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Trends and Developments in Fuzzy Logic for Medical Diagnosis: A Bibliometric Analysis

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Abstract. The complexity and uncertainty inherent in medical diagnosis pose significant challenges for accurate and timely decision-making. To address these challenges, advanced technologies such as clinical decision support systems have gained prominence. Integrating fuzzy logic (FL) into these systems offers a practical solution for managing uncertainty, as it provides a more flexible framework than traditional binary (on–off, zero–one) approaches. In particular, FL has contributed to improved diagnostic accuracy, the handling of uncertainty and vagueness in patient-reported symptoms, and the support of decision-making when data is incomplete or ambiguous. This study presents a bibliometric analysis of the leading research trends in this field, offering insights into the evolution and impact of FL in medical diagnosis. By facilitating the representation of nuanced degrees of clinical parameters such as pain intensity or fever severity, FL enables the modeling of complex disease patterns, the development of predictive analytical models, and the construction of intelligent healthcare systems. This capability enhances diagnostic precision, supports early detection, and extends the applicability of decision support tools to complex and uncertain clinical scenarios. At the time of conducting this bibliometric analysis, searches in Scopus databases revealed no prior bibliometric studies focused on the application of FL in medical diagnosis.

Keywords: Clinical decision support systems, uncertainty modeling, artificial intelligence in healthcare, bibliometric mapping, research trends

1. Introduction

A primary challenge confronting both developed and developing nations pertains to the provision of adequate medical care to the indigent population (Awotunde et al., 2014). A significant number of hospitals grapple with a shortage of skilled medical professionals, prompting nations to allocate substantial resources to address this issue (Kanchanachitra et al., 2011). Despite these endeavors, numerous nations encounter difficulties in fulfilling the demand for quality healthcare services. In some regions, accessing affordable healthcare services can be time-consuming, yet certain illnesses require immediate attention due to their nature. Delayed treatment can result in the spread of infectious diseases and increased risks of mortality (Matinfar and Golpaygani, 2022).

Hence, it is crucial to consider reducing costs and providing prompt treatment within the healthcare system. To address these challenges, modern medical diagnostics increasingly rely on computer-related technologies, which are continually advancing (Charanbir et al., 2023).

The employment of FL is driven by the necessity to account for uncertainty and vagueness that are inherent in conventional medical diagnostic practices. Uncertainty constitutes a foundational component in disease diagnosis, wherein numerous variables contribute to the complexity of the diagnostic process (Ahmadi et al., 2018). This uncertainty is frequently associated with imprecise observations and subjective experiences reported by patients. For instance, patients may respond to questions regarding symptoms of weakness with responses that are ambiguous, such as "somewhat weak" (Ohayon, 1999). The pervasive uncertainty and lack of clarity in medical data pose challenges for traditional diagnostic methods, complicating the process of accurately identifying illnesses without error (Meyer et al, 2021). In this scenario, the integration of FL into decision support systems (DSSs) is regarded as the most effective method for addressing the complex nature of human illness. FL offers robust reasoning techniques capable of managing uncertainties and imprecision (Tang and Ahmad, 2024). Utilizing scientific principles that address imprecision, FL can provide a framework for managing the inconsistencies in medical data. The development of fuzzy models is informed by the expertise, observations, and experiences of medical professionals, thereby serving as the foundational element for medical diagnostic systems (Phuong and Kreinovich, 2001). The integration of FL technology facilitates the extraction of definitive conclusions from vague, imprecise, and ambiguous medical information, thereby enhancing the reliability and precision of diagnostic decisions.

In the domain of medicine, particularly in oriental medicine, numerous medical concepts are characterized by ambiguity. The vague nature of these concepts and their interconnections necessitates the application of "FL" (Pandey, 2016). Zadeh (1965) introduced a theory outlining the formalization of "fuzzy" (non-binary) properties. In fuzzy set theory, X is represented as a set of possible values ranging from 0 to 1, while a fuzzy property is described by a function $\mu \rightarrow [0.1]$. The value $\mu(x)$ denotes the extent to which x possesses the property (e.g., the degree of pain experienced by x). Fuzzy set theory differs from traditional binary logic in that it recognizes the gray area between truth and falsehood. This representation of therapeutic conditions and indications is less inflexible than a basic on-off or zero-one arrangement would imply (Phuong and Kreinovich, 2001). In fuzzy set theory, linguistic terms, symbolic and numerical values are mapped to each fuzzy variable and fuzzy set, respectively.

In practice, the membership degree serves as an input to the rule-based inference mechanism of diagnostic systems such as CADIAG-2. For example, if a patient’s temperature is $38.8\circ$C, the membership degree for the fuzzy set “High Fever” is μHF = 0.6 indicating a 60% presence of this symptom. Each symptom (e.g., high fever, rash, fatigue) is represented by a corresponding fuzzy value in [0,1]. In CADIAG-2, these values are combined through fuzzy rules, such as

IF High Fever AND Rash THEN Measles (high likelihood),

where the logical AND is often implemented using the minimum operator

$$\mu_{\text{Measles}} = \min(0.7,0.9) = 0.7.$$

If symptoms have different diagnostic importance, weighted aggregation can be applied as

$$\mu_{\text{Measles}} = \frac{w1 \times 0.7 + w2 \times 0.9 + w3 \times 0.6}{w1 + w2 + w3}.$$

The resulting degree of membership for a disease can be interpreted as a risk score: low values may lead to routine monitoring, medium values to additional testing, and high values to immediate clinical action. This process bridges the abstract mathematical definition of a fuzzy set with concrete medical decision-making.

Zadeh's seminal work pioneered a novel approach to FL rules of inference, characterized by logical operations over membership functions (Zadeh, 1983). These rules, exhibiting an "if–then" structure, have been successfully applied in various domains, including forecasting and medical diagnosis. In the medical context, such rules facilitate the interpretation and processing of patient data to generate clinically relevant outputs (Stoean and Stoean, 2013).

Each fuzzy rule consists of an antecedent (the "if" part) and a consequent (the "then" part). For example, in a clinical setting:

IF temperature is high AND rash is present, THEN the likelihood of measles is high.

Formally, a fuzzy "if–then" rule, also referred to as a fuzzy implication, can be expressed as

$$\text{IF } x = A, \text{ THEN } y = B$$

where A and B are linguistic fuzzy values determined by the corresponding membership functions for variables x and y. For multiple variables $x_1, x_2, \ldots, x_n$, a set of such rules can be aggregated as

$$\text{IF } x_1 = A_1 \text{ AND } x_2 = A_2 \ldots \text{ AND } x_n = A_n, \text{ THEN } y = B.$$

Here, $x_1, x_2, \ldots, x_n$ represent the features of the n-dimensional input vector X. This formulation allows complex medical conditions to be described as combinations of multiple symptoms and clinical findings, enabling the system to model uncertainty and support diagnostic reasoning beyond the limits of binary logic.

FL (FL) provides a powerful framework for modeling uncertainty in medical decision-making, bridging human reasoning with computational intelligence. Through processes such as fuzzification, rule inference, and defuzzification, FL systems can represent vague clinical concepts and handle imprecise data effectively (Vyas et al., 2022). This interpretability and flexibility have led to its integration into modern medical decision-support systems and hybrid computational models, such as fuzzy neural networks and IoT-based healthcare architectures (Mohod et al., 2025).

