furthermore, the findings demonstrate a shift from purely technical model development toward the integration of explainability, ethics, and user interaction in decision-making systems. This study contributes by offering a structured overview of EDSS research and identifying key directions for future studies, particularly in developing standardized evaluation frameworks and expanding applications beyond dominant domains such as healthcare.

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1. INTRODUCTION

In recent years, the rapid advancement of data-driven technologies has significantly reshaped organizational decision-making processes. The integration of artificial intelligence (AI), machine learning (ML), and big data analytics has transformed traditional Decision Support Systems (DSS) into more sophisticated, intelligent, and automated systems. While

these developments have enhanced analytical capabilities and decision accuracy, they have simultaneously introduced critical challenges related to transparency, interpretability, and user trust [1], [2]. The increasing reliance on complex algorithmic models—often perceived as “black boxes”—limits stakeholders’ ability to understand how decisions are generated, raising serious concerns in high-stakes domains such as

healthcare, finance, public policy, and legal systems [3].

In response to these challenges, the concept of Explainable Decision Support Systems (EDSS) has emerged as a crucial research direction that seeks to bridge the gap between predictive performance and interpretability. EDSS integrates traditional DSS frameworks with explainable artificial intelligence (XAI) approaches, emphasizing not only the accuracy of system outputs but also the clarity of the reasoning behind them [4], [5]. This shift is increasingly driven by ethical, legal, and regulatory pressures. Notably, frameworks such as the General Data Protection Regulation (GDPR) have institutionalized the “right to explanation,” requiring organizations to provide meaningful insights into automated decision-making processes [6], [7]. As a result, explainability is no longer a technical preference but a fundamental requirement in modern decision systems.

Despite the growing scholarly attention to EDSS, the existing body of literature remains highly fragmented across multiple disciplines, including computer science, information systems, healthcare informatics, and business analytics. Prior studies tend to focus on specific methods or application contexts—such as interpretable machine learning models, visualization techniques, or user-centered system design—without offering a comprehensive synthesis of the field. This disciplinary dispersion has resulted in a limited understanding of the overall intellectual structure, key research streams, and knowledge evolution within EDSS research. Consequently, identifying research gaps, consolidating theoretical foundations, and formulating future research agendas remain challenging [8]–[10].

To address this limitation, a systematic and integrative approach is required to map the development and structure of EDSS research. Bibliometric analysis provides a robust methodological framework for examining large-scale scientific publications and uncovering patterns of knowledge production. By analyzing citation networks, co-authorship

relationships, and keyword co-occurrences, bibliometric techniques enable researchers to identify influential contributors, dominant themes, and emerging research trends. The use of advanced visualization tools such as VOSviewer further enhances the ability to interpret complex relationships within the literature and reveal the underlying intellectual architecture of a research domain.

Accordingly, this study conducts a comprehensive bibliometric analysis of EDSS research published between 2010 and 2024 using data retrieved from the Scopus database. Specifically, this study aims to: (1) examine the growth trajectory of EDSS publications over time; (2) identify the most influential authors, institutions, and countries contributing to this field; (3) analyze the dominant research themes and their evolution; and (4) map the intellectual structure that characterizes the EDSS research landscape.

This study contributes to the literature in three significant ways. First, it provides a comprehensive overview of the development and dynamics of EDSS research over a 15-year period. Second, it offers a structured understanding of the field by identifying its core thematic clusters and intellectual foundations. Third, it highlights emerging research directions, thereby offering valuable insights for scholars and practitioners seeking to advance explainable and trustworthy decision-making systems. By addressing the fragmentation of existing studies, this research contributes to the consolidation of knowledge in EDSS and supports the development of more transparent, accountable, and human-centered decision support technologies.

