Granular Computing: Trends, Insights, and Bibliometric Review

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Abstract

In human-computer interaction, translating information from binary and numerical concepts to human concepts and back to binary is a subject of ongoing research focused on bridging the gap and facilitating the transition while maintaining the core values of the information. The field that examines this transition, translation, and transformation of information is known as Human-Centric Computing (HCC). In this context, employing a human-centered approach to information, such as categorization, grouping, and summarization into groups or particles (i.e., information granules) through various forms of granulation, imbues these granules with semantics and fosters understanding around them, integrating the information into the paradigm of Granular Computing (GrC). This approach to information and semantics in systems and programming has experienced continuous growth in both the development of concepts and interest in the methodology. This paper aims to explore this research area from 1990 to 2024, emphasizing the evolution of the field's publications. It will begin with a description of Granular Computing, a brief history, and an explanation of its techniques. Publications since 1990 will be analyzed statistically and reviewed for common themes and research trends. Additionally, a collection of research papers will be examined under specific categories for further discussion. This paper seeks to illuminate the evolution of the field of Granular Computing and predict future trends in the approach to research.

Keywords— Fuzzy set, Granular computing, Granularity, Granulation, Interval set, Rough set

1 Introduction

Granular Computing is a concept that emerged in the late 1970s through the introduction of information granularity in 1979 Zadeh, 1996. The concept was built upon the development of several areas within artificial intelligence and pattern recognition, such as fuzzy and rough set theory and interval computing T. Lin and Liau, 2005; Zadeh, 1965. The term granular computing itself refers to a model of information processing built upon concepts such as information granules and granulation. In terms of information, granulation is a manifestation of abstraction Pedrycz and Gomide, 2007a and a way to represent the data and develop a perspective to contain the flood of detail in the data. Data abstraction in the realm of programming is the process of creating data types, usually classes, that represent the data and facilitate processing Gannon et al., 1981. Granular computing as development is not recent but has been in use under different names across many fields of programming and theory, the likes of cluster analysis, data compression, and chunking T. Lin and Liau, 2005. Among the terms that were granular computing placeholders are fuzzy sets, rough sets, interval sets, and shadow sets. All rely on the same concept: Data can be imprecise, incomplete, uncertain, and unreliable, but the use of certain mathematical approximation methods can produce classes capable of higher levels of pattern recognition.

An information granule consists of data points organized based on similarities, spatial or temporal proximity, or functional characteristics Gaeta et al., 2021. This entity (i.e., information granule) will serve as the building block for processing information, and making decisions in AI models means that computation will shift from numerical levels to a more abstract level. The level of abstraction can be adjusted as needed. Increased abstraction leads to higher summarization and generalization of grouped data and vice versa. For instance, describing the weather conditions can be done in two ways: first, by stating that the weather is generally warm in May; second, by noting that the average temperature in May is 30°C, with daily highs reaching 35°C and lows around 27°C. The first provides a more general summary of the weather in May, while the second summarizes the weather with a more specific description. The placeholder mentioned above produced a level of abstraction by

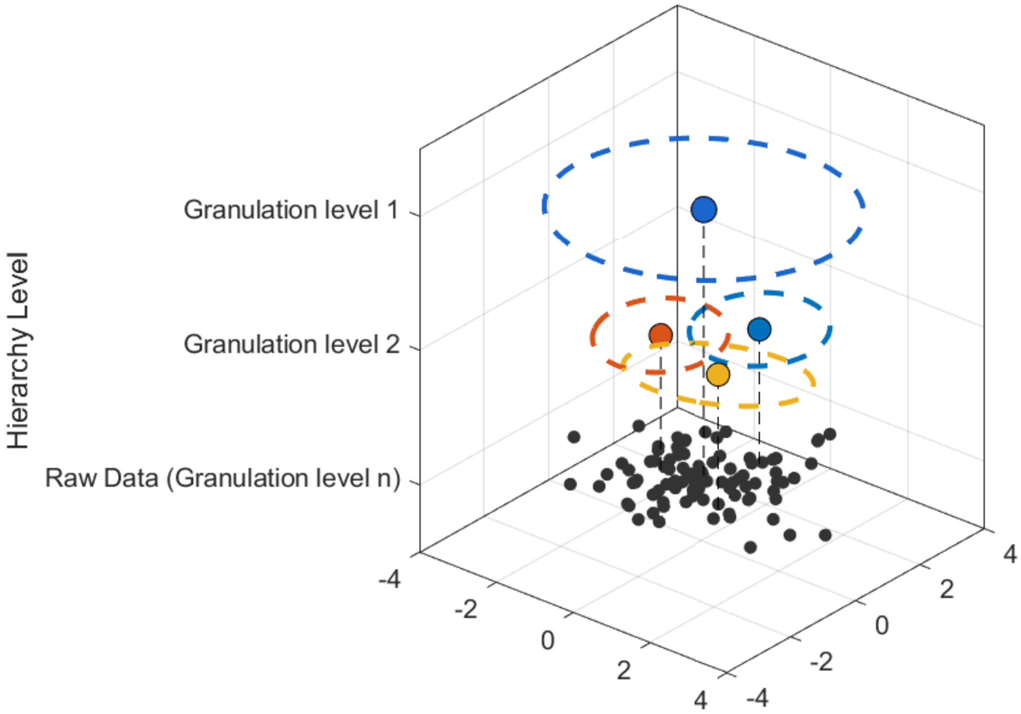

Figure 1: Information granules in terms of levels of granulation.

providing mathematical solutions to approximations, vagueness, and impreciseness and producing a meaningful representation of the data that maintains its generality while continuing to serve the information being portrayed.

Producing the aforementioned information granules must take into account the necessary amount of information. How much detail is sufficient? How small should the granules be? This becomes evident when considering time intervals regarding the information in question: How should a time period be represented? In years, months, days, or seconds? Each level of detail (i.e., granularity) can serve its purpose and contribute to solving the problem Hobbs, 1990. To further illustrate this concept, Figure 1 provides a general idea of granulation and granularity. As the granulation and granularity of information increase, the level of detail improves, making generalizations more informative. However, not all applications necessitate the highest level of granularity; this balance is considered during the production of information granules. This paper aims to highlight the key components of granular computing, along with their evolution and the future of this field, by analyzing all papers that fall under the term granular computing. This is not a new approach to analyzing a scientific field Thompson and Walker, 2015, as social sciences and others have been analyzed Pritchard, 1969. Therefore, this paper aims to produce an overview of the whole Granular Computing research field and analyze its concepts and evolutionary flow into the mainstream, using research terms related to granular computing in the time period from 1990 to 2024. The contribution of the paper can be summarized as:

1. Conduct a comprehensive biometric analysis of granular computing.
2. Determine the themes and future direction of granular computing. The paper will follow this structure: first, formal approaches to granular computing are discussed in Section 1, followed by the classification of research areas in Section 2. The method for evaluating scientific literature is detailed in Section 3. Section 4 describes the bibliographic dataset on granular computing, including statistical indicators related to performance (e.g., the number of published documents, citations, most productive authors, and publishers and journals, among others). Next, a bibliometric approach is employed to examine the most prominent and recurring research areas within the collected data, from which some notions of thematic evolution can be hypothesized and predictions about future interest in the area can be made in Section 5. The paper concludes in Section 6.