In the domain of medicine, a considerable number of DSSs have been developed. In 1980, a real-time fuzzy control drug delivery system was utilized to regulate blood pressure in patients with open heart surgery. Smets (1983) developed a fuzzy model that employs expected utility theory and fuzzy numbers to optimize decision-making regarding renal transplants. Phuong and Kreinovich (2001) developed a fuzzy system for diagnosing various lung diseases by integrating diagnostic methods from Eastern and Western medicine based on patient symptoms. Hayward and Davidson (2003) presented a study of a DSS for automating the application of clinical practice guidelines based on fuzzy methods. Beig et al. (2011) designed another model of a FL medical diagnosis control system. This system utilizes FL design, comprising a fuzzifier, an inference engine, a rule base, and a defuzzification process. It is capable of medical diagnosis with five inputs (protein, red blood cells, lymphocytes, neutrophils, and eosinophils) and three outputs. A systematic review titled "Medical Applications of FL Inference Systems" was conducted by Thukral and Bal (2019), encompassing literature from the past decade (2008-2018) on the use of FL in various medical applications and methodologies developed during that time frame. The paper focuses on eight prevalent medical conditions, including heart disease, asthma, liver disease, breast cancer, Parkinson's disease, cholera, dental issues, and diabetes. It explores the potential of implementing FL in different medical domains in the future based on these applications. Matinfar and Golpayegani (2022) developed a fuzzy expert system for the early diagnosis of multiple sclerosis. This system mapped symptoms to fuzzy sets and established rules for predicting the disease. Concurrently, Myrzakerimova et al. (2024) spearheaded research endeavors focusing on advanced mathematical models for disease diagnosis and prediction. Their research led to the development of automated systems based on these models. These systems were designed to reduce subjectivity through computational assessment of imprecision and uncertainty. Additionally, they sought to enhance diagnostic modeling using fuzzy set theory. Building upon these findings, Myrzakerimova and Kolesnikova (2024) created a fuzzy system capable of diagnosing kidney diseases.

While many researchers have explored FL and medical diagnosis, there is a lack of studies addressing the evolution and mapping of this scientific domain. This study dwells on the issues related FL and medical diagnosis in the context of today's research by identifying the most important lines of research, researchers, and research concentration areas. To explore the trends in the area of fuzzy set theory and medical diagnosis, this study used bibliometric analysis. Bibliometric analysis is a methodology that employs statistical and quantitative techniques to evaluate academic literature. These techniques are designed to identify influential authors, map collaboration networks, and uncover emerging research trends. The application of these techniques provides comprehensive insights into research landscapes and enhances understanding of various domains (Kumar, 2025). The present study employed VOSviewer, a software program designed to facilitate the analysis of bibliometric data. This software offers a comprehensive visualization of literature relevant to the subject of material selection, thereby enabling an in-depth analysis of the associated research trends. The utilization of VOSviewer facilitates a thorough exploration of the evolution of decision-making processes in material selection, leading to the identification of significant trends and connections within the existing literature. The software assists in mapping essential studies, authors, and collaborative efforts, thereby providing a more holistic view of the research landscape. This approach not only illustrates the development of research concepts but also emphasizes the interrelationships among various contributors and institutions (Sahoo et al., 2024). This study aims to answer the overarching question: "What are the main trends and developments in the research on the application of FL in medical diagnosis, and how does this field appear in terms of scientific publications, prevalent topics, leading authors, and future directions?"

To achieve the aim of this paper, the sub-research questions (RQs) are formulated as follows:

RQ1: What is the distribution of research in the field of FL and medical diagnosis?
RQ2: What is the distribution of research in the field of FL and medical diagnosis in different periods of time?
RQ3: Who are the prolific researchers in the field of FL and medical diagnosis?
RQ4: What was the contribution of each university in the field of FL and medical diagnosis?
RQ5: Which journals mainly published FL and medical diagnosis research?
RQ6: What languages are the publishes in the field of FL and medical diagnosis mainly in?
RQ7: What was the distribution of each country in the field of FL and medical diagnosis publishes?
RQ8: What are the most important themes in the field of FL and medical diagnosis?

2. Methodologies

To address the research inquiries and discern patterns in the evolution of FL in medical diagnosis, a comprehensive bibliometric analysis is undertaken, focusing on the most significant scholarly contributions and areas of research concentration. This analytical method, which employs mapping and clustering techniques, consists of three primary phases: data acquisition, data processing, and results extraction (da Silva and de Souza, 2021).

The Scopus database is selected as the singular data repository for this bibliometric study due to its extensive scope, rigorous quality assurance protocols, and comprehensive citation analysis capabilities. Scopus is recognized as the foremost curated repository for abstracts and citations, encompassing a vast collection of scientific journals, conference proceedings, and academic monographs from over 5,000 international publishers across various disciplines (Salleh et al., 2023). Furthermore, Scopus offers advanced profiling for both authors and institutions and is fully compatible with bibliometric visualization instruments such as VOSviewer, thus facilitating efficient data extraction and analysis (Zainuldin and Lui, 2022). In comparison to databases like Web of Science, Scopus provides broader global coverage and a more heterogeneous array of content, thereby enabling a thorough and unbiased perspective of the research landscape (Salleh et al., 2023). The attributes of Scopus render it particularly suitable for executing comprehensive bibliometric analyses in our investigation. Scopus is regarded as one of the largest databases for abstracts and citations. It encompasses journal articles and conference proceedings across diverse fields and offers high compatibility with bibliometric tools such as VOSviewer. Its export functionalities are user-friendly and well-supported for bibliometric mapping. A total of 356 documents are acquired after the application of the search criteria. Although using only one database may introduce some bias, Scopus provides extensive coverage and is widely accepted in bibliometric studies, especially when using network mapping tools like VOSviewer.

For quantitative data analysis and visualization of bibliometric networks, the free-access VOSviewer (version 1.6.17) software is used, and co-authorship and co-words networks are constructed. VOSviewer is intended primarily for analyzing bibliometric networks, and it provides three visualizations: network visualization, overlay visualization, and density visualization (Skačkauskienė, 2022). The bibliographic data retrieved from Scopus is examined using VOSviewer following its import. The data is exported straight from the Scopus database in CSV format to ensure complete compatibility with VOSviewer. A thesaurus document is meticulously constructed to amalgamate synonymous terminology and to consolidate variations of author names (e.g., 'Smith J.' and 'Smith, John'). The document adhered to VOSviewer's bifurcated format, wherein synonyms are categorized beneath a singular preferred designation. To ensure methodological rigor and transparency, this study followed the systematic mapping process outlined by Kitchenham and Charters (2007). We applied the PICOC framework to define the scope of our research and guide the formulation of search strings:

- Population (P): Studies focusing on FL applications in medical diagnosis
- Intervention (I): Bibliometric analysis of published literature
- Comparison (C): Not applicable (no intervention comparison is made)
- Outcome (O): Identification of publication trends, active contributors, and thematic clusters
- Context (C): Peer-reviewed scientific publications indexed in the Scopus database.

Based on this framework, we develop a structured search query: TITLE-ABS-KEY (fuzzy AND logic AND medical AND diagnosis). The query is applied in the Scopus database in January 2025, without restrictions on publication year, document type, or subject area. All retrieved records containing English titles, abstracts, or keywords are included to ensure linguistic consistency for bibliometric analysis. The extracted data is then analyzed using VOSviewer for network visualization and mapping.

The methodological framework for data collection and analysis is structured according to a predefined research protocol, which ensures transparency and reproducibility while allowing for minor adjustments depending on the specific research questions or stages of the inquiry. Consistent with this protocol, a comprehensive dataset was retrieved from the Scopus database and systematically analyzed using bibliometric mapping techniques. The parameters of the data collection and analytical process are summarized in Table 1.

Table 1. Data collection and analytical protocol

Topic	**Research Questions (Q1-Q8)**
Keywords	"FL" AND "Medical diagnosis" (including related terms identified during query refinement)
Database	Scopus (chosen for its broad coverage of multidisciplinary journals and compatibility with VOSviewer)
Search type	Title, Abstract, Keywords
Document type	Articles, reviews, conference papers
Analysis techniques	Co-occurrence, co-authorship, co-citation, trend analysis
Period	1974 to 2025 (January)

Following this protocol, the bibliometric search was executed in the Scopus database. The retrieved records were exported in CSV format and processed through VOSviewer (version 1.6.17) and Microsoft Excel for data visualization and network analysis. This workflow enabled the construction of co-authorship, keyword, and citation networks to identify research trends and collaborations within the domain. Figure 1 provides an overview of the steps taken in this research.