2. RESEARCH DESIGN

This study adopts a quantitative bibliometric approach to systematically analyze the development and intellectual structure of Explainable Decision Support Systems (EDSS) research. The research design follows a structured workflow consisting of four stages: data identification and retrieval, data cleaning and preprocessing, bibliometric analysis, and

visualization and interpretation. This approach ensures methodological rigor, transparency, and reproducibility in line with established bibliometric standards. The dataset was obtained from the Scopus database, selected for its extensive coverage and standardized indexing of high-quality academic publications. The search strategy employed Boolean operators to capture relevant literature, using the query: TITLE-ABS-KEY (“explainable decision support system” OR “explainable AI” OR “interpretable machine learning” AND “decision support system” OR “decision-making system”)*. The analysis was limited to publications between 2010 and 2024, including articles, conference papers, and review papers published in English to ensure consistency and academic rigor.

The retrieved data were subjected to a rigorous screening and preprocessing process to ensure quality and relevance. Duplicate records and documents with incomplete metadata were removed, while irrelevant publications were excluded through manual review of titles and abstracts. Furthermore, data cleaning involved standardizing author names, institutional affiliations, and keywords to minimize inconsistencies. For instance,

variations such as “XAI,” “Explainable AI,” and “Explainable Artificial Intelligence” were harmonized to improve the accuracy of co-occurrence and network analyses. This preprocessing stage is critical in bibliometric studies to enhance the reliability and validity of the resulting knowledge mapping.

The analysis combines performance analysis and science mapping techniques to provide both descriptive and relational insights into the EDSS research landscape. Performance analysis evaluates research productivity and impact through indicators such as publication trends, leading authors and institutions, influential journals, and citation metrics. Meanwhile [11], [12], science mapping explores the structural relationships within the field through co-authorship, co-citation, and keyword co-occurrence analyses, as well as clustering techniques to identify thematic groupings. The results were visualized using VOSviewer [13], [14], which enables the construction of network, overlay, and density maps. These visualizations facilitate the interpretation of complex bibliometric data, allowing for the identification of collaboration patterns, thematic evolution, and emerging research trends within the EDSS domain