2 Granular Computing Categorization

The first explicit use of the term "granular computing" occurred in 1997 Y. Yao, 2008; Zadeh, 1998, but the concept of granular computing was first introduced in the context of fuzzy sets by Lotfi Zadeh in 1979 Y. Yao, 2008; Zadeh, 1979 as the "granulation" of information. This provides insight into the connection between granular computing, set theoryH. Liu, Li, and Li, 2017, and fuzziness. Within the scope of granular computing, there are several subcategories focused on the techniques of decomposition, clustering, granulation, and handling imprecise data Pawlak, 2012. For the purposes of this paper, the relevant techniques are formalized into rough sets, interval sets, shadow sets, and fuzzy sets J. T. Yao et al., 2013a. Sets refer to any totality of a definite number, a theory dating to the late 1800sReck, 2023. A classical set has crisp boundariesCzogała and Łęski, 2000, a definition that was sufficient until data variety and purpose became unavoidable, leading to multiple techniques follow:

- *Interval sets*
  Interval analysis or interval calculus represents perhaps the simplest clustering technique, where a single value can overcome its vagueness or imprecision by being represented by an interval within the universe, making it an information granule J. T. Yao et al., 2013b. Each interval requires that every value in the universe is indicated by whether it falls within that interval or not. An interval set can be defined as:

$$A = [a^-, a^+] \tag{1}$$

  where a^- and a^+ are the lower and upper bounds, respectively. Operations on interval sets include:

  Addition:

$$A + B = [a^- + b^-, a^+ + b^+] \tag{2}$$

  Multiplication:

$$A \times B = [\min(a^-b^-, a^-b^+, a^+b^-, a^+b^+), \max(a^-b^-, a^-b^+, a^+b^-, a^+b^+)] \tag{3}$$

  Intersection:

$$A \cap B = [\max(a^-, b^-), \min(a^+, b^+)] \tag{4}$$

  Union:

$$A \cup B = [\min(a^-, b^-), \max(a^+, b^+)] \tag{5}$$

  f non-decreasing function:

$$f([a, b]) = [f(a), f(b)] \tag{6}$$

  f non-increasing function:

$$f([a, b]) = [f(b), f(a)] \tag{7}$$

  Interval analysis allows for the representation of uncertain or imprecise quantities by bounded ranges. The treatment of interval operations, however, should extend beyond basic addition or intersection. Interval analysis and granular computing are integrated by treating intervals as fundamental information granules and using interval arithmetic with guaranteed bounds Leite et al., 2010; H. Liu, Li, et al., 2017; Skowron, 2023. Data and model parameters are represented as intervals (or hyperboxes), enabling uncertainty propagation, error control, and multiresolution analysis Jaulin and Walter, 2001; Skowron, 2023. Core methods include hyperbox-based classification, interval arithmetic with enclosure techniques, branch-and-bound bounded error estimation, distributed interval structures, justifiable granularity design, evolving interval learners, and interval valued neural models trained with evolutionary algorithms Cimino et al., 2014; Kreinovich, 2008; Kreinovich and Aló, 2002; Leite et al., 2010, 2016; Tahayori et al., 2007; D. Wang et al., 2016. This supports robust applications in classification, regression, parameter estimation, nonlinear system solving, streaming model adaptation, sensor fusion, and optimization—offering interpretability and guaranteed uncertainty bounds Jaulin and Walter, 2001; Skowron, 2023; Tahayori et al., 2007; D. Wang et al., 2016. Moreover, intervals often appear as statistical summaries of variability over time or across populations, using means, variances, or confidence intervals. These granules are especially valuable in time series analysis, where they help convert high-resolution data into meaningful abstractions.

- *Rough sets*
  Rough sets were first introduced through rough set theory Pawlak, 1982 as a mathematical approach to managing imperfect data. The defining text explains that while precision is necessary for mathematics, vagueness is essential in computer science. In rough sets dealing with imprecise data, vagueness is represented as bounded regions. This means all data can be grouped to form a granule of information. A rough set is an approximation of a crisp set with values that either strictly belong or do not belong to the set, where the approximation results from insufficient information. Rather than being defined by precise information (i.e., crisp), a rough set is characterized by an approximation of its upper and lower boundsTripathi and Madan, 2025. In rough sets, approximations are used to deal with uncertainty. Given a universal set U and an equivalence relation R, a rough set is defined by its lower and upper approximations: **Lower Approximation:**

  $$\underline{R}(X) = \{x \in U \mid [x]_R \subseteq X\} \tag{8}$$

  Upper Approximation:

  $$\overline{R}(X) = \{x \in U \mid [x]_R \cap X \neq \emptyset\} \tag{9}$$

  Boundary Region:

  $$B_R(X) = \overline{R}(X) - \underline{R}(X) \tag{10}$$

  The rough set framework introduces the idea of lower and upper approximations to model uncertainty arising from indiscernibility. Recent developments extend this into three-way decision theory, a framework that goes beyond binary classification to enable deferment or abstention under uncertainty. Y. Yao, 2010 's work has been pivotal in this area, demonstrating how three-way approximations improve decision-making by incorporating cost-sensitive and probabilistic strategies. Rough sets integrate with granular computing by treating lower and upper approximations as operations over information granules within multilevel frameworks Artiemjew, 2020; Sun et al., 2014; Zadeh, 2007. Objects are grouped into granules (e.g., equivalence classes, neighborhoods, fuzzy relations), and rough approximations are generalized for probabilistic and fuzzy uncertainty modeling Inuiguchi et al., 2003; Sun et al., 2014. Multilevel zooming and quotient-space methods enable reasoning at different granular scales, while granule-based rule induction and reduct computation produce compact, interpretable decision models Skowron and Ślęzak, 2022; Y. Yao, 1999; Zadeh, 2007. Entropy and granulation-based measures guide uncertainty quantification and attribute selection in incomplete systems Skowron and Stepaniuk, 2008. Applications include classification, rule extraction, feature reduction, multiscale knowledge representation, and engineering tasks like sensor fusion and pattern analysis Inuiguchi et al., 2003; T. Y. Lin et al., 2013; Skowron and Ślęzak, 2022; Skowron and Stepaniuk, 2008.

