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Fuzzy Logic and Swarm Intelligence Algorithms in Modern Healthcare Applications

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Abstract. The management of uncertainty and imprecision is characteristic of medical information and can complicate the decision making for the medical doctors. Fuzzy logic, which can model imprecise reasoning, has become an important and useful way to tackle these challenges. However, building fuzzy systems that include membership functions, fuzzy rules, and inference mechanisms often requires optimization to achieve high accuracy, robustness, and interpretability. This paper presents a review of medical applications that integrate fuzzy logic with optimization methods. We summarize the theoretical foundation of fuzzy logic, describe relevant optimization approaches, analyze key medical applications, and present bibliometric results from Scopus and VOSviewer. Trends reveal an increasing fusion of fuzzy logic with machine learning, evolutionary algorithms, and hybrid intelligent systems driven by the needs for improved and personalized medicine. The paper concludes with future research directions.

Keywords. Evolutionary algorithms, fuzzy logic, medical applications, optimization methods, neuro-fuzzy systems, bibliometric analysis, VOSviewer, Scopus.

1 Introduction

Today, healthcare is very important, medical data is often noisy, incomplete, and uncertain; decision-making involves a complex process.

Classical deterministic methods can fail in such environments. In addition, healthcare systems today require good performance optimization: scheduling patients, managing supply chains, selecting features for diagnosis, and routing in Medical Internet of Things networks. Fuzzy logic, introduced by Lotfi A. Zadeh [45, 46], provides a mathematical way to represent and compute uncertain or imprecise information. It enables modeling of linguistic concepts; for example, “high risk,” “medium glucose” through membership functions and fuzzy inference systems that mimic human reasoning. Swarm intelligence algorithms such as Particle Swarm Optimization (PSO), Firefly Algorithm, Ant Colony Optimization are bio-inspired metaheuristics that efficiently search complex solutions with a collective behavior. If these methods are combined with fuzzy systems, they can build customized fuzzy models and adapt dynamically to changing environments.

In this paper, we argue that fuzzy logic and swarm intelligence are particularly potent in modern healthcare, enabling interpretable, robust, and optimized decision making systems. In this paper, we analyze theoretical foundations, present key applications, discuss empirical results, and propose future trends. In recent years, the exploitation of such systems with such methods has become extremely popular because these systems have a huge potential to solve complex problems and optimization processes. Systems that are robust to uncertainty and imperfect data thus represent one of the methods to advance the adaptability and robustness with which evolutionary algorithms can operate [32].

Several fuzzy system paradigms have been proposed, including Type-1, Type-2, and more recently Type-3 fuzzy systems. These fuzzy models are an evolution within the domain of fuzzy analysis: the more complex our way will be to predict the uncertainty, and in so doing enhance the ability to represent non-categorical information making it useful when solving difficult problem domains [36].

The primary challenge lies in determining parameter configurations that yield optimal performance. Integration of adaptive systems has been shown to enhance these algorithms by dynamically tuning control parameters, thus improving convergence behavior and increasing the diversity of solutions.

The hybridization of fuzzy logic systems and swarm intelligence algorithms has been widely applied in various domains such as healthcare, robotics, unmanned aerial vehicle (UAV) path planning, engineering optimization, financial forecasting and machine learning [38]. Type-1 fuzzy systems have been commonly used to build fuzzy fitness functions, facilitate autonomous control mechanisms, and support decision-making in evolutionary and swarm optimization frameworks.

Type-2 fuzzy systems, based on this, have better ability to represent and process uncertainty and provide robustness when dealing with inaccurate, noisy, or incomplete information. In contrast, Type-3 fuzzy systems have become a new computational paradigm to tackle higher-order uncertainties and have exhibited improvements over standard types in complex and very dynamic environments. The purpose of the paper is to describe the gradual development of fuzzy logic systems and swarm algorithms in order to analyze the functions and contributions that they can provide for applications in healthcare.

The article then outlines key theoretical developments and practical applications and comparisons in the performance of these approaches to provide a closer look at some promising developments in healthcare applications. It further touches upon new research directions, issues currently confronting swarm intelligence and fuzzy systems within such a diverse healthcare application to offer an overall picture of the continued evolution of swarm intelligence and fuzzy systems concerning healthcare applications with upcoming research directions.