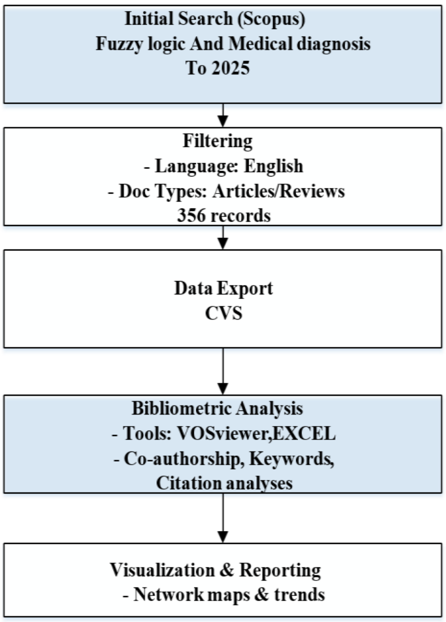

Figure 1. The stages of research

3. Results

In this section, the answers to the previously stated RQs are presented, with the results accompanied by the corresponding tables and graphs as follows.

3.1. What is the distribution of research in the field of FL and medical diagnosis? (RQ1)

As illustrated in Figure 2, the field of FL has been demonstrated to intersect with medical diagnosis. Among the various academic disciplines, computer science has demonstrated the most interest in this concept, with 31% of research, followed by engineering sciences (19%), medicine (13%), and mathematics (11%).

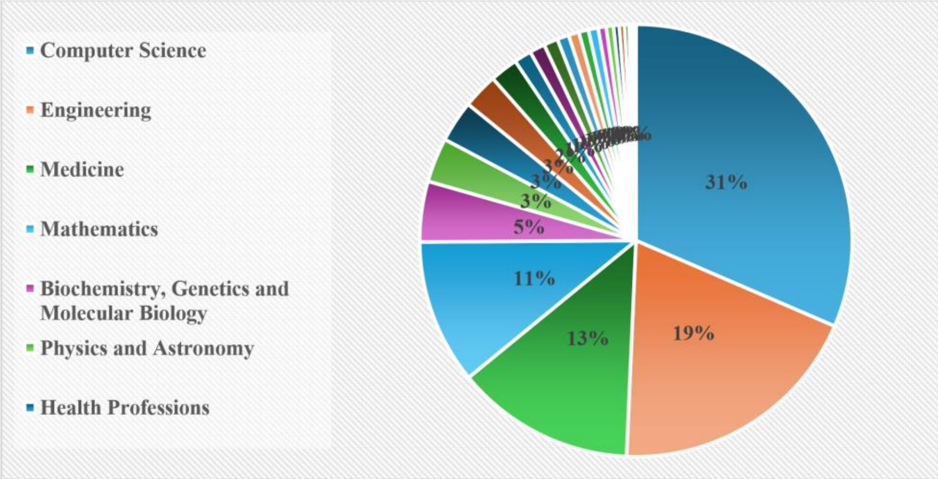

Figure 2. The distribution of research in the field of FL and medical diagnosis

Computer Science (31%): The highest percentage indicates that computer scientists are extensively involved in developing FL algorithms, AI models, and DSSs for medical applications. These contributions likely focus on areas such as expert systems, machine learning, and health informatics.

Engineering Sciences (19%): Engineers, particularly those in biomedical and electrical engineering, contribute to hardware implementations, sensor technology, and medical imaging applications using FL.

Medicine (13%): While medical professionals apply FL in clinical decision-making, disease classification, and personalized treatment strategies, their contribution is lower, possibly due to the field being more application-oriented rather than being theory-driven.

Mathematics (11%): The involvement of mathematicians suggests foundational research on FL theory, the development of new mathematical models, and the improvement of fuzzy inference mechanisms.

3.2. What is the distribution of research in the field of FL and medical diagnosis in different periods of time? (RQ2)

As illustrated in Figure 3, there has been an increasing trend in research studies concerning the application of FL in the field of medical diagnosis. The earliest documented studies in this domain date back to 1974, with two studies being conducted in that year. Notably, the year 2024 stands out as a significant peak in research activity, with 128 studies related to this subject being published. Note that the analysis was conducted in January 2025.

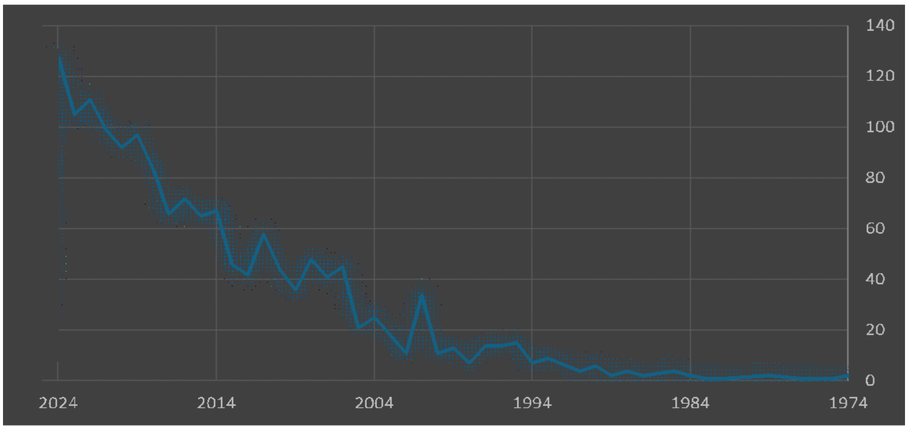

Figure 3. Distribution of research in the field of FL and medical diagnosis

The earliest documented studies on this topic show that researchers began exploring FL applications in medical decision-making nearly five decades ago. The small number of studies (only two) suggests that it is an emerging concept with limited adoption. Over the years, the number of studies has grown, reflecting a rising interest in FL for medical diagnosis. This trend likely corresponds to advancements in computational power, artificial intelligence, and the increasing complexity of medical decision-making.

The sharp rise in publications after 2020 (Figure 3) is closely tied to the global COVID-19 pandemic. Healthcare systems faced immense pressure and uncertainty, prompting the adoption of artificial intelligence (AI) and telemedicine tools. FL played a crucial role in handling imprecise symptom data, enabling diagnostic systems to triage patients based on indicators such as fever, oxygen saturation, and comorbidities. This surge in real-world relevance likely fueled the growing academic interest in FL-based medical applications.

COVID-19 has catalyzed the expansion of telemedicine and highlighted the imperative for uncertainty modeling within the healthcare sector. During the pandemic, there was a global demand for advanced health monitoring and diagnostic frameworks tailored for individuals with severe medical conditions (Rahman et al., 2023). The unprecedented scale of the crisis compelled healthcare systems worldwide to rapidly and substantially reconfigure their service delivery strategies (Temesgen et al., 2020). As a result, the application of FL in healthcare has attracted growing attention since 2020. Intelligent clinical DSS for triage has contributed to improving the quality of care in the emergency departments as well as identifying the challenges they have been facing (Fernandes et al, 2020). FL models can also be used for classifying the risk of medical equipment. Since FL is closer to the way humans think, it is expected to improve the prioritization of devices (Tawfik et al., 2013). FL is used in AI-based diagnostic systems, particularly for predicting heart disease, brain disease, prostate disease, liver disease, and kidney disease (Kaur et al, 2020).

The year 2024 marks a record high in research activity, with 128 studies published. This peak could be attributed to several factors, such as:

• Increased adoption of AI and machine learning in healthcare.
• Growing interest in explainable AI and interpretable decision-making models, where FL plays a key role.
• The expansion of digital health technologies and data-driven diagnostics.
• A possible surge in funding and interdisciplinary collaborations in medical informatics.

3.3. Who are the prolific researchers in the field of FL and medical diagnosis? (RQ3)

A total of 7 researchers have demonstrated remarkable productivity in the domain of FL applied to medical diagnosis, with each researcher having at least 9 studies in this field. Among these researchers, Adlassnig, K.P., has published 17 studies, while Al-Kasasbeh, R.T., has published 15 studies, positions them as the most prolific researchers in this area. The complete list of these researchers and the number of their publications are presented in Table 2.