- *Fuzzy sets*
  Fuzzy sets form one of the most foundational models for information granulation, representing vague concepts via gradual membership functions. A fuzzy information granule encapsulates a region of the input space along with a membership profile indicating the degree to which each element belongs. As highlighted in Fuzzy Systems Engineering by Pedrycz and Gomide, 2007b, granules serve as the building blocks of fuzzy inference and modeling, often emerging in hierarchical and context-sensitive forms.

  In contrast to rough sets, *fuzzy sets* rely on the gradual nature of belonging to represent vagueness. Instead of approximation, fuzzy sets establish a degree of membership between 0 and 1 Klir and Yuan, 1995, where full membership indicates total certainty. Similarly, in the context of fuzzy sets, elements belong to a set with a degree of membership. Given fuzzy sets A and B, where each element has a membership function $\mu_A(x)$ or $\mu_B(x)$, fundamental operations include:

  Union:

  $$\mu_{A\cup B}(x) = \max(\mu_A(x), \mu_B(x)) \tag{11}$$

  Intersection:

  $$\mu_{A\cap B}(x) = \min(\mu_A(x), \mu_B(x)) \tag{12}$$

  Complement:

  $$\mu_{\neg A}(x) = 1 - \mu_A(x) \tag{13}$$

  Granulation in fuzzy systems is not limited to the data domain; fuzzy granules of parameters and fuzzy rules with linguistic granules allow systems to operate under imprecise or evolving conditions. Advanced fuzzy granules may also incorporate type-2 fuzzy sets, enabling the modeling of secondary uncertainty in membership functions. Fuzzy sets serve as information granules for representing imprecise, user-centric concepts, with granular computing offering multilevel abstraction, organization, and processing to manage uncertainty and complexity Pedrycz, 2008; Zadeh, 1997a. Their integration happens via fuzzy granulation, fuzzy-rough hybrid models, granular ball representations, and granule-based preprocessing, enabling interpretable, efficient learning Maji and Pal, 2012; Xia et al., 2022. Fuzzy-rough systems combine graded membership, boundary approximations, and entropy-based measures to boost robustness and rule extraction Bello et al., 2008; Maji and Pal, 2012, while granular ball fuzzy models enhance scalability and noise tolerance in classification tasks like SVMs Xia et al., 2022. Applications include classification, pattern recognition, data mining, and control systems, where granule compression, multilevel reasoning, and uncertainty quantification improve robustness, interpretability, and efficiency Pedrycz and Vukovich, 1999; Stefanini et al., 2008; Xia et al., 2022.

- *Shadow sets*
  Shadow sets were first introduced in 1998 Pedrycz, 1998. They are a development of fuzzy sets that build upon the idea of continuous boundaries found in fuzzy sets Pedrycz, 1999, by providing a mapping with set mapping values Pedrycz, 2005a. When capturing vagueness, the use of fuzzy tools and gradual membership was an effective descriptive method, but it introduced a burden of computational overhead Pedrycz, 2005a. The adoption of shadow sets to encapsulate the core function of fuzzy sets comes with a lesser computational load while maintaining high functionality. The element of fuzziness in part of a set produces shadow sets, representing a fuzzy set of information where the membership of values can fall into one of three categories: complete belonging, partial belonging, and complete exclusion. Shadow sets provide a further refinement of rough sets by classifying elements into three distinct regions: full membership, full exclusion, and shadow. Let $\mu_A(x) \in [0,1]$ be the membership degree of element x in the fuzzy set A, and let $\alpha \in [0,1]$ define the shadow width (uncertainty parameter).

  The shadow set $S_A(x)$ is defined as:

$$S_A(x) = [\max(0, \mu_A(x) - \alpha), \min(1, \mu_A(x) + \alpha)] \tag{14}$$

  Based on this, the universe X is partitioned into three regions:

  Full Membership Region (Certain Inclusion):

$$x \in X \quad \text{such that} \quad \mu_A(x) \geq 1 - \alpha \tag{15}$$

  Full Exclusion Region (Certain Non-membership):

$$x \in X \quad \text{such that} \quad \mu_A(x) \leq \alpha \tag{16}$$

  Shadow Region (Uncertainty Region):

$$x \in X \quad \text{such that} \quad \alpha < \mu_A(x) < 1 - \alpha \tag{17}$$

Shadowed sets are three-valued abstractions of fuzzy sets classifying elements into full membership, non-membership, and an intermediate shadow (uncertainty) region Pedrycz, 2005b, 2009. Introduced by Pedrycz to localize uncertainty and simplify fuzzy information, they transform fuzzy membership through an optimization process, yielding a concise and interpretable three-way representation. Research has established properties and developed algorithms for stable partitions Pedrycz, 2009; Zhou et al., 2019. Extensions such as entropy-based approximations and complex shadowed sets expand decision-making and clustering applications Campagner et al., 2020; H. Wang et al., 2018. Shadowed sets facilitate three-way decision models, fuzzy clustering, preprocessing, and hybrid fuzzy systems, providing efficient, uncertainty-aware granular computing applications Pedrycz, 2005a; Yang, Wang, et al., 2024.

Table 1 summarizes the formal granular computing models, while Fig. 2 provides an example of a graphical representation of these formal models.

2.1 Research Area Classification

The field of granular computing can be classified into the following research areas:

- Foundational Concepts and Theory in Granular Computing: Concerns the evolution of the triarchic theory of granular computingY. Yao, 2018 and the development of theoretical foundations of granular computing, including granulation, granular relations, and the formalization of granules. The triarchic theory provides that the three perspectives of granular computing, philosophical, methodological, and computationalY. Yao, 2008, form a complete view of granular computing. Research classifiable under this class is still being produced in niche and broad areas of varied interest, continuing the growth of this field.