The structure of this paper is as follows. Section 2 addresses the evolution of fuzzy logic systems and swarm intelligence with a short description of each of these techniques. Section 3 describes applications of fuzzy logic and swarm intelligence on healthcare; in this Section, we present the applications of this fascinating field. Section 4 presents a discussion of future trends in these techniques applied to healthcare. Finally, in Section 5, the conclusion of this paper is presented.

2 Evolution of Fuzzy Logic Systems and Swarm Intelligence

The evolution of fuzzy systems and swarm intelligence represents one of the most significant developments in computational intelligence, building a hybrid paradigm capable of addressing complex, nonlinear, and uncertainty-dominated problems. When Artificial intelligence research progressed, early integrations of fuzzy logic with swarm intelligence algorithms such as Particle Swarm Optimization (PSO) [21], Ant Colony Optimization (ACO) [9], Artificial Bee Colony (ABC) [20] and Firefly Algorithm (FA) sought to improve the interpretability and adaptability of Type-1 fuzzy systems. These hybrid Type-1 fuzzy swarm models enabled automated parameter tuning, reductions in expert dependency, and improvements in convergence behavior, laying the foundation for the best fuzzy models with swarm intelligence [17, 18, 4, 5, 15]. Also, despite the application of artificial intelligence in important areas like healthcare and medicine being more and more developed, the limits of Type-1 fuzzy systems are visible when considering their inability to clearly specify the uncertainty in membership functions. This drives the move toward Type-2 fuzzy logic systems [28, 8, 29], which embed uncertainty directly into the membership structure. This integration of Type-2 fuzzy systems with swarm intelligence has, especially, been proven to be beneficial in applications involving medical concerns in which there is noise, variability, and ambiguity. There is ample evidence that Type-2 fuzzy model enhancement for swarm-based models facilitates strong medical image segmentation for the detection of tumors, lesions, and anatomical structures in imaging modalities such as MRI, CT, and ultrasound [14].

For disease characterization, PSO, DE, ABC and FA optimized Type-2 fuzzy classifiers of diabetes, cardiovascular diseases, neurological disorders and different cancers have shown better diagnostic accuracy by adjusting rule bases in real-time with heterogeneous clinical datasets [41, 33]. In addition, swarm improved Type-2 fuzzy controllers are successfully applied in personalized treatment systems, including adaptive insulin control, depth control of anesthesia, and rehabilitation robotics, with dynamic variability of physiological responses [6]. Recently, attention has turned to Type-3 fuzzy systems, which is an evolving model that aims to deal with higher-order uncertainties in very flexible medical situations. Although the theoretical model for Type-3 is still in development, early work finds promising characteristics when used in conjunction with modern swarm intelligence algorithms [39]. Such models have the potential to increase the reliability of real-time monitoring of physiological parameters, predicting disease progression, precision medicine, intelligent biomedical device control, among others, where traditional uncertainty modeling techniques are not feasible.

Outside of medicine, fuzzy logic and swarm intelligence for hybridization have impacted many applications. In robotics, fuzzy–swarm systems aid in autonomous navigation, adaptive control, and human-robot cooperation under unexpected conditions. For UAV and aerospace, these approaches enable real-time path planning, fault detection, and adaptive flight control. The industrial engineering and smart manufacturing process, with such hybrid models, is enhanced process optimization, predictive maintenance, and quality assurance. Environmental applications like climate prognosis, pollution detection, and natural resource use cases also make good use of the fuzzy powered swarm intelligence by the flexibility and robustness to cope with noise driven data streams. Financial forecasting is also improved by more dynamic modeling and less incomplete understanding of market information and dynamics of fluctuations. Combining the step of Type-1, Type-2 and currently Type-3 fuzzy systems, while the progress of swarm intelligence approaches is also remarkable. Especially in such advanced fields as healthcare and medicine, such an evolution would allow more reliable diagnostic tools, intelligent clinical decision support systems, and personal treatment strategies to be created.

As more research is carried out, it is anticipated that the amalgamation of fuzzy reasoning and swarm-based optimization will be fundamental in our next generation of computational intelligence systems, which are able to perform in high-risk or uncertain environments.