Table 2. The prolific researchers in the field of FL and medical diagnosis

Author (s)	**Document number**
Adlassnig, K.P	17
Al-Kasasbeh, R.T	15
Hata, Y.	11
Straszecka, E.	11
Singla, J.	11
Obot, O.U.	9
Uzoka, F.M.E.	9

Figure 4 delineates the co-authorship network, constructed using VOSviewer software, among scholars engaged in the exploration of FL within the domain of medical diagnosis. This examination addresses pertinent research inquiries concerning the patterns of collaboration and scientific alliances prevalent in this discipline. By rendering a visualization of the interrelationships and clusters of authors, the figure elucidates principal contributors and their collaborative networks, thereby offering insights into the mechanisms of knowledge dissemination and collective advancement. As depicted in Figure 4, the investigation of authors conducting research in the realm of FL in medical diagnosis has identified 4,697 authors. Of these, 28 authors have disseminated more than five scholarly documents, which are categorized into five distinct clusters (Figure 4). The nodes symbolize authors engaged in collaborative relationships, and the dimensions of the nodes likely represent the significance or frequency of publications or collaborative endeavors. The connections between nodes are represented by lines, indicating instances of co-authorship. Lighter lines between groups denote less substantial or infrequent collaborations. This analysis underscores that a mere 0.6% of the authors have produced five or more publications in the designated field (28 authors), with only 11 authors having released seven or more documents.

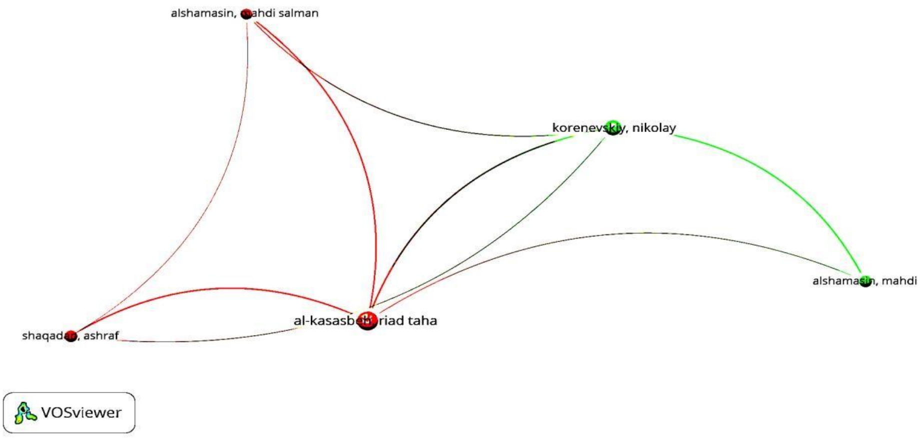

Figure 4. Analysis of authors contribution conducting research on areas of FL in medical diagnosis

3.4. What was the contribution of each university in the field of FL and medical diagnosis? (RQ4)

The following universities have been identified as the most prominent in the field of FL research in disease diagnosis: Lovely Professional University, Southwest State University, and Vellore Institute of Technology. Table 3 presents a comprehensive list of the most active universities in this field and the number of studies they have conducted.

Table 3. The contribution of each university in the field of FL and medical diagnosis

University	Number of studies
Lovely Professional University	24
Southwest State University	21
Vellore Institute of Technology	20
Silesian University of Technology	18
Al-Balqa Applied University	17
Medizinische Universität Wien	14
University of Uyo	13
Amirkabir University of Technology	11
University of Toronto	11
Jadavpur University	11

3.5. Which journals mainly published FL and medical diagnosis research? (RQ5)

The most prominent journals in the domain of FL studies in medical diagnosis include AI in Medicine, Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), and Journal of Medical Systems. These journals and the number of their publications in this field are outlined in Table 4.

Table 4. Most important journals in FL and medical diagnosis research

Journals	Number of documents
Artificial Intelligence in Medicine	42
Lecture Notes in Computer Science Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics	40
Journal of Medical Systems	35
Computer Methods and Programs in Biomedicine	33
Computers in Biology and Medicine	32

3.6. What languages are the publishes in the field of FL and medical diagnosis mainly in? (RQ6)

It is important to note that in this study, documents with English titles, keywords or abstracts are searched and reviewed, so documents that are entirely in other languages are not included in the search scope. Although most publications are in English, a few non-English records (e.g., in Chinese, German, Russian, Turkish, etc.) were also identified. Therefore, the inclusion of Figure 5 provides a complete representation of the language diversity observed in the dataset, even though the dominance of English is visually overwhelming.

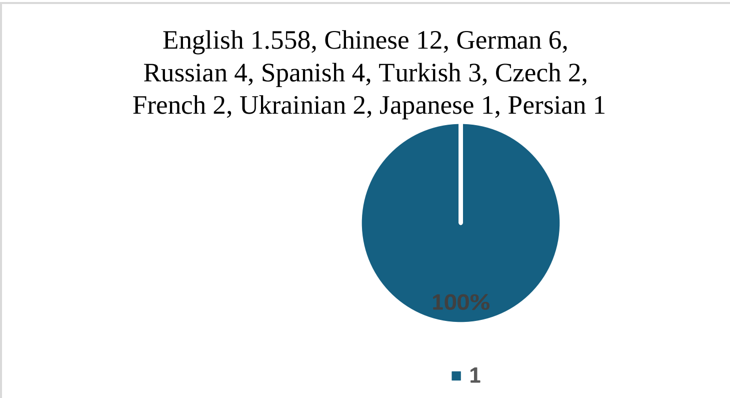

Figure 5. The distribution of studies on FL and medical diagnosis across different languages

3.7. What was the distribution of each country in the field of FL and medical diagnosis publishes? (RQ7)

Figure 6 presents a visual representation of the countries that have demonstrated the most activity in the domain of FL studies in medical diagnosis. These countries have conducted a minimum of 30 studies within this specific field. The three countries that have exhibited the most activity in this domain are India, China, and the United States of America.

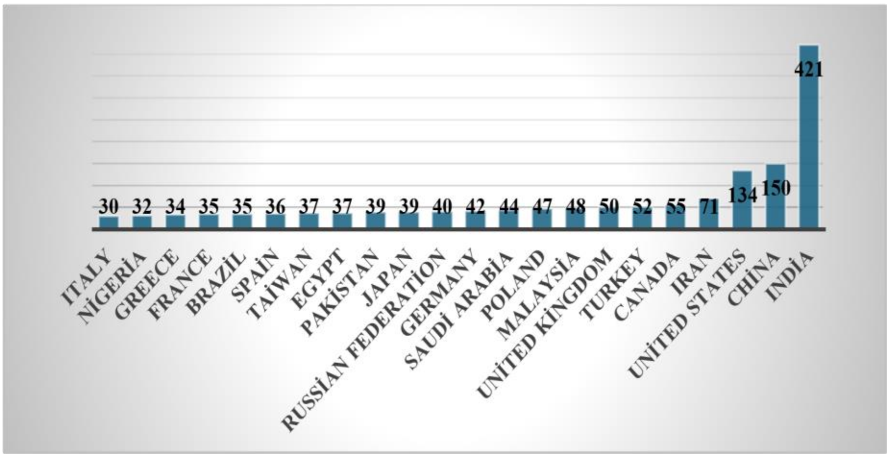

Figure 6. Distribution of each country in the field of FL and medical diagnosis publishes

India and China are leading the way in innovative research on intelligent disease detection, primarily due to significant governmental efforts and substantial investments in digital health infrastructures. The Ayushman Bharat Digital Mission (ABDM) of India, launched in 2021, aims to create an extensive national digital health ecosystem that improves accessibility, affordability, and quality of healthcare through interoperable platforms and real-time data exchange. Building upon India's vast digital public infrastructure, which includes over 1.2 billion Aadhaar digital identities and widespread internet connectivity, this initiative has accelerated the deployment of AI-driven and fuzzy-logic-based technologies in both urban and rural environments (Sharma et al., 2023; Velan et al., 2024).