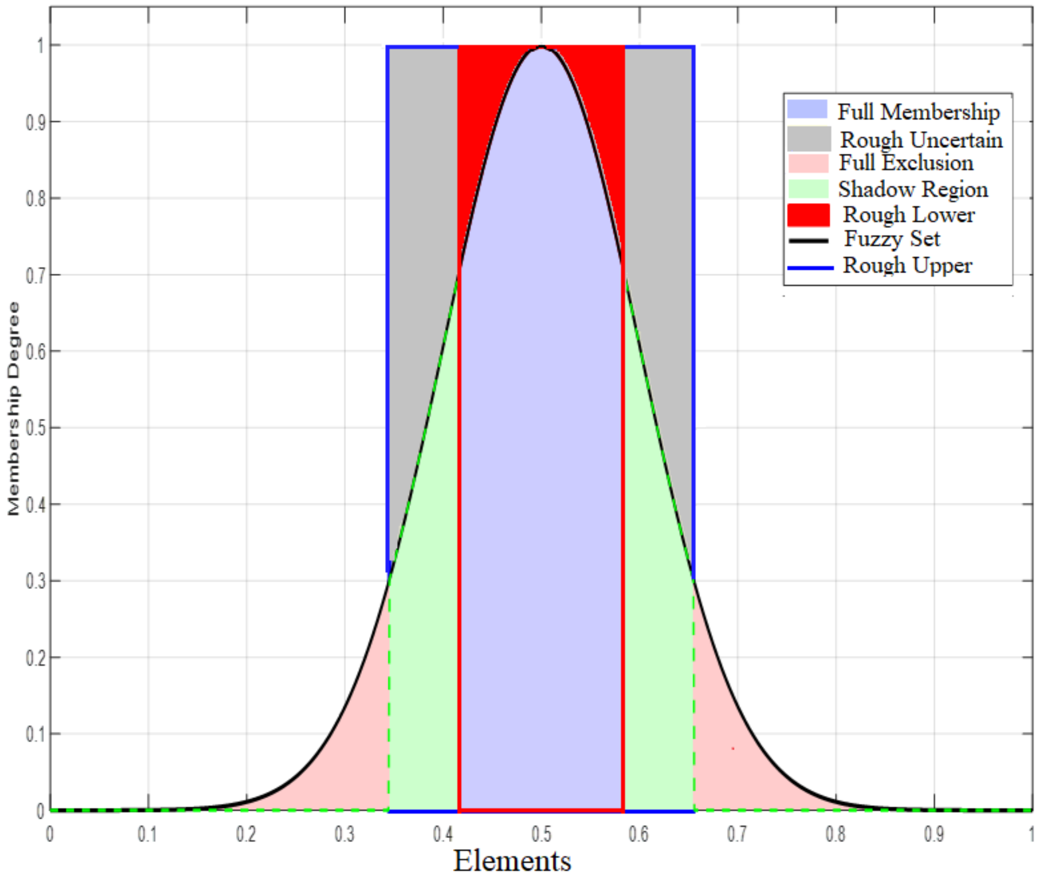

Figure 2: Fuzzy set vs Rough set vs Shadow set.

Feature	Interval Set	Fuzzy Set	Rough Set	Shadow Set
Granulation Type	Bounded Range (Intervals)	Gradual Membership	Approximation (Lower/Upper)	Approximation with Shadow Region
Data Representation	$[a^-, a^+]$	$\mu(x) \in [0,1]$	$(\underline{X}, \overline{X})$	$S_T(t) = [\max(0, \mu_{\tilde{T}}(t) - \alpha), \min(1, \mu_{\tilde{T}}(t) + \alpha)]$
Example	$T = [25, 30]°\text{C}$	$\mu_T(t) = \begin{cases} 0 & t \leq 23 \text{ or } t \geq 32 \\ \frac{t-23}{2} & 23 < t < 25 \\ 1 & 25 \leq t \leq 30 \\ \frac{32-t}{2} & 30 < t < 32 \end{cases}$	$\underline{T} = [26, 29]$ $\overline{T} = [25, 30]$ $BND(T) = \overline{T} - \underline{T}$	$S_T(t) = \begin{cases} 0 & \mu_T(t) \leq 0.2 \\ 1 & \mu_T(t) \geq 0.8 \\ a & otherwise \end{cases}$

Table 1: Granular computing formal models summary.

- Human-Centered Computing: Human Centric Computing (HCC), in simple terms, is an area studying the link between 2 values logic (binary) and human informationPedrycz and Gomide, 2007b, with the purpose of bringing computing closer to human understanding.
- Set Theory Based Granular Computing: Within the theory related to granular computing, there is a direction of foundational evolution related to developing fuzzy set or rough set concepts. etc, to the goal of ultimately advancing granular theory built upon it Pawlak, 1982; Pedrycz, 1998, 1999.
- Applications: Applied use of granular computing is an important perspective into the significance of the field. Using concepts of granular computing has produced significant results in areas of data analysis, medical diagnosis, image processing, and moreChen and Zhang, 2014; Deng et al., 2024; Hu et al., 2024; Qin et al., 2024; Shen et al., 2024; J. Yao, 2010.

2.2 Significant Topics

The following concepts represent key methodologies and frameworks that have greatly contributed to the advancement of granular computing. Below is a brief overview of some of the most significant concepts in this field:

- Justifiable Granularity: In the realm of GrC, creating a granule involves adhering to specific criteria to establish a meaningful and justifiable existence. In Pedrycz and Homenda, 2013, the concept of justifiable granularity is introduced, alongside the criteria for producing the optimal information granule. The optimally constructed granule, based on these specified criteria, is sufficiently large to encompass all related data, providing Coverage, while still maintaining meaning pertinent to the Specificity of the semanticsLi et al., 2024; Pedrycz, 2011. The author discusses the contradictory relationship between specificity and coverage at the core of this concept in Pedrycz and Homenda, 2013. While coverage can be mathematically represented as a function that increases with the size of the data within the granule, specificity diminishes as the granule size increases. This relationship offers a way to fine-tune the construction of information granules.
- Three-way Decision (3WD): The 3-way decision is a problem-solving techniqueT. Wang and Huang, 2025 that bases the solution on three questions or levels of analysis Y. Yao, 2018. Regarding granular computing, the 3-way decision incorporates a human aspect into understanding information. The interpretation of these three approaches can be considered in various ways: It may involve applying three levels of granulation or categorizing objects into three groups Kong et al., 2022, among othersQin et al., 2024. By taking this 3-way approach, decision-making applications gain a reduction in ambiguity, particularly that of classification Yang, Liu, et al., 2024, where this approach can manifest in the form of rejecting, accepting, or a boundary case of classification.
- Fuzzy C-Means (FCM): Clustering is a method of grouping elements based on a certain degree of similaritySuganya and Shanthi, 2012. This process utilizes boundaries defined by membership functions, such as those used in Fuzzy C-Means (FCM). While K-means is a clustering technique that proposes each point belongs to only one cluster, fuzzy clustering allows objects to belong to multiple classes, assigning a degree of membership to each class and creating a fuzzy partition among the clusters. In numerical analysis, similarity grouping information is often absent; thus, membership is typically determined by the distance between a point and the center of the cluster- the further a point is, the lower its membershipBargiela and Pedrycz, 2005; Ruspini et al., 2019. The goal of an FCM algorithm is to generate optimal partitions of the known data cluster centersLu and Yan, 2015; Nascimento et al., 2000; Yu et al., 2024.