3. RESULTS AND DISCUSSION

3.1 Author Collaboration Analysis

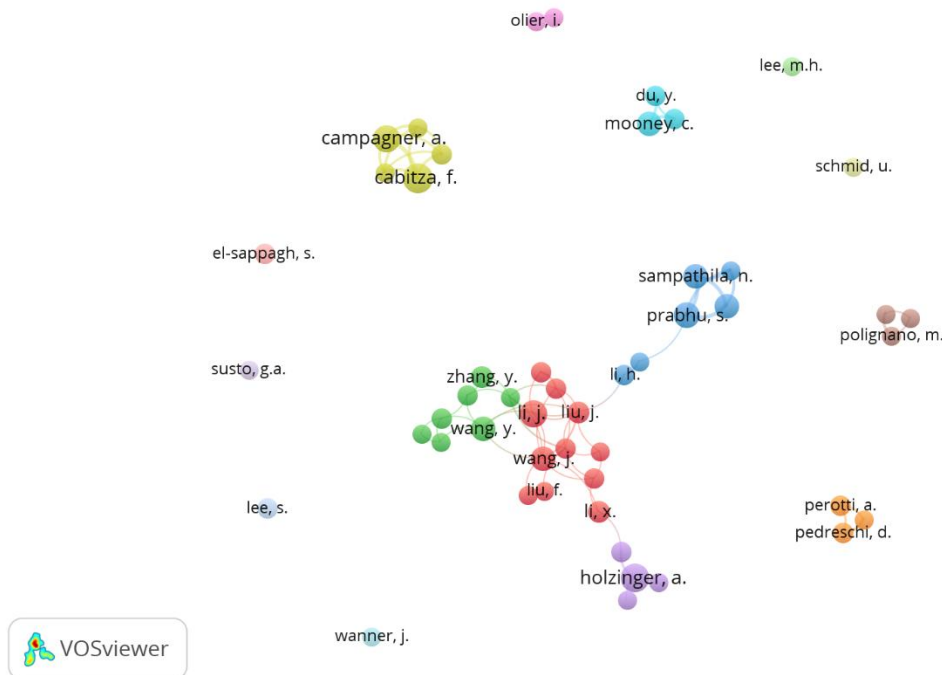


Figure 1. Author Visualization

Source: Data Analysis

Figure 1 presents the author co-authorship visualization generated using VOSviewer, illustrating the collaborative structure within the Explainable Decision Support Systems (EDSS) research domain. The network reveals several distinct clusters, each represented by different colors, indicating groups of authors who frequently collaborate on related topics. A central cluster, dominated by authors such as Liu, Wang, and Li, appears to act as the core of the network, suggesting that these researchers have strong collaborative ties and significant influence in the field. Surrounding this core, smaller clusters—such as those involving Zhang, Mooney,

and Sampathila—indicate emerging or more specialized research groups. The presence of connecting links between clusters reflects interdisciplinary collaboration, although some authors remain isolated, highlighting limited interaction across certain research streams. Overall, the structure suggests that while EDSS research is growing and forming strong core collaborations, there is still fragmentation, offering opportunities to strengthen cross-cluster collaboration and knowledge integration in future studies.

3.2 Citation Analysis: Influential Publications

Table 1. Most Cited Article

Citations	Author and Year	Title	Publication
1010	[15]	The false hope of current approaches to explainable artificial intelligence in health care	The Lancet Digital Health
729	[16]	Deep learning in cancer diagnosis, prognosis and treatment selection	Genome Medicine
713	[17]	From Artificial Intelligence to Explainable Artificial Intelligence in Industry 4.0: A Survey on What, How, and Where	IEEE Transactions on Industrial Informatics

Citations	Author and Year	Title	Publication
664	[18]	Effect of confidence and explanation on accuracy and trust calibration in AI-assisted decision making	FAT* 2020 - Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency
649	[19]	To Trust or to Think: Cognitive Forcing Functions Can Reduce Overreliance on AI in AI-assisted Decision-making	Proceedings of the ACM on Human-Computer Interaction
644	[20]	Explainable AI: A Brief Survey on History, Research Areas, Approaches and Challenges	Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)
580	[21]	A systematic review of trustworthy and explainable artificial intelligence in healthcare: Assessment of quality, bias risk, and data fusion	Information Fusion
538	[22]	A Multidisciplinary Survey and Framework for Design and Evaluation of Explainable AI Systems	ACM Transactions on Interactive Intelligent Systems
523	[23]	Current challenges and future opportunities for xai in machine learning-based clinical decision support systems: A systematic review	Applied Sciences (Switzerland)
454	[24]	Opening the Black Box: The Promise and Limitations of Explainable Machine Learning in Cardiology	Canadian Journal of Cardiology

Source: Scopus, 2026

Table 1 highlights the most cited articles in the domain of Explainable Decision Support Systems (EDSS), revealing that the intellectual foundation of this field is strongly rooted in explainable artificial intelligence (XAI), particularly within high-stakes application domains such as healthcare and Industry 4.0. The most influential work by Marzyeh Ghassemi emphasizes critical limitations of current XAI approaches in clinical contexts, indicating that explainability is not merely a technical feature but a fundamental requirement for safe and ethical decision-making. Similarly, highly cited studies in medical AI—such as cancer diagnosis and clinical decision support—demonstrate that healthcare

serves as a primary driver of EDSS research, where transparency directly impacts trust and adoption. Contributions published in leading venues like *The Lancet Digital Health* and *IEEE Transactions on Industrial Informatics* further reinforce the interdisciplinary nature of the field, bridging computer science, medicine, and industrial systems. Moreover, several influential papers focus on human-AI interaction, trust calibration, and cognitive biases, highlighting a shift toward human-centered explainability. Overall, the citation pattern indicates that EDSS research is shaped by a combination of technical advancements in XAI, domain-specific applications, and increasing attention to trust, ethics, and

decision reliability, reflecting the maturation of the field from purely algorithmic development to socio-technical integration.