2.1 Applications of Fuzzy Logic and Swarm Intelligence on Healthcare

Fuzzy logic systems incorporated with swarm intelligence and evolutionary algorithms have gained much attention and popularity in healthcare because of their capability of handling nonlinearity, uncertainty, and high-dimensional medical data. In clinical decision support systems (CDSS), fuzzy and hybrid models have been applied to disease diagnosis, prognosis and patient risk stratification effectively in many complex states, when clinical information is imprecise or incomplete [25].

These intelligent systems enhance the diagnostic accuracy and facilitate in evidence based decision making, aiding physicians through the modeling of expert knowledge and optimization of fuzzy rules by collective behavior. In the area of medical imaging, fuzzy evolutionary and swarm intelligence techniques have been applied extensively to image segmentation, feature extraction, and abnormality detection in domains like MRI, CT, mammography, and ultrasound [37].

These hybrid approaches enhance robustness towards noise and imaging artifacts while increasing sensitivity across tumor detection, boundary extraction, and organ localization. In addition, in pattern recognition of biomedical data, fuzzy genetic and swarm-based methods achieved better results when applied for electrocardiogram (ECG), electroencephalogram (EEG), and genomic data for disease classification and early anomaly detection [2]. In the fields of medicine and smart treatment planning, fuzzy swarm optimization has been leveraged to optimize drug dosage,

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radiation therapy planning, and adaptive therapy design that can take into account patient-specific physiologic variability and uncertainty in clinical parameters [24]. These approaches allow adaptable, interpretable medical decision models superior to common optimization approaches.

Moreover, fuzzy swarm approaches were exploited in smart healthcare and biomedical applications such as wearable health monitoring, physiological signal processing, and real-time patient monitoring systems with the aim of enhancing healthcare delivery and providing medical response [23].

In addition, the widespread adoption of wearable technologies, particularly Apple and Garmin devices, has significantly transformed data driven healthcare by enabling continuous and real time physiological monitoring through consumer grade but clinically relevant sensors. Apple Watch integrates advanced biosensors for heart rate, electrocardiogram (ECG), blood oxygen saturation (SpO), physical activity, and sleep analysis, and has demonstrated strong clinical utility in large scale cardiovascular screening studies, especially in the detection of atrial fibrillation [44, 35]. Similarly, Garmin devices have shown high accuracy and reliability in monitoring heart rate variability (HRV), energy expenditure, and physical performance, making them widely applicable in sports medicine, rehabilitation, and chronic disease management [40, 13]. From a research perspective, the data collected from these wearable platforms support predictive analytics, remote patient monitoring, and personalized healthcare models through the integration of artificial intelligence and machine learning techniques for disease prediction and behavioral pattern recognition [26]. Furthermore, the interoperability of the Apple Health and Garmin Connect ecosystems with cloud based healthcare software and electronic health record (EHR) systems enhances their role in medicine, population health surveillance and smart healthcare infrastructures, highlighting their growing importance in both clinical practice and biomedical research [42].

In recent years, a significant number of fuzzy models and swarm intelligent systems have been developed with the objective of achieving optimal performance in highly complex healthcare problems. As shown in Table 1, this study reports the most frequently cited publications employing fuzzy logic and swarm intelligence in medical and healthcare applications. The publications listed in Table 1 were retrieved from the Scopus database, revealing a substantial growth in scientific production over the last decade. The search was conducted using the topic “fuzzy healthcare swarm optimization” with a specific focus on healthcare and biomedical applications. This search yielded a total of 96 publications indexed in Scopus. From these, 90 articles were identified as directly relevant, and the top 10 most-cited papers were selected for detailed analysis. Furthermore, Figure 1 illustrates the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram [34], summarizing the complete selection and screening process.