- Fuzzy-Rough Sets and Rough-Fuzzy Sets: In handling imprecise, uncertain, and approximate information, the combination of fuzzy set theory and rough set theory produces a new approach to the problemJha et al., 2022. The order in which aspects of the data are handled changes the method. For data that has both fuzzy characteristics and incompleteness or imperfection, first describing the fuzzy aspects with an appropriate membership function, followed by employing rough set theory to establish boundary conditions, yields a fuzzy-rough approach. In contrast, the rough-fuzzy approach begins with rough set theory by outlining the boundaries of the data and then creating a membership function. This method was first introduced in 1990 Dubois and Prade, 1990, referring to information as "granule. " It has since seen application in various avenues of decision-making and data analysis.
- Interval-valued fuzzy sets : IVFs were introduced in 1975 Zadeh, 1975 Grattan-Guinness, 1976. An IVF is defined by a membership function that assigns intervals. Atanassov Atanassov, 1986 proposed defining a fuzzy set using two functions: a membership function and a non-membership function. He ensured that the sum of these functions does not exceed 1 for any element. This concept is called "Intuitionistic Fuzzy Sets" Dubois et al., 2005, though its foundational idea differs from IVFs.
- Type-2 fuzzy sets: extend traditional fuzzy sets by allowing the membership degree itself to be fuzzy Zadeh, 1975. A widely used subclass of Type-2 fuzzy sets is the interval Type-2 fuzzy set (IT2FS), where the secondary membership function is represented as an interval Castillo, 2010. In this context, interval-valued fuzzy sets can be viewed as a special case or an approximation of interval Type-2 fuzzy sets, capturing uncertainty in membership without the full complexity of general Type-2 modeling Hernández et al., 2022.
- Interactive Granular computing:: Interactive GrC extends traditional granular computing by incorporating interactions between imperfect, granulated information (information granules) and physical entities (considered on either time or space) known as "hunks" Skowron and Jankowski, 2016, modeling complex intelligent systems through interactive processes using structures referred to as complex granules (c-granules). These c-granules consist of three suits: soft-suit (information granules like descriptors or fuzzy sets), link-suit (relations binding info to physics), and hard-suit (physical hunks). Computations progress via agent societies in interactive intelligent systems (IIS), approximating vague concepts through rough-set-inspired methods amid uncertainty, vagueness, and noise. IGrC supports modeling complex adaptive systems, process mining, risk management, and IoT optimization by handling human-like granularity in problem-solving. It integrates rough sets, fuzzy sets, and multi-agent systems for perceptual approximations in real-time interactions Soma Dutta, 2019.

2.3 granulation goals and challenges

As provided earlier, the use of granular computing went through multiple stages of development, and application-specific definitions. However, the definitions maintained that granules are clusters of information that possess properties like cardinality, specificity, and coverage Y. Yao, 2008. Definitions also maintain that granules provide an approximation to incomplete, vague, imprecise, or uncertain data, providing deeper comprehension and facilitating better pattern recognition Kang and Miao, 2016, which is the ultimate goal of granulation and granular computing.

Achieving the benefits does not come without challenges. Chief among them is the compatibility between data, method, and application, necessary to achieve the desired results Ross, 2025. Furthermore, granulation can face and sometimes produce overlap and uncertainty of classes, particularly in iterative situations Muda, 2022. Another major issue faced is the lack of standardization in the field of GrC, resulting in systems that lack interoperability and regulation D. Liu et al., 2023.

Granular Computing (GrC) provides a computational framework for managing complexity, uncertainty, and interpretability through the use of information granules, defined as groups of entities formed based on similarity or functional relationships Zadeh, 1997b. This paradigm is particularly suitable for high-dimensional, noisy, and multi-scale data environments. A central challenge in GrC is the discovery of relevant granules, often referred to as the granulation design problem. The goal is to construct granules that balance abstraction with representational precision. Overly coarse granules may conceal important patterns, whereas excessively fine granules may reduce generalization capability.

One widely adopted approach is the principle of justifiable granularity Pedrycz, 2013, where granules are formed by optimizing the trade-off between coverage and specificity. Granule discovery may also be achieved through data-driven methods such as fuzzy clustering and rough set approximations Bargiela and Pedrycz, 2003; Pawlak, 1991, as well as optimization-based techniques that adjust granule parameters to improve interpretability and predictive performance. Additionally, multi-granulation frameworks enable knowledge representation at multiple abstraction levels, supporting hierarchical reasoning and cross-scale analysis Pedrycz, 2013. Knowledge-guided granulation further incorporates expert insight to enhance semantic interpretability.

3 Methods of Evaluating Scientific Literature

For a quantitative study and an analysis of the research field and the literature produced from it, bibliometrics are employed as study methodsCobo et al., 2011. In this work, bibliometrics were utilized to examine the area of interest; further performance analysis was conducted to visualize the thematic evolution of the field of study using keyword co-occurrence analysis and additional metrics. From themes and recurring keywords, a visual representation can be created in the form of clusters and networks, a visualization that bridges the gap to interpretation rather than data, according toKrsul, 2002, while highlighting the strength of association. To create such visualizations, referred to as strategic diagrams, the use of centrality and density is essential. Centrality, in terms of thematic analysis, is a metric that indicates the influence of a theme within certain thematic groupsGiannakos et al., 2020. Specifically, the centrality examined here measures the influence of a theme on a scale of 0-1. It is calculated using equation ref eq1, where e refers to the number of occurrences of k, a keyword belonging to the theme, and h belongs to other themes.