3.3 Keyword Co-Occurrence and Research Themes

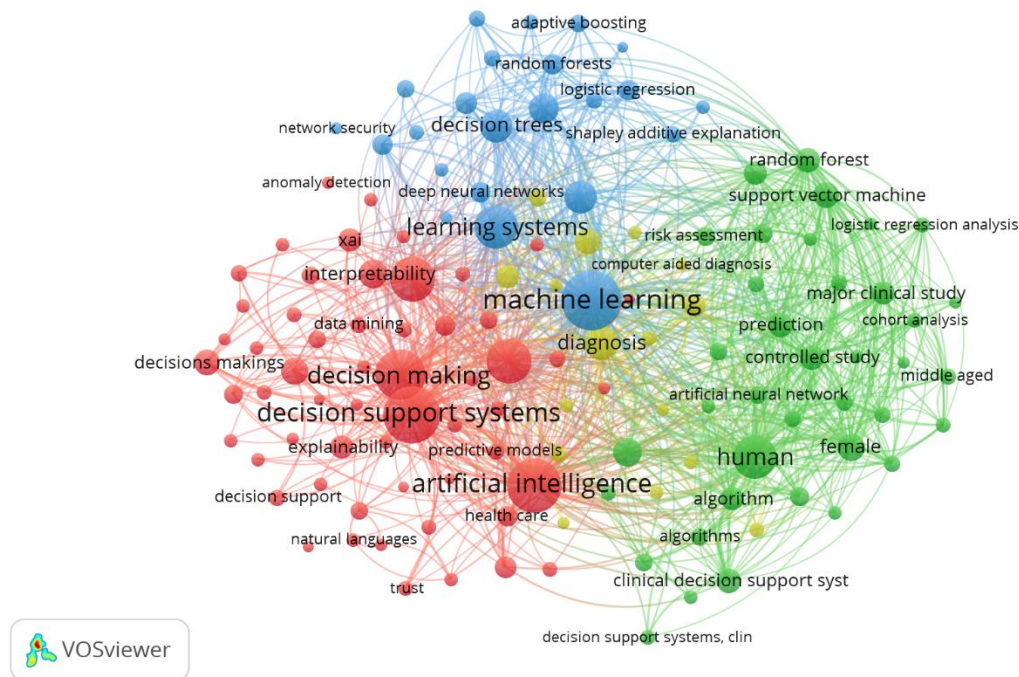


Figure 2. Network Visualization
Source: Data Analysis

Figure 2 illustrates the keyword co-occurrence network generated using VOSviewer, revealing the conceptual structure of Explainable Decision Support Systems (EDSS) research. The network is divided into several distinct clusters, each represented by different colors. The red cluster is primarily associated with “decision support systems,” “decision making,” “artificial intelligence,” and “explainability,” indicating the foundational role of DSS integrated with AI and interpretability concepts. The blue cluster centers around “learning systems,” “decision trees,” and “deep neural networks,” reflecting the technical backbone of machine learning models used in EDSS. Meanwhile, the green cluster highlights application-oriented terms such as “human,” “clinical decision support system,” and “prediction,” suggesting a strong

emphasis on healthcare and human-centered applications. The proximity and interconnection among these clusters demonstrate the integration between technical methodologies and real-world decision-making contexts.