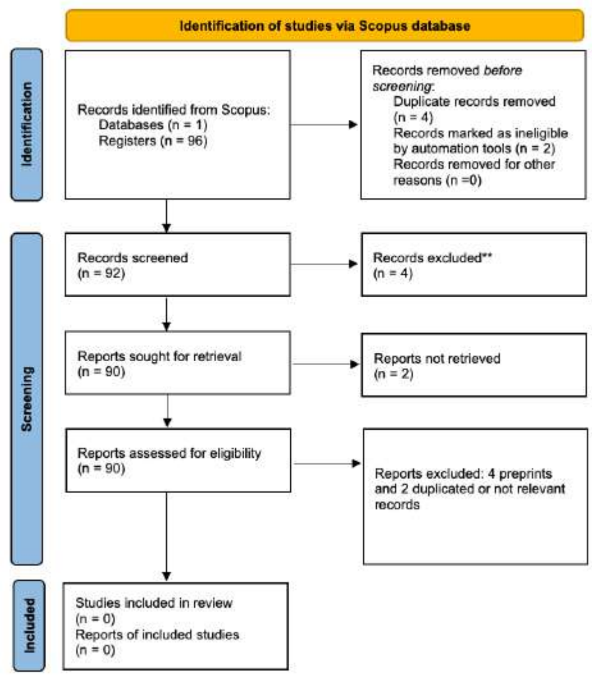

Fig. 1. PRISMA Figure for the topic “Fuzzy Healthcare Swarm Optimization”

In addition, Figure 2 uses the bibliographic data from the Scopus database to illustrate the

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Table 1. Years, authors, references and citations of "Fuzzy Healthcare Swarm Optimization"

Year	Authors	Ref	Citations
2020	Khan, M.A. Algarni, F.	[22]	258
2020	Elaziz, M.A. et al.	[1]	122
2017	Cosma, G. et al.	[7]	103
2022	Talaat, F.M. et al.	[43]	77
2024	Gupta, S.S. et al.	[16]	73
2016	Gambhir, S. et al.	[12]	62
2021	Hoyos, W. et al.	[19]	59
2020	Nayyar, A. et al.	[31]	48
2022	Munagala, N. et al.	[30]	35
2023	Mbouteu M. et al.	[27]	34

distribution of the top ten authors according to number of publications. Publication productivity does not necessarily equal citation impact, and several of the most prolific authors are different from those listed as the top ten most cited authors in Table 1. This discrepancy highlights the distinction between research output volume and scientific influence within the field.

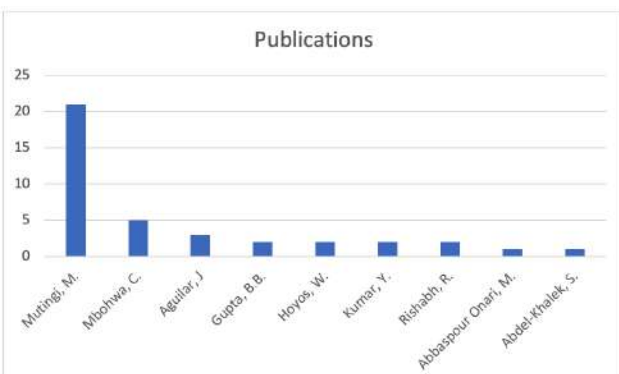

Fig. 2. Top 10 authors by number of publications

2.2 Type-1 Fuzzy Swarm Algorithms on Medicine

In this section, a series of structured queries was formulated to enable a depth exploration of the Scopus database and the use of dedicated bibliometrics for analysing selected research topics. The literature was systematically examined according to the defined subject scope. Table 2 shows the three most cited publications when "Fuzzy Swarm Algorithms on Medicine" search was made. From this initial search, 42 papers were retrieved from the Scopus database. In order to ensure that studies with rich literature, an additional filter was utilized to limit that the results be derived from authors that published not less than 2 articles in this area (two papers per theme), thereby minimizing the dataset to 4 candidate works for a final analysis. Table 2 shows the significant and most widely cited literature where fuzzy swarm algorithms are used for healthcare and medical use. All collected information from this table are taken from Scopus only. Recently, a significant rise in articles with implications has been noted, reflecting a higher level of scientific interest in this area. The table was created using the search term "Fuzzy Swarm Algorithms on Medicine" to achieve precise retrieval of domain specific studies. Although 42 publications were first identified based on this query, only three of the top cited articles were ultimately included in Table 2, using the frequency of citations as an indicator of scientific influence.