$$c = 10 \times \sum e_{kh} \tag{18}$$

Density: A theme is conceived through a clustering of keywords. The density of a theme refers to the number of ties between keywords relative to the total number of keywords. Ties here refer to instances of co-occurrences of the keywords throughout the literature. This is shown through equation 19, where i and j are keywords from the theme and T the number of keywords in the theme.

$$d = 100 \sum \frac{e_{ij}}{T}, \tag{19}$$

The themes produced were analyzed using centrality and densityCobo et al., 2013 to categorize them into quadrants as follows:

- QI: Representing the Motor themes of the field, themes within this quadrant can be labeled as "main-stream"Herrera Viedma et al., 2020 in their field and essential to its construction. This is quantified by the high centrality (association with other themes) and high density (internal development of the theme)
- QII: With high density but low centrality, this quadrant represents specialized and niche fields (with varying degrees of niceness) with low relations to other themes appearing in the field. Often composed of outer field and cross-disciplinary topics and concepts, this quadrant can represent new developments in the field. Themes within this quadrant are nicknamed as "ivory towers", well-developed internally but scarcely connected outward.
- QIII: Themes with low centrality and low density fall into this quadrant. They can be considered emerging in the process of gaining density or centrality, providing a starting point for new trends or growth in the field. Themes within this quadrant can suffer a decline of centrality and density, possibly in the process of diminishing in interest and development in the concerned period of time and field.
- QIV: The high centrality characterizing this quadrant provides a high level of inter-theme relation, but a low density describe low development of each theme internally. Considering the time period being studied, this quadrant can highlight older themes that have a strong influence on the field but lack dedicated interest, categorized as a "bandwagon" (i.e., tailing other themes) in the field.

To visualize an evolution or time-related change, the field is studied over different periods, analyzed thematically across various time spans, and strategic diagrams are produced. In addition, several statistics will be generated, including:

- The number of produced research documents: A statistic that will be monitored throughout the specified years, providing an insight into interest in the field.
- The citations and most cited papers: Indicate the most influential cited sources and their consequential influence.
- The most productive authors in the field: Similar to the most cited papers, a look into the sources of the papers can provide some outlook into the diversity of the field's production.
- The most productive publishers: Similarly important in highlighting the diversity in produced literature.

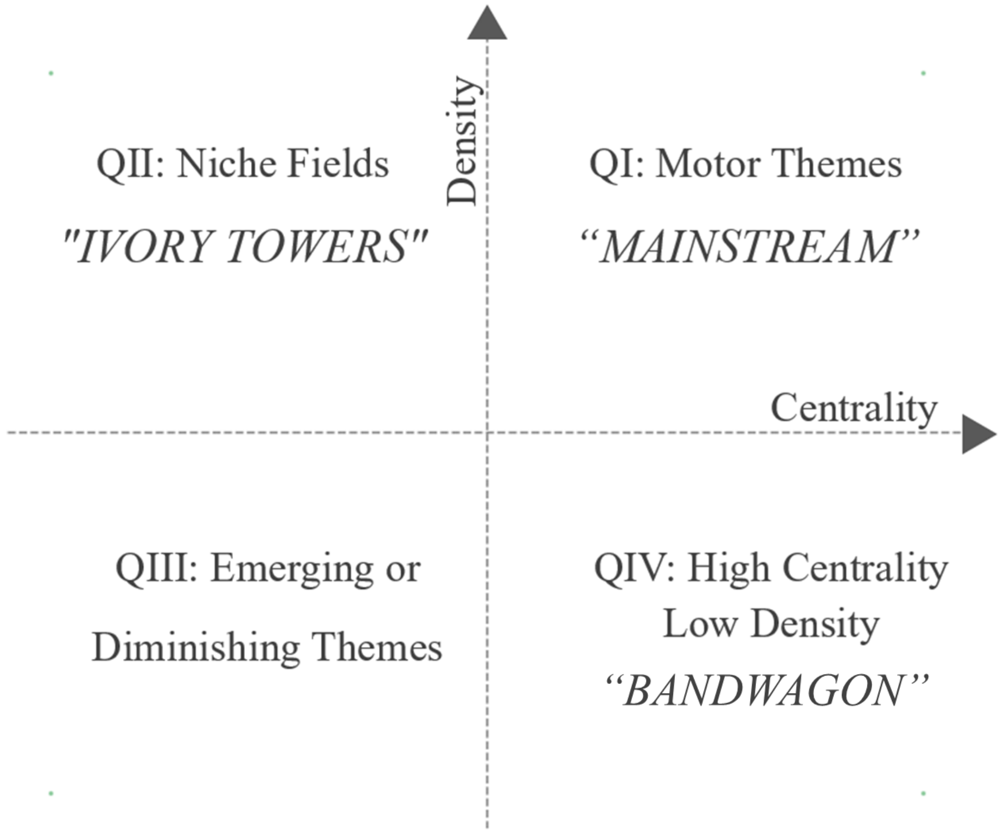

Figure 3: Interpretation of quadrants as dictated by the Centrality vs the Density (i.e., strategic diagram)

4 Granular computing bibliographic dataset

To begin exploring the world of publications, data were collected for studies. The data were collected as of March 2025, following a process that started with the gathering of raw data from Google Scholar (https://scholar.google.com/) keyword search pages, restricted to the years 1990 to 2024. The search targeted instances containing the phrases "granular computing" or "information granules. " Specifically, it focused on instances of usage of the words "Granular Computing"; however, due to their core relation to granular computing, the phrases "fuzzy set, " "rough set, " "interval set, " and "shadow set" were also used as keywords.

No. of papers	15605
No. of citations	423061
Average citation per item	27.1

Table 2: Granular computing papers and citations.

The raw data was extracted, processed, and key information was collected in an Excel sheet. Table 3 shows a sample of the produced data. The key information extracted includes: 1. Title, 2. Brief summary of the publication/abstract, 3. Keywords occurring in the publication(particularly in the abstract and title), 4. The area of research it belongs to, 5. The link to the publication, 6. The author (s), 7. The sources, 8. The year of publication, and 9. The number of citations recorded. The extracted information was then further cleaned by removing incomplete records and duplicates, resulting in 15605 entries from an extracted 15888. Analyzing the collected data, occurrences of the keywords "rough set," "fuzzy set," "interval set," and "shadow set" were examined to illustrate figure 4.

In the collected literature, the use of rough sets and fuzzy sets holds the highest rank within the scope of our investigation (refer to Figure 4). This is likely due to their long history and solid foundations, which naturally provide them with more activity and grounding in the realm of GrC. This is particularly true for fuzzy sets, which are closely related to the initial use of the term "granular information"Zadeh, 1979.