Furthermore, the prominence of keywords such as “machine learning,” “diagnosis,” and “algorithm” at the center of the network indicates that EDSS research is heavily driven by data-driven approaches. The presence of terms like “interpretability,” “trust,” and “risk assessment” suggests an evolving focus toward ensuring transparency and reliability in AI-assisted decisions. Notably, healthcare-related terms dominate a significant portion of the network, reinforcing the role of medical applications as a key driver of explainable decision systems. Overall, the network structure highlights that

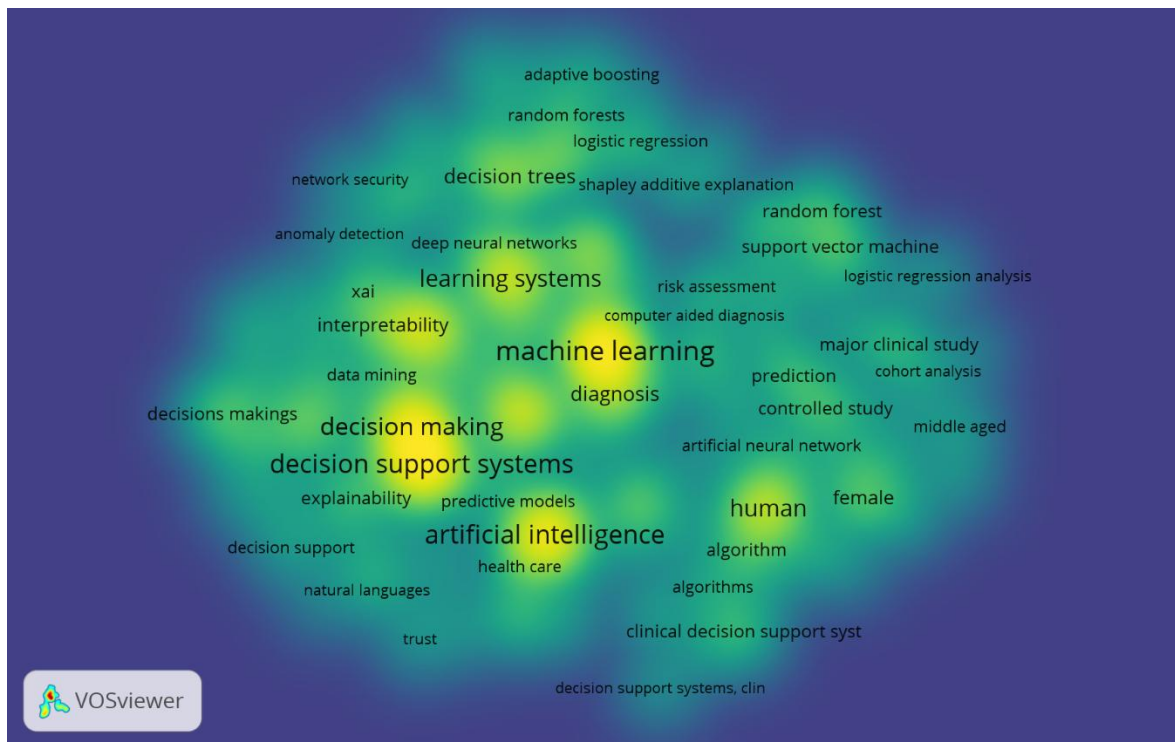


Figure 4. Density Visualization
Source: Data Analysis

Figure 4 presents the density visualization generated using VOSviewer, which highlights the concentration of research activity within the Explainable Decision Support Systems (EDSS) domain. Areas shown in bright yellow indicate topics with the highest frequency and strongest co-occurrence, notably “machine learning,” “decision support systems,” “decision making,” and “artificial intelligence,” confirming their role as the core focus of the field. Surrounding these hotspots are moderately dense areas (green tones) such as “interpretability,” “learning systems,” and “human,” suggesting growing but slightly less dominant research attention. In contrast, darker regions (blue tones) represent emerging or less explored topics, including “trust,” “natural languages,” and certain domain-specific applications. This distribution indicates that while EDSS research is heavily centered on machine learning-driven decision frameworks, there is an expanding interest in human-centered and explainability-related

aspects, pointing to opportunities for future research in integrating technical performance with user trust and contextual applicability.