Table 2. Years, authors, references and citations of "Fuzzy Swarm Algorithms on Medicine"

Year	Authors	Ref	Citations
2023	Feleki. et al.	[10]	14
2024	Bardamova, M. et al.	[3]	3
2023	Feleki. et al.	[11]	3

Figure 3 shows the Network with Strength links and Co-authorship, with the queries used to find the information from the used database. This information was saved in a csv file to build the Network in Vosviewer program to make Figure 3 and 4. In addition, Figure 4 shows, in detail, the density of the clusters, where researchers who work with "Fuzzy Swarm Algorithms on medicine".

For this network, the citations were not considered for all authors in Figures 3 and 4. Of the

Table 3. Keywords, occurrences, link strength of “Fuzzy Swarm Algorithms on Medicine”

Keyword	Ocurrences	Link strength
PSO	16	147
Fuzzy logic	12	146
Algorithm	9	135
Article	8	125
Human	7	125

587 authors, 587 met the threshold and Strength links were calculated. In conclusion, the researchers who take the highest strength were chosen for the analysis. In Table 3, the results obtained from Vosviewer are shown to know the Top 5 keywords most used with the query presented in Figure 3.

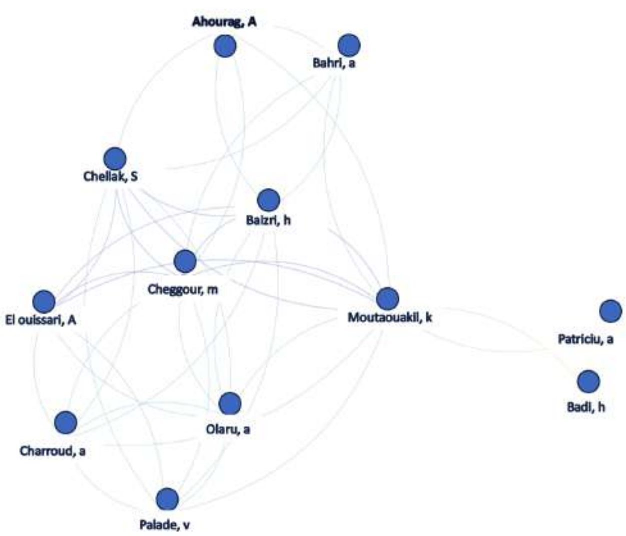

Fig. 3. Network of authors with the query “Fuzzy Swarm Algorithms on Medicine”

Additionally, we examined the Scopus database to analyze the publications by authors. In Figure 5, it is evident that the publication rate has seen an upward trend in recent years.

Figure 6 shows the Network with Strength links and Co-ocurrence, with the queries used to find the information from the used database. In addition,

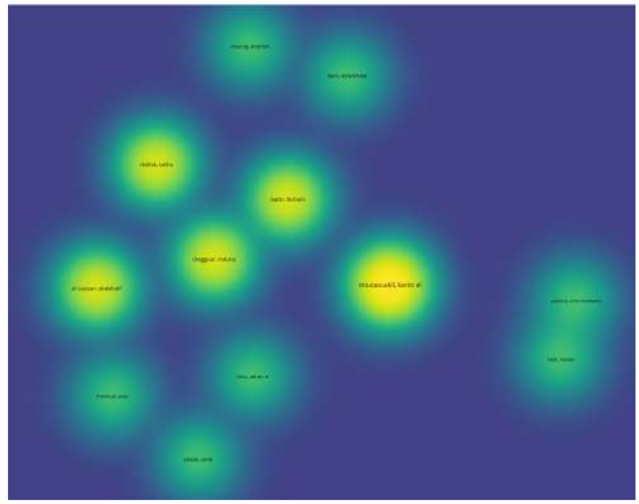

Fig. 4. Density cluster for the topic “Fuzzy Swarm Algorithms on Medicine”

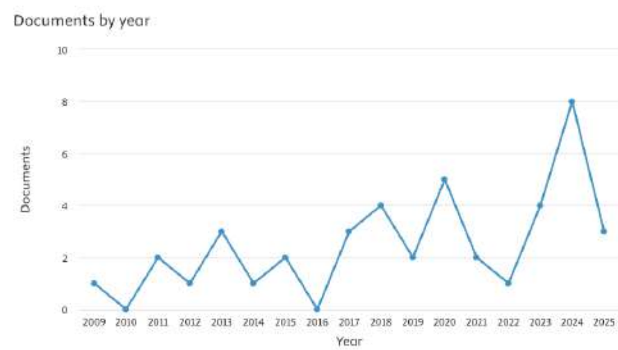

Fig. 5. Publication by year for the topic “Fuzzy Swarm Algorithms on Medicine” . Source: Scopus