Title	Abstract / Document Snippet	Keywords	Authors	Journal	Year	Link / DOI	Citations
Consensus model driven by interpretable rules in large-scale group decision making with optimal allocation of information granularity	of the relation in the format of a certain information granule (e.g., interval, fuzzy set, rough set)	['ROUGH set', 'FUZZY set', 'INTERVAL set', 'GRANULAR']	B Zhang, Y Dong, W Pedrycz	IEEE Transactions on Human-Machine Systems	2022	https://9858107w	17
Multi-granularity probabilistic rough fuzzy sets for interval-valued fuzzy decision systems	The probabilistic rough set (PRS) model, through the incorporation of error levels, represents	['ROUGH set', 'FUZZY set', 'INTERVAL set', 'GRANULAR']	W Li, T Zhan	International Journal of Fuzzy Systems, 2023	2023	https://s40815-023-01577-z	18
Generalized interval type-II fuzzy rough model-based feature discretizations for mixed pixels	Feature discretizations algorithms of remote sensing images are often based on the assumption	['ROUGH set', 'FUZZY set', 'INTERVAL set']	X Huang	IEEE Transactions on Fuzzy Systems	2022	https://9829247	28
Algebraic structure through interval-valued fuzzy signature based on interval-valued fuzzy sets	This paper delivers three different ways to establish the initial structure of the interval-valued	['ROUGH set', 'FUZZY set', 'INTERVAL set']	S Palanisamy, J Periyasamy	Granular Computing, 2023 - Springer	2023	https://s41066-023-00372-3.pdf	3
Three-way conflict analysis based on interval-valued Pythagorean fuzzy sets and prospect theory	Conflict analysis gives guidelines for conflict resolution, which has been thoroughly studied	['ROUGH set', 'FUZZY set', 'INTERVAL set']	L Zhang, B Huang, X Zhou	Artificial Intelligence Review, 2023 - Springer	2023	https://s10462-022-10327-w	24

Table 3: Sample of collected data in a table.

5 Bibliometrics

5.1 Number of published Papers

Since its inception, granular computing has remained a topic of interest. When surveying the volume of research conducted under the umbrella of granular computing, particularly regarding publications produced since 1990, there is an unmistakable upward trend (see Figure 5). The total number of publications in 2024 is the highest to date. Furthermore, when examining the citations referenced in the available literature, the year with the most citations for overall produced research is 2020. This suggests that 2020 is particularly rich in sources that contributed to subsequent years of research.

5.2 Citations and most cited author

As a basis for researchers, the documents cited can provide a perspective on the time the authors were producing their work and the influences they were under citewohlin2008analysis. Examining the most cited year for publications (see Figure reffig2), 2008 stands out as the most cited year among all works published that year. However, when considering the average citations per publication across each year (see Figure reffig1.5), the most cited publications, on average, were produced in 1990. This interpretation reveals the lasting influence of the paper Glover, 1990 on the evolution of literature in GrC for years to come, an influence unmatched to date within this time frame. The high overall citations linked to 2008 indicate that the significant growth spurt that occurred that year also impacted subsequent publications.

The top 10 most cited papers are listed in table4, most of which are theoretical and conceptually relevant.

To further understand the literature produced, it is important to know the most influential authors, as this highlights the evolution of the subject. The authors with the highest number of publications in granular computing, as well as the most cited authors from 1990 to 2024, are shown in Table 5. For the sake of posterity, being part of a group of authors counts as a publication and contributes to the overall tally. It is notable to highlight the continuous collaboration among the authors listed below and the considerable overlap in their focus areas.

Some authors, such as Professor Witold Pedrycz and Professor Lotfi Zadeh, have a high citation-to-publication ratio due to their contributions, which provided core concepts and cornerstones in the field of GrC. This makes their work among the most cited literature in the discipline, alongside Professor Yiyu Yao.

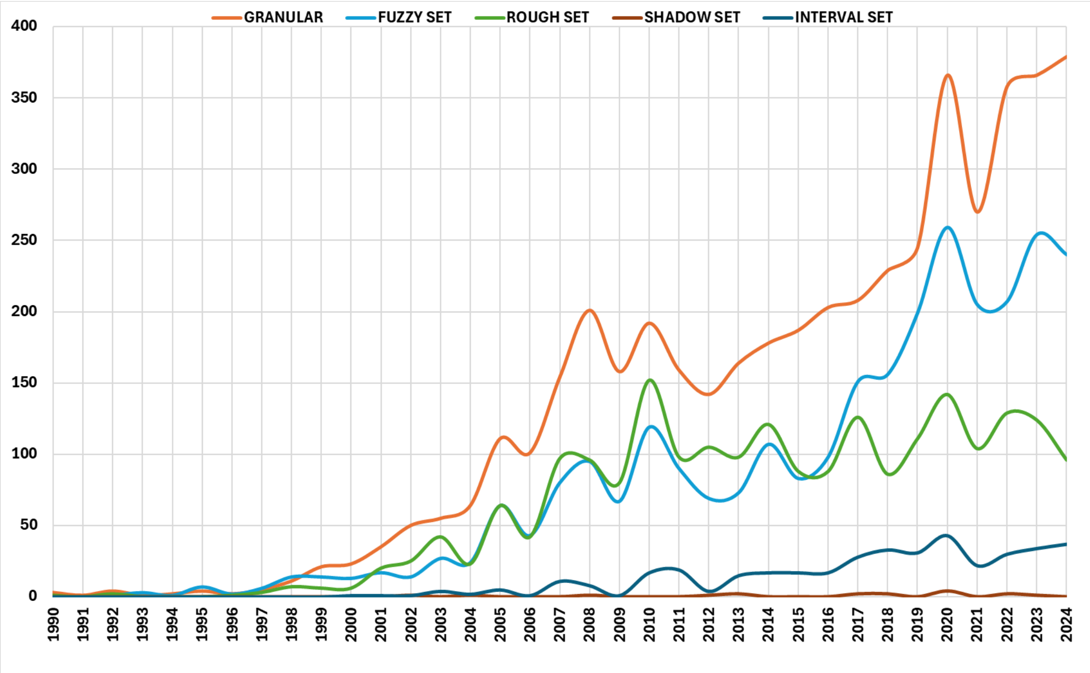

Figure 4: Trend of keyword occurrence in publications (1990 to 2024).