China's preeminence in intelligent disease detection research is closely linked to its national health initiative, Healthy China 2030, which promotes the integration of digital health tools and AI-based diagnostics to strengthen disease prevention, early detection, and healthcare management (Tan et al., 2017). Consequently, both countries exhibit strong thematic clusters in fuzzy modeling for chronic disease management and diagnostic decision support, reflecting the translation of national policy priorities into measurable research outputs.

Conversely, the United States displays a relatively lower academic publication volume, which may be attributed to the predominance of proprietary, industry-led research activities within private technology and biotechnology companies. This divergence suggests a structural difference in knowledge dissemination, where publicly funded open-access research dominates in Asian countries, while innovation in the United States often remains confined to industrial settings.

3.8. What are the most important themes in the field of FL and medical diagnosis? (RQ8)

The keywords co-occurrence network helps in the identification of main themes that are focused therein. The clusters of keywords of high relevance can be interpreted as research themes. Out of 10612 keywords, 2010 meet the co-occurrence threshold of 20 times. The highly connected keywords that appeared in FL in medical diagnosis, formed 4 clusters with 14926 links having a TLS of 106432. Figure 7 displays a simplified keyword network. Each cluster is represented by a color representing nodes of keywords. As shown in Figure 7, several keywords, such as FL, diagnosis, humans, disease, fuzzy inference, fuzzy sets and medical images have been the most frequently used in documents related to FL in medical diagnosis.

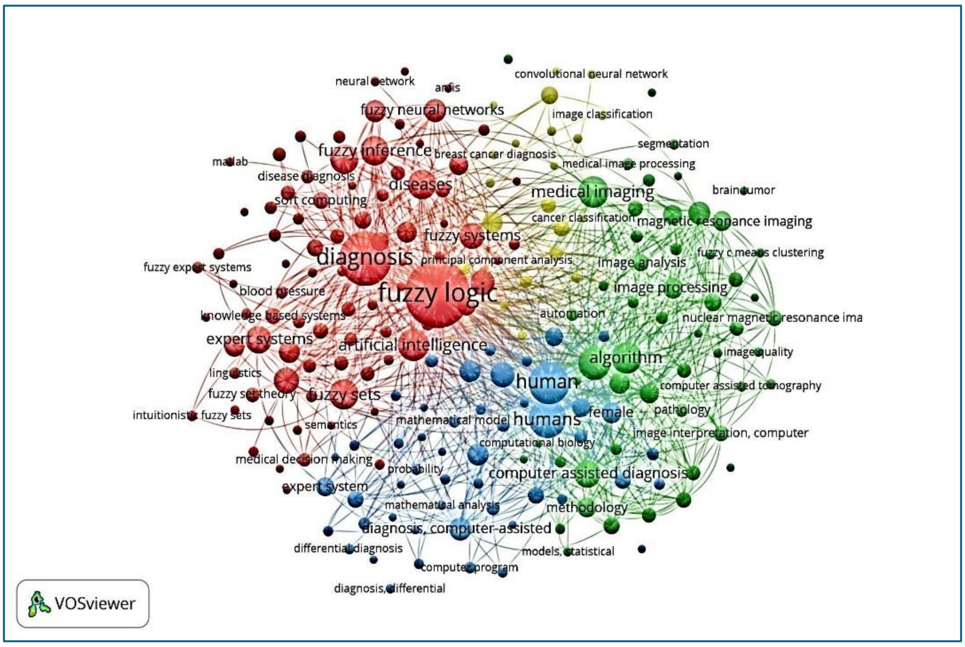

Figure 7. Keywords co-occurrence network in the field of FL and medical diagnosis

The keyword co-occurrence network in Figure 7 shows the main research topics and interrelationships in FL applications for medical diagnosis. Each color-coded cluster represents a specific research focus:

1. Red Cluster (FL in Medical Diagnosis): This cluster is centered around "FL", "diagnosis", and "diseases", indicating that FL is widely applied to medical decision making and disease classification. Other closely related terms include "fuzzy

inference", "fuzzy neural networks", "artificial intelligence", and "expert systems", suggesting a strong link between AI-based fuzzy methods and diagnostic accuracy.

2. Blue cluster (human-centered applications and statistical methods): Keywords such as "human", "computer-aided diagnosis", "statistical models", and "mathematical models" highlight research that focuses on patient-oriented diagnosis and computational methods. This suggests that a significant proportion of studies in this area involve human subjects and statistical tools to improve diagnostic accuracy.

3. Green Cluster (Algorithms and Image Processing in Diagnostics): This cluster contains terms such as "algorithm," "image analysis," "image processing," and "nuclear magnetic resonance imaging," indicating that machine learning and computer vision techniques are being integrated with FL for medical image analysis. These technologies are likely to be used to improve diagnostic accuracy by analyzing radiological and pathological images.

4. Yellow Cluster (Neural Networks and Automation in Diagnostics): The presence of "convolutional neural network (CNN)", "image classification", "medical imaging", and "automation" suggests the growing role of deep learning models and automation in medical image diagnosis. The most cited keywords in the field of FL and medical diagnosis are shown in Table 5.

Table 5. The most cited keywords in the field of FL and medical diagnosis

Cluster1 (85)	**Cluster2 (53)**	**Cluster3 (50)**	**Cluster4 (21)**
Anfis Artificial intelligence Bioinformatics Biomedical engineering Blood Blood pressure Cardiology Cardiovascular disease Classification Classification (of information) Classification accuracy Cognitive systems Computation theory Computer aided diagnosis Computer Circuits Data mining Data sets Decision making Decision support system Decision theory Decision tree Decision trees Diabetes mellitus Diagnosis	Algorithm Algorithms Automated pattern recognition Automation Biology Brain Brain tumor Breast neoplasms Breast tumor Cluster analysis Clustering algorithms Comparative study Computational biology Computer assisted diagnosis Computer assisted tomography Computer simulation Computerized tomography Diagnostic imaging Echography Entropy Fuzzy c means clustering Fuzzy clustering	Accuracy Adolescent Adult Aged Artificial neural network Clinical article Clinical decision making Clinical decision support system Computer program Controlled study Data analysis Data base Decision support system Decision su systems, clinical Decision su techniques Diagnosis, computer assisted Diagnosis, differential Diagnostic accuracy Diagnostic test accuracy Diagnostic value	Biological organs Breast cancer Breast cancer diagnosis Cancer classification Cancer diagnosis Classification algorithm Convolutional neural network Convolutional neural networks Database, factual Deep learning Early diagnosis Extraction Feature extraction Feature selection Fuzzy Genetic algorithm Image classification Lung cancer Machin learning Neural networks, computer Support vector machine

Disease diagnosis Disease Electrocardiography Expert systems Forecasting Formal logic Fuzzy expert systems Fuzzy inference Fuzzy inference system Fuzzy inference systems Fuzzy expert systems FL Fuzzy neural networks Fuzzy rules Fuzzy set theory Fuzzy sets Fuzzy systems Fuzzy-logic Genetics algorithms Healthcare Heart Hearth disease Hospitals Information science Intelligent systems Internet of things Intuitionistic fuzzy sets Knowledge base Knowledge base systems Knowledge representation Learning algorithms Learning systems Linguistics Machine-learning Mathematical models MATLAB Medical applications Medical computing Medical data Medical Decision making Medical Decision support system Medical diagnosis Medical diagnostics Medical expert system Medical information systems Medical knowledge Medical problems Medicine Membership functions Neural network Neural networks	Fuzzy filters Image analysis Image enhancement Image fusion Image interpretation, computer assisted Image processing Image processing, computer assisted Image quality Image segmentation Magnetic resonance imaging Mammography Medical image processing Medical imaging Methodology Models, statistical Nuclear magnetic resonance imaging Pathology Pattern recognition, automated Positron emission tomography Procedures Reproducibility of results Segmentation Sensitivity and specificity Signal processing Statistical model Textures Three dimensional image Tissue Tomography, X-ray computed Tumors	Differential diagnosis Disease classification Evaluation Expert system Female Fuzzy control Fuzzy system Human Humans Information processing Information retrieval Logic Major clinical study Male Mathematical analysis Mathematical model Medical informatics Medical record Middle aged Model Neural networks (computer) Patient monitoring Prediction Predictive value Priority journal Probability Prognosis Review Risk factor Software	