Figure 7 shows, in detail, the density of the clusters, where researchers work with “Fuzzy Swarm Algorithms in medicine”. For this network, keywords were considered in Figures 6 and 7. Of the 671 keywords, 104 met the threshold and Strength links were calculated. In conclusion, the keywords that take the highest strength were chosen for the analysis.

3 Discussion of Future Trends

Based on a thorough examination of the Scopus database, we present the main future research di-

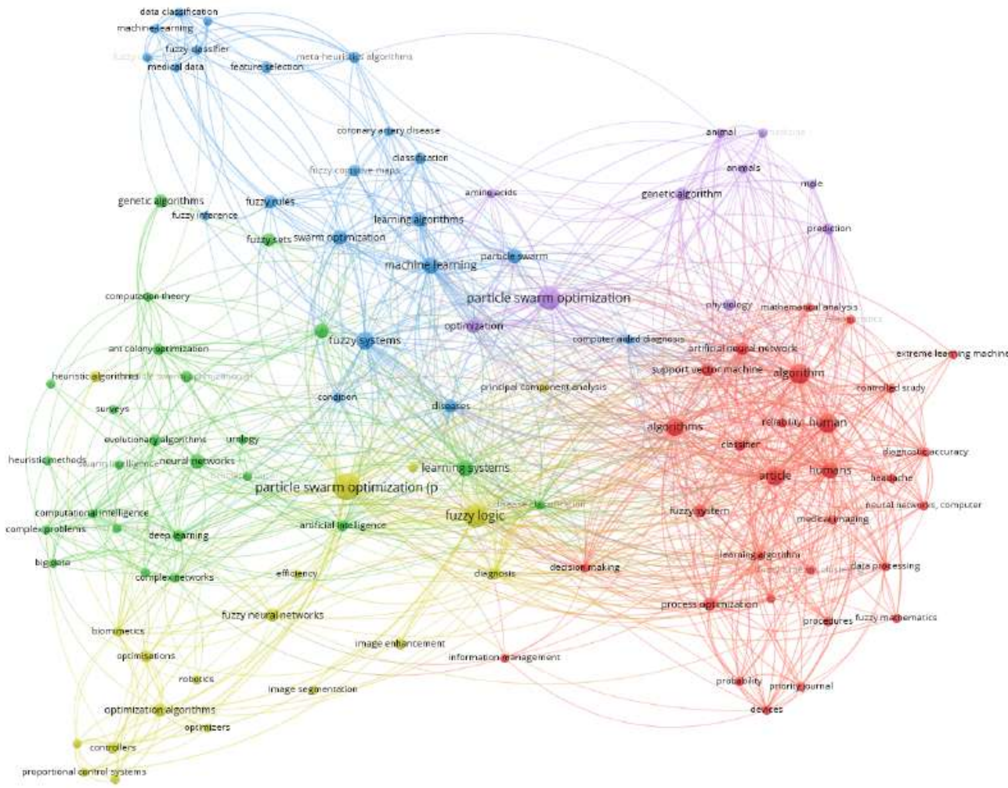

Fig. 6. Network of keywords with the query “Fuzzy Swarm Algorithms on Medicine”

rections in the field of fuzzy systems combined with swarm intelligence and evolutionary algorithms in the fields of healthcare and medical computing. An important observation is that, while hybrid fuzzy swarm approaches have proliferated in the literature, article titles, abstracts, and keywords are not consistently explicit in their classification, highlighting the rapid and interdisciplinary progress of this area of research.

Existing work suggests that the fusion of fuzzy systems with swarm intelligence is mainly aimed towards the design of such hybrid adaptive frameworks to enhance diagnostic capability, treatment choice, and decision robustness in uncertain clinical scenarios. Dynamic adaptation of parameters on the basis of optimized fuzzy rule bases and membership functions allowed in them enhances performance in data-driven and individual patient-driven healthcare models.