3.4 Discussion

The findings of this bibliometric analysis demonstrate that research on Explainable Decision Support Systems (EDSS) has experienced substantial growth, particularly in the last five years. This trend reflects the increasing reliance on artificial intelligence and machine learning in decision-making processes across various sectors. However, the rapid adoption of these technologies has also intensified concerns regarding transparency, accountability, and trust. The strong presence of keywords such as “machine learning,” “decision support systems,” and “artificial intelligence” confirms that EDSS research is deeply rooted in data-driven methodologies, while the emergence of “interpretability” and “explainability” indicates a paradigm shift toward more transparent systems.

Furthermore, the intellectual structure of EDSS reveals a clear integration between technical and application-oriented research. On one hand, clusters related to algorithms, such as decision trees, random forests, and deep neural networks, highlight the importance of developing robust and accurate predictive models. On the other hand, clusters associated with healthcare, clinical decision support, and human-centered systems emphasize the need to apply these models in real-world contexts where decision outcomes have significant consequences. This duality suggests that EDSS research is not only concerned with improving model performance but also with ensuring that these models can be effectively understood and utilized by end users [1], [2], [25].

Another important insight from the analysis is the growing emphasis on human-AI interaction and trust. Highly cited studies and emerging keywords such as “trust,” “risk assessment,” and “human” indicate that researchers are increasingly focusing on how users perceive and interact with explainable systems. This shift highlights that explainability is not solely a technical challenge but also a cognitive and behavioral one. The effectiveness of EDSS depends not only on the quality of explanations but also on how these explanations influence user confidence, decision accuracy, and reliance on AI systems.

In addition, the dominance of healthcare-related applications in the network and density visualizations underscores the critical role of EDSS in high-stakes environments. In domains such as clinical diagnosis and treatment decision-making, the need for explainable systems is particularly urgent, as decisions directly impact human lives. This has driven significant research efforts toward developing explainable models that can provide clear, interpretable, and reliable insights

to practitioners [5], [26]. However, this concentration also suggests that other domains, such as public policy, education, and environmental management, remain underexplored and offer opportunities for future research.

Finally, this study highlights several gaps and future research directions. There is a need for standardized frameworks and evaluation metrics to assess the effectiveness of explainability in decision support systems. Additionally, future research should focus on integrating user-centered design principles to ensure that explanations are meaningful and actionable for different stakeholders. Expanding EDSS applications beyond healthcare and improving interdisciplinary collaboration will also be crucial for advancing the field. Overall, the evolution of EDSS research indicates a transition toward more holistic systems that balance technical performance, transparency, and human usability, paving the way for more trustworthy and impactful decision-making technologies.

4. CONCLUSION

This study systematically maps the development and intellectual structure of Explainable Decision Support Systems (EDSS) research from 2010 to 2024. The findings indicate that EDSS has emerged as a rapidly expanding and interdisciplinary field, driven by the growing integration of artificial intelligence into decision-making processes and the increasing demand for transparency and trust. Bibliometric results reveal that the field is strongly rooted in machine learning and decision support paradigms, while progressively evolving toward more human-centered, ethical, and application-oriented perspectives. In particular, healthcare appears as a dominant application domain, highlighting the critical importance of explainability in high-stakes environments. Furthermore, the emergence of key themes such as trust, interpretability, and human-AI interaction reflects a broader

paradigm shift toward holistic and user-oriented system design.

Despite these advancements, several critical research gaps remain, including the absence of standardized evaluation metrics, limited cross-domain applications, and insufficient integration of user perspectives in EDSS development. This study contributes to the literature by offering a comprehensive and structured overview of the field, while also identifying emerging trends and future

research directions. Accordingly, further research is needed to strengthen interdisciplinary collaboration, develop robust and practical evaluation frameworks, and extend EDSS applications across diverse sectors. Addressing these challenges is essential for advancing EDSS as a foundation for transparent, reliable, and human-centered decision-making in the era of intelligent systems.

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