Optimization Patient treatment Pattern recognition Principal component analysis Problem solving Risk assessment Semantics Soft computing Support vector machine Uncertainty Uncertainty analysis			

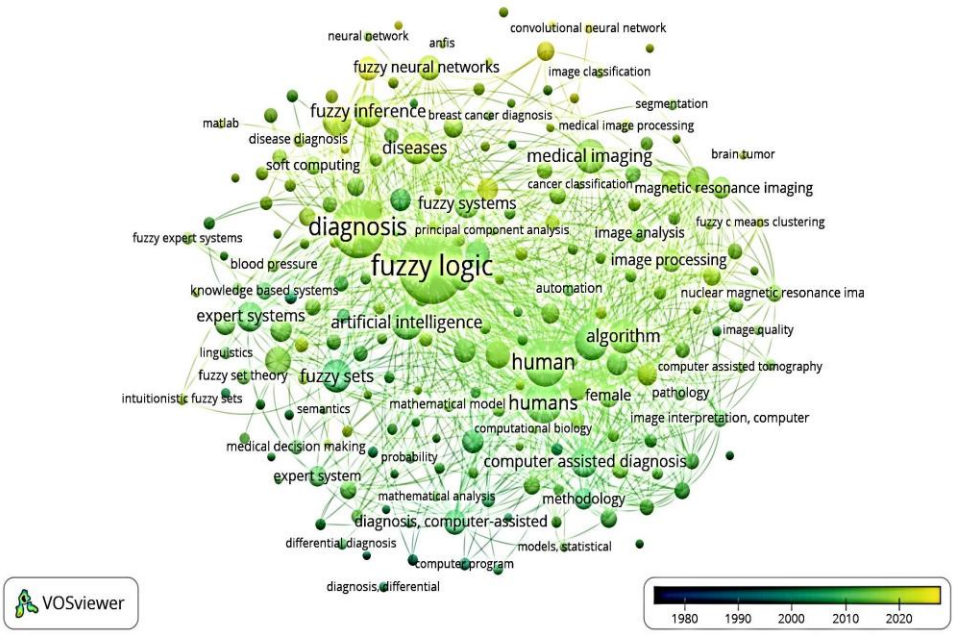

Figure 8. Co-occurrence based on keywords in the overlay visualization in the field of FL and medical diagnosis

Figure 8 shows co-occurrence based on keywords in the Overlay visualization. The color of each item is determined by the average score of the year of publication. The yellow color indicates that these keywords are associated with the post-2020 period. In other words, they have attracted the attention of researchers in recent years, and they can be used in further research. The items related to the year 2000 and earlier (blue color) mean that the keywords associated with these years have been the focus of articles and research in the field of FL in medical diagnosis in the early years. Nowadays, they are less addressed. The fundamental research domains, depicted in darker green and blue shades, encompass "FL," "diagnosis," "fuzzy inference," "expert systems," and "artificial intelligence." This observation indicates that the initial research endeavors are predominantly centered on the development of FL-based decision-making systems for medical diagnosis. The presence of bright yellow nodes, such as "convolutional neural networks (CNNs)," "image classification," "segmentation," and "deep learning," signifies the latest advancements in the field. This suggests a shift toward AI-driven medical imaging techniques, where neural networks and deep learning are now integrated with FL for more precise medical diagnosis. The presence of "automation," "brain tumor," and "medical image processing" indicates that modern AI techniques are being applied to automate medical image analysis.

Based on this overlay visualization, the most important recent keywords in the field of FL in medical diagnosis are shown in Table 6.

Table 6. The most important recent keywords in the field of FL in medical diagnosis

Keywords	**Avg.pub.year**
Machin-learning	2023.05
Convolutional neural network	2022.61
Deep learning	2022.58

In the Density Visualization map, the concentration of research emphasis and the prevalence of cooccurring keywords within the domain of FL in medical diagnosis are illustrated through a chromatic gradient. Regions characterized by vibrant yellow tones signify the most recurrent and conceptually rich clusters, whereas green and blue zones pertain to terms that are less frequent or in the process of emerging. Fundamental terms such as "FL," "diagnosis," "medical imaging," "human," and "algorithm" are positioned at the nucleus of the research landscape, thereby indicating their pivotal role and considerable importance within the discipline. The elevated density in these sectors signifies the advancement and aggregation of academic research, especially in image-based diagnosis, decision-support algorithms, and the incorporation of AI methodologies. Conversely, less densely populated areas may denote underexamined research prospects or novel interdisciplinary intersections that warrant additional scrutiny. Figure 9 illustrates this concept. Density visualization is a data representation technique that employs color coding to depict the frequency and intensity of keyword occurrences within a given dataset. Areas imbued with bright yellow in the visual representation denote keywords that exhibit high frequency and robust interconnections, while green areas signify keywords of moderate frequency. In contrast, blue/dark regions indicate keywords that manifest with less frequency within the dataset. As depicted in Figure 9, the most luminous regions, centered on "FL," "diagnosis," "human," and "artificial intelligence," signify these as the most impactful and frequently co-occurring keywords. The co-occurrence of "diagnosis" and "FL" at the epicenter of Figure 9 accentuates the importance of these constructs. The peripheral blue regions encompass keywords such as "pathology," "brain tumor," "segmentation," and "image classification," suggesting that while these domains are integral to the research landscape, they are explored with less frequency in comparison to the core subjects.

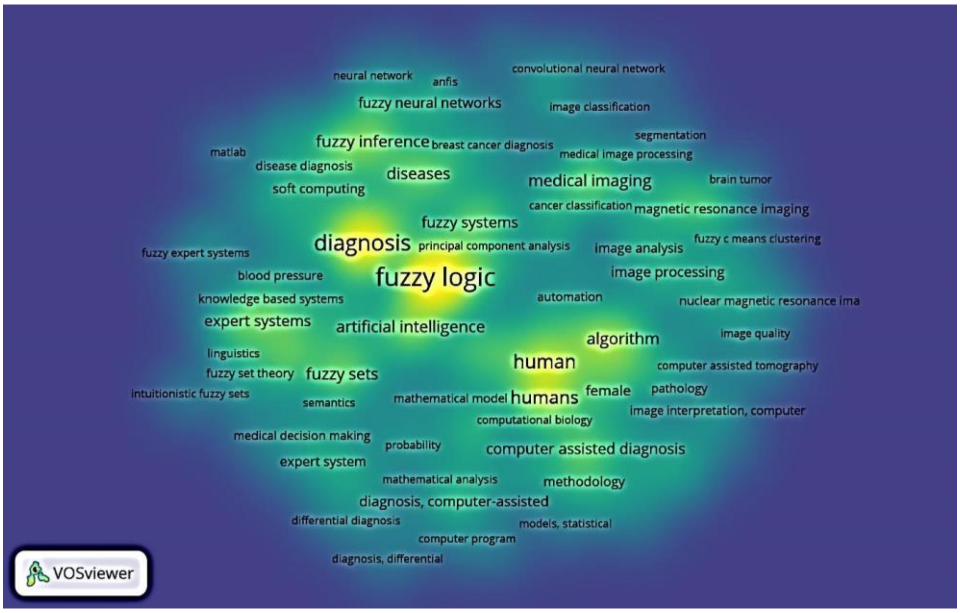

Figure 9. Co-occurrence based on keywords in the density visualization in the field of FL in medical diagnosis

4. Discussions

To provide a deeper understanding of how FL contributes to medical diagnosis, the discussion is structured into two complementary parts. First part explores its clinical relevance and real-world applications, while second one focuses on the computational mechanisms, advantages, and prospects of FL–based diagnostic systems.