Moreover, fuzzy–swarm intelligence is developing towards dynamic parameters based on intelligent systems that adapt according to self-adaptive and learning centered optimization based frameworks, able to address high-dimensional, non-linear, and multi-objective problems for problem types prevalent in medicine such as medical image analysis, bio-signals, clinical decision support, and personalized treatment planning.

New directions also indicate the promising integration of these approaches and bio-inspired optimization, deep learning, digital twins, quantum-inspired computation, and large-scale intelligent medical control systems. In addition, their growing role in medical imaging, remote patient monitoring,

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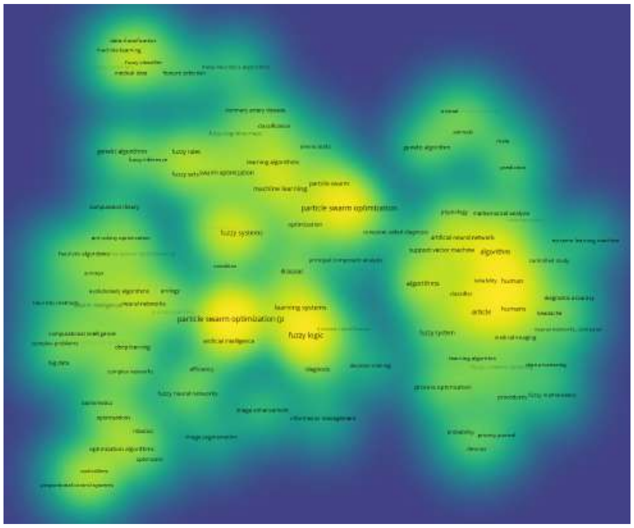

Fig. 7. Density network of keywords with the query "Fuzzy Swarm Algorithms on Medicine"

and smart healthcare infrastructures reflects the expanding role of fuzzy swarm intelligence in contemporary medicine.

Many of these research paradigms are relatively nascent, yet the need for mature, interpretable, and adaptive intelligence systems in healthcare will lead to fuzzy systems and swarm intelligence as potential underpinnings of upcoming medical and biomedical optimization technologies.

4 Conclusions

This paper provides a bibliometric analysis of recent research on the integration of fuzzy logic systems and swarm intelligence used in the healthcare and medical domains. The findings suggest that the titles, abstracts, and keywords of the reviewed documents in their article do not explicitly distinguish between types of fuzzy systems but rather cover fuzzy systems in general. This demonstrates the interdisciplinary character of this field as well as the emergent trend towards a unified approach of hybrid intelligent frameworks. From systematic data gathering from the Scopus database and selection towards the relevant studies combining fuzzy logic, swarm, and evolutionary algorithms, results, in this paper, are proven the growing usage of these hybrid methods for tackling the intricate problems of clinical decision support, medical imaging, bio-signal analysis, disease diagnosis, therapeutic optimization, and intelligent healthcare infrastructures. This rapid development of global scientific output also underpins the need and maturity of this research direction.

This work adds to our understanding by building and analyzing scientific collaboration networks, keyword co-occurrence networks, and citation structures to uncover the international presence of research activity and the level of organizational connectivity. These network structures also reveal that control oriented medical applications and advanced image based biomedical systems are among the top areas emerging in the area of new fuzzy systems research. The findings illustrate the indispensable role of bibliometric software tools such as Vosviewer, in the systematic identification of research fronts, knowledge clusters, and trends that are difficult to map by conventional narrative reviews. Such tools allow for a neutral mapping of scientific knowledge while discovering powerful publications and research communities and guiding us in identifying research directions for healthcare-related artificial intelligence based on evidence.

The primary limitation of the current study was that the bibliographic dataset was exclusively sourced from the Scopus database, which although it is one of the most widespread and curated scientific databases at present, does not cover all publications.

We would also consider adding other databases like Web of Science and Google Scholar to improve coverage and reinforce the detected trend. However, the methodological framework discussed here is completely replicable across various data sources and can be easily expanded for more generalized comparisons.

The combination of other queries with an improved bibliometric software will enrich our knowledge on the evolution, convergence, and clinical impact of fuzzy logic and swarm based intelligent systems in optimizing medicine and healthcare applications in the future.

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