4.1. Applications and clinical relevance of FL in medical diagnosis

In fields such as cardiovascular and infectious diseases, there is a growing need for decision-making tools that can manage diagnostic uncertainty. FL-based systems have proven effective in these areas by reducing diagnostic ambiguity and improving clinical decision support, particularly when patient information is incomplete or imprecise. FL's ability to handle uncertainty and vagueness improves decision-making, medical diagnosis, and treatment (Abdalla et al., 2024).

The increasing prevalence of diseases like cardiovascular conditions, cancer, and COVID-19 underscores the growing complexity of medical data and the critical need for personalized treatment approaches. This complexity often leads to significant decision uncertainty in clinical settings. Cardiovascular diseases, for instance, are influenced by a myriad of interconnected genetic, environmental, and lifestyle factors, generating vast amounts of heterogeneous data. Similarly, cancer diagnosis and treatment involve intricate pathways, with patient responses varying widely based on tumor characteristics and individual physiology. The recent COVID-19 pandemic further highlighted the challenge of managing rapidly evolving, often incomplete, and uncertain clinical information. These diseases are characterized by a confluence of factors: the sheer volume and complexity of patient data, the necessity for highly individualized treatment plans to maximize efficacy and minimize side effects, and the inherent uncertainty in diagnosis and prognosis due to overlapping symptoms or varying disease manifestations.

A key characteristic of FL is its capacity to address the inherent uncertainty and imprecision of medical diagnosis. As a branch of mathematical logic, it is designed to resolve problems involving explicit, imprecise, or approximate reasoning, providing a framework to derive definitive outcomes from uncertain, ambiguous, imprecise, noisy, or incomplete input data (Aslan and Hızıroğlu, 2024). FL is particularly adept at managing complex and uncertain clinical information, often encountered in conditions like cardiovascular diseases and cancer. It allows examining data that cannot be easily categorized, offering a more nuanced understanding of patient health. FL methods have specifically improved clinical decision-making and diagnostic accuracy by reducing misdiagnosis, enabling earlier detection, and supporting more effective treatment planning. For example, in cardiovascular diseases, fuzzy systems can integrate diverse risk factors (e.g., blood pressure, cholesterol levels, lifestyle habits) to provide a nuanced risk assessment, going beyond traditional binary classifications and enabling personalized preventative strategies. In cancer diagnosis, FL can process ambiguous imaging data or biomarker levels to assist clinicians in identifying subtle indicators of malignancy earlier. During the COVID-19 pandemic, fuzzy inference systems were developed to assess disease severity and predict patient outcomes based on a range of symptoms and laboratory findings, providing critical support for resource allocation and treatment prioritization.

The integration of fuzzy inference systems with technologies such as the Internet of Things (IoT) has further enhanced the accuracy and efficiency of disease diagnosis, as demonstrated in applications for COVID-19 and malaria (Ferreira, 2023). These systems can simulate expert decision-making, offering personalized risk assessments and treatment recommendations, which is especially valuable in cardiovascular diseases where individual risk factors vary significantly among patients (Casalino et al, 2018). While precise real-world implementations can be challenging to track due to proprietary development and varied clinical settings, the literature indicates growing use. For instance, FLbased DSSs have been explored for integration into hospital information systems to aid clinicians in realtime diagnosis. During the COVID-19 pandemic, FL models were utilized in telemedicine platforms to help healthcare providers remotely assess patient conditions and provide timely advice, thus contributing to better patient management and reducing the burden on physical healthcare infrastructure. Measurable impacts reported in various studies include improved diagnostic accuracy rates, reduced rates of misdiagnosis, and more timely initiation of appropriate treatments, all contributing to better patient outcomes.

Based on the bibliometric mapping of FL applications in medical diagnosis, the synthesis of thematic clusters and citation trends shows key development directions with significant potential for practical impact. The leading research areas include combining fuzzy reasoning with large-scale, real-world clinical datasets and electronic health records (EHRs). This allows for adaptive and personalized decision support across diverse patient populations (Rachel et al., 2025). Related high-impact domains involve hybrid architectures that mix FL with machine learning and deep learning techniques.

This combination offers advantages in performance and interpretability (Dalkılıç et al., 2025). From a practical standpoint, studies focusing on lightweight fuzzy-based modules for use in resource-limited clinical settings (Menacuer et al., 2025) align well with global healthcare priorities. Addressing the gaps found in the bibliometric analysis, such as dependence on benchmark datasets and lack of explainability in system design, will be crucial. Concentrating on these emerging areas while ensuring regulatory compliance, integrating into clinical workflows, and maintaining transparency can help close the gap between research and practice and enhance the real benefits of FL in medical diagnosis.

FL's increasing application in clinical decision-making stems from its ability to handle the imprecision and uncertainty inherent in medical data. This methodology emulates human cognitive processes, enabling more nuanced and adaptable decision-making frameworks. FL systems are particularly advantageous in areas where establishing precise mathematical models is challenging, such as medical diagnostics and prognosis.

By integrating linguistic variables and expert insights, which are often characterized by imprecision and subjectivity, FL significantly augments diagnostic precision. This approach is highly beneficial for analyzing complex medical data and symptoms that do not fit into binary classifications (Gürsel, 2015). Fuzzy inference systems are used to address the uncertainties in diagnostic data, thereby improving the reliability of medical diagnostics (Tency and Harish, 2024). The FL paradigm has been applied in various contexts, including the diagnosis of infectious diseases (Arji et al, 2019), prediction of allergens (Saravanan and Lakashmi, 2014), diagnosis of Covid-19 (Jayalakshmi et al, 2021), management of cardiac patients (Hussain et al, 2016), and prediction of lung cancer (Aslan and Hızıroğlu, 2024), among numerous other applications.

The purpose of this research is to offer an extensive viewpoint for academics interested in FL for medical diagnosis, which benefits researchers by keeping them informed about key trends in this area to stay current. Since this article used only the Scopus database to review research literature regarding the application of FL in medicine, future research can use other databases such as Web of Science to perform bibliometric analysis. The future is focused on improving interpretability, of these systems, rigorously validating them across various real-world environments, seamlessly incorporating them into clinical workflows, and persistently tackling the ethical aspect of AI in healthcare, while also investigating new data sources and applications.

Although the implementation of FL in the realm of medical diagnosis presents numerous advantages, it is not without its inherent challenges. The interoperability of medical terminologies is imperative for the efficient exchange and analysis of data. FL systems frequently encounter difficulties in assimilating varied medical terminologies, which may result in the emergence of isolated systems and impede the fluid interpretation of medical data. The heterogeneity and variability inherent in medical data, encompassing symptoms, patient history, and demographic factors, present considerable obstacles. Consequently, FL systems must adeptly navigate this complexity to yield precise and timely diagnoses. (Shoaip et al., 2024). Also FL systems can experience a "rules explosion" challenge, resulting in an overwhelming number of rules that hinder the scalability and efficiency of the system. This problem calls for creative solutions, like the single-input rule module, to enhance system parameters and boost diagnostic precision (Zhang and Wen, 2019).

While the quantitative results presented in this study may appear largely descriptive, bibliometric analysis provides a methodological framework that goes well beyond counting publications, authors, or countries. It offers systematic and reproducible metrics to chart the intellectual structure and evolution of FL applications in medical diagnostics, revealing not only the scale of research activity but also knowledge gaps, emerging trends, and strategic research priorities (de Oliveira et al., 2019). Through network-based analyses such as co-authorship mapping, co-citation analysis, and thematic clustering, this study identifies key foundational works that serve as conceptual cornerstones, highlights emerging research frontiers, and uncovers interdisciplinary links that promote the dissemination of knowledge across medical subfields (Dai et al., 2022). Bibliometric analysis thus helps align research efforts with clinical needs, guides effective collaboration strategies, and provides evidence-based insights for policy and funding decisions (McQuire et al., 2024). In doing so, it offers a detailed knowledge map for the field, supports hypothesis generation by identifying research gaps, and enables researchers and institutions to position their work within the broader context of FL's role in advancing medical diagnostics (Akhtar et al., 2024).

4.2. Advances and challenges in FL–based medical diagnostic systems

FL (FL) is an effective method for modeling unclear and ambiguous information. It connects human language and computer decision-making models. Human communication has built-in uncertainty, and FL uses fuzzy set theory to assign meanings to vague traits. In this setup, each language term links to a fuzzy subset. This allows for approximate reasoning in uncertain situations (Shukla et al., 2025). Membership functions, which are often triangular, trapezoidal, or sigmoidal, show degrees of membership on a scale from 0 to 1. Here, 0 indicates no membership and 1 indicates full membership, which helps in making nuanced interpretations (Vyas et al., 2022).

Fuzzy models generally use the Mamdani rule-based inference system, structured in these layers:

1. **Fuzzification:** Numeric input values are changed into fuzzy sets represented by membership functions. This allows inputs to be described in everyday terms with degrees of belonging (Vyas et al., 2022).

2. **Rule Evaluation**: The fuzzy inference engine applies relevant if–then rules to the fuzzified inputs to create fuzzy outputs.

3. **Defuzzification**: These fuzzy outputs are then converted back into clear, actionable results for decision-making.

Medical diagnosis systems often use specialized software called expert system shells. These shells include inference methods like forward chaining, backward chaining, or hybrid approaches to process knowledge encoded as production rules. Object-oriented expert system shells make it easier to integrate with outside clinical databases, allowing real-time data use (Sikchi and Sikchi, 2013). The knowledge base contains definitions of diseases encoded as collections of if-then rules that reflect clinical understanding, such as tuberculosis symptoms structured as discrete production rules. The fact base holds observed patient data, which the inference engine uses to reason and produce new conclusions.

Medical decision support (MDS) systems have developed over the last fifty years to handle various clinical decisions, using fuzzy methods for their ability to manage uncertainty and ambiguity. Research shows that MDS accuracy increases with the modeling of unclear and changing data, integration of information from multiple patient sources, and improvements in algorithmic reasoning (Wagholikar et al., 2012). Soft computing techniques like FL combined with data mining can accurately predict diseases such as heart attacks by analyzing patient data and identifying the best diagnostic models (Dianirani and Claudia, 2021).

The field benefits from hybrid models that mix FL with other computational intelligence techniques such as Swarm Intelligence, Evolutionary Computing, Neural Networks, and deep learning. These combined frameworks offer scalable, context-sensitive, and personalized healthcare solutions by mimicking complex clinical reasoning processes (Dianirani and Claudia, 2021; Tariq et al., 2024). Recent studies highlight pairing fuzzy systems with IoT-enabled real-time data, which improves system flexibility and resilience across diseases like hypertension, diabetes, and multimorbidity (Mohod et al., 2025).

FL systems make use of membership function design, compositional inference, and new techniques like type-2 fuzzy sets to better represent uncertainty. Various system architectures have been examined through case studies, showing strong agreement with expert clinician decisions, especially in borderline cases where deterministic models do not perform well (Mohod et al., 2025). Improved architectures confirm model accuracy, strength, and adaptability in different clinical situations.

Fuzzy expert systems offer clear and understandable decision-making processes, durability against incomplete or noisy data, and flexibility in diverse healthcare settings. However, they face challenges including scaling rule bases, difficulties with system integration, regulatory issues, and the computational demands of hybrid approaches (Vyas et al., 2022; Wagholikar et al., 2012). Understanding deep hybrid models and ensuring data quality are still crucial concerns.

The growth of hybrid fuzzy-AI techniques, fueled by data-driven optimization and IoT-enabled health monitoring, aims to advance precision medicine. There is a rising need for explainable, clinically appropriate AI tools, and FL—known for its transparency and fit with medical reasoning—serves as an important enabler (Mohod et al., 2025). Future research should focus on increasing dataset diversity, automating rule creation, improving integration with clinical workflows, and navigating regulatory challenges to support real-world use. In the end, fuzzy expert systems are likely to transform into collaborative tools that support patient-centered care alongside clinicians.The employment of fuzzy sets and rules facilitates the consideration of uncertainty and membership degrees, thereby enabling healthcare providers to efficiently interpret and navigate the intricate information present within medical databases (Castaneda et al., 2015). The utilization of FL not only improves the precision of diagnostic findings but also improves their comprehensibility, a development that is vital in the creation of sophisticated decision-making tools that can assist healthcare professionals in the identification and management of various illnesses (Edison, 2023).

5. Limitations

This investigation utilized the Scopus database to procure of bibliometric data, which may have resulted in the omission of pertinent studies that are indexed within alternative databases, such as Web of Science or PubMed. While Scopus is recognized for its extensive coverage, this limitation has the potential to influence the comprehensiveness and representativeness of the dataset. Furthermore, the emphasis on publications that feature English titles, abstracts, or keywords introduces a risk of linguistic bias, which could lead to an underrepresentation of research disseminated in other languages, especially from regions where English is not the primary language. These considerations must be taken into account when analyzing the results, particularly within global contexts. Additionally, the potential biases inherent in co-authorship and keyword clustering can significantly impact the interpretation of research findings, thereby underscoring the necessity for transparency and meticulous analysis in bibliometric investigations. A notable limitation of this bibliometric analysis is the possibility of bias arising from both co-authorship and keyword clustering methodologies. Within co-authorship networks, closely collaborating research entities may induce interdependence among outcomes, possibly leading to an inflated visibility of specific authors or clusters if such variables are not properly addressed. Similarly, keyword clustering may inadequately capture the full spectrum of research themes, as algorithmic categorization may merge articles that share keywords yet exhibit divergent content or perspectives. These methodological constraints highlight the imperative for careful interpretation of co-authorship and keyword clustering results in bibliometric studies (Glänzel and Schubert, 2005; Zupic and Čater, 2015). The search is executed within the Scopus database employing the query TITLE-ABS-KEY (fuzzy AND logic AND medical AND diagnosis). Only documents with titles or abstracts in English are considered for inclusion. No limitations are imposed regarding subject categories. The analysis encompasses peer reviewed journal articles and conference proceedings, while editorials, letters, and book chapters are excluded.

Furthermore, to overcome the aforementioned limitations, future bibliometric investigations may consider integrating data from multiple databases (e.g., Web of Science, PubMed, and IEEE Xplore) to ensure broader coverage and to mitigate potential database-specific biases. Expanding the scope to include non-English publications could also alleviate linguistic bias and improve the representativeness of global research contributions. Beyond bibliometric mapping, combining these analytical findings with real-world clinical datasets would strengthen the practical relevance of FL–based diagnostic models. Future efforts should also emphasize explainability and interpretability in such systems to foster transparency and trust in clinical decision support applications.

6. Conclusions

A review of the Scopus database reveals that research on the application of FL to medical diagnosis has garnered increasing attention over time. Machine learning has emerged as the predominant theme in this domain. China, India, and the United States have emerged as the most active countries in this field, with the vast majority of studies being published in English. The Journal of Artificial Intelligence in Medicine has been identified as the most prominent journal in this field, and Lovely Professional University has been recognized as the most active university. The most prolific researchers in this field are Adlassnig, K.P. and Al-Kasasbeh, R.T., with computer science demonstrating the most interest in this concept, accounting for 31% of documents. Future research could build upon these trends by exploring hybrid approaches that combine FL with advanced deep learning architectures, thereby improving diagnostic accuracy in complex clinical scenarios. Moreover, expanding applications beyond computer science into biomedical engineering, public health, and personalized medicine could open new interdisciplinary opportunities. The focused research areas, such as hybrid fuzzy and machine learning frameworks, uncertainty management systems, and clinical decision support integration, point toward a trend that seeks to balance diagnostic accuracy with interpretability in various healthcare settings. From these trends, clear directions for future research arise. Future studies should focus on: (i) validating findings in large, real-world settings across various clinical environments and patient groups to improve generalization; (ii) creating lightweight, efficient fuzzy systems that can work in resource-limited settings; (iii) integrating FL models with electronic health records and real-time patient monitoring for better decision-making; and (iv) exploring user interface designs and transparency methods to build clinician trust and encourage use. Following these pathways will connect bibliometric insights with real-world clinical practice, helping advance interpretable AI in medical diagnostics.

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