Rank	Paper	No. of citations
1	C.L. Philip Chen, Chun-Yang Zhang 2014Chen and Zhang, 2014	4481
2	Zadeh, Lotfi 1997 Zadeh, 1997a	3866
3	Zdzisław Pawlak, Andrzej Skowron 2007Pawlak and Skowron, 2007b	2787
4	Lotfi Zadeh 2008Zadeh, 2008	1983
5	Fred Glover 1990Glover, 1990	1926
6	Adil Rasheed, Omer San, AND Trond Kvamsdal 2020Rasheed et al., 2020	1651
7	Yiyu Yao 2010Y. Yao, 2010	1650
8	Zdzisław Pawlak,Andrzej Skowron Pawlak and Skowron, 2007a	1554
9	Lotfi Zadeh 2005Zadeh, 2005	1534
10	Ahmed Oussous, Fatima-Zahra Benjelloun, Ayoub Ait Lahcen, Samir BelfkihOussous et al., 2018	1513

Table 4: Top cited papers.

5.3 Publishers and Publications

The following table shows the sources with the highest numbers of produced publications (refer to table 6). The sources varied from conference proceedings to books, among the journals and periodicals.

Starting in 1990, the oldest paper in our collected data is a tutorial on Tabu-search Glover, 1990, which is still being cited in 2025 in the areas of flexible networks and optimization problems. The paper describes a search technique that employs a unique memory structure, strategic constraints, and varying memory functions to enhance the search process. This technique was used to solve employee scheduling problems and other large variables with better results compared to its predecessors Jaumard et al., 1991, Gloyer and Mcmillant, 1986, Glover, 1989. The research focuses on the short-term memory process, which considers a collection of candidate moves to find the best solution. The creation of candidate lists can be seen as an early use of information granules. Lists filled with locally relevant items can parallel the use of set values instead of precise values. This paper Glover, 1990 represents one of the most influential publications in the field of granular computing and is one of the most cited resources in subsequent publications.

In addition to the journals producing GrC-related literature, there have been multiple highly influential books on the subject. The likes of:

- Granular Computing: An Introduction by Witold Pedrycz published in 2000Pedrycz, 2000.
- Handbook of Granular Computing by Witold Pedrycz, Andrzej Skowron, and Vladik Kreinovich, published

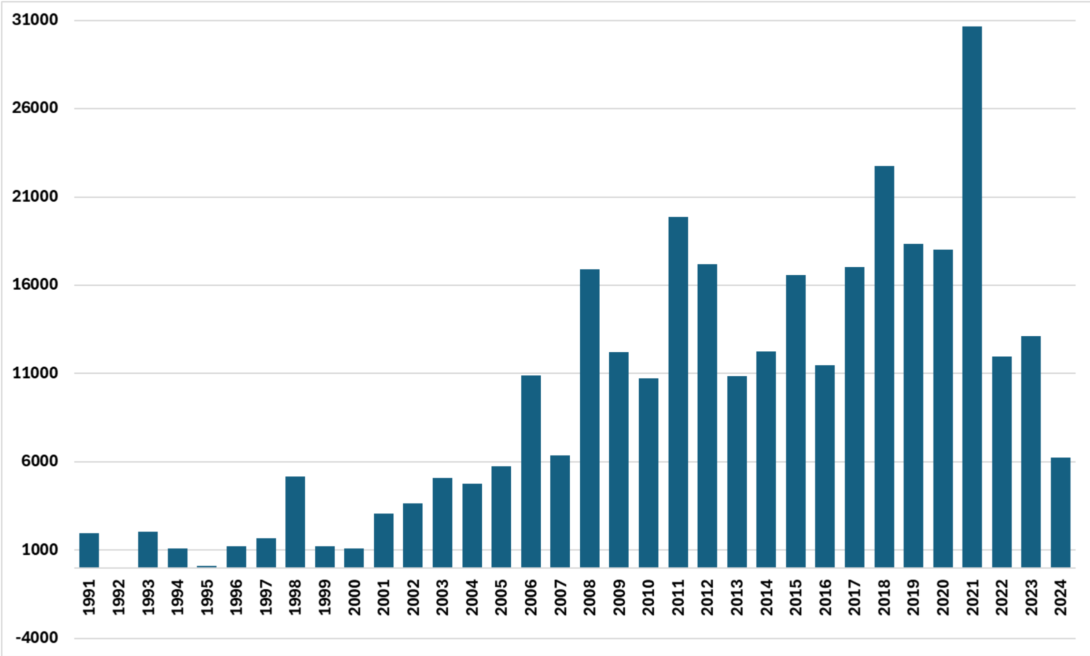

Figure 5: Number of publications per year in the topic of granular computing.

Author	Publications	Author	Citations
Witold Pedrycz	181	Witold Pedrycz	23153
Yiyu Yao	139	Yiyu Yao	15043
G Wang	134	Lotfi Zadeh	12240
Andrzeij Skowron	93	Andrzeij Skowron	9256
Tsau Young Lin	81	Lior Rokach	8137
Muhammad Akram	41	Jerry M. Mendel	6737

Table 5: Most productive authors (1990-2024)

in 2003Pedrycz et al., 2008.

- Novel Developments in Granular Computing: Applications for Advanced Human Reasoning and Soft Computation by

- JingTao Yao published in 2010J. Yao, 2010.

- Granular Computing and Decision-Making by Witold Pedrycz and Shyi-Ming Chen, published in 2015Pedrycz and Chen, 2015.

- While beginning with theory, much of the published landscape of granular computing matured into reaching other fields of research.

5.4 Thematic Analysis and Direction of Literature

Areas of interest in the publications produced over 34 years varied among related disciplines. The relevant time period was divided into four sub-periods: 1990 to 2005, 2006 to 2014, 2015 to 2019, and 2020 to 2024. This is described through recurring keywords (refer to table 7).

Areas of interest can be grouped based on the frequency of keyword co-occurrences and their thematic relevance. The centrality and density of the resulting thematic clusters were calculated to create their strategic diagram:

Grouped thematic clusters (refer to table 8) represent closely related keywords. The keyword with the most occurrences in each cluster encapsulates it. Some of the most recurring keywords are shown in table 7. The thematic structure can also be visualized in the strategic diagram shown in Fig. 8.

Although it is ultimately impossible to evaluate the meaning of a cluster change without a field study involving interviews with the relevant scientists, a look into the recorded themes provides some insight into the progression of interest related to the field of Granular Computing (refer to Fig. 9.). Granular terms, such as "granularity" and "granulation," have maintained a position of mainstream relevance throughout the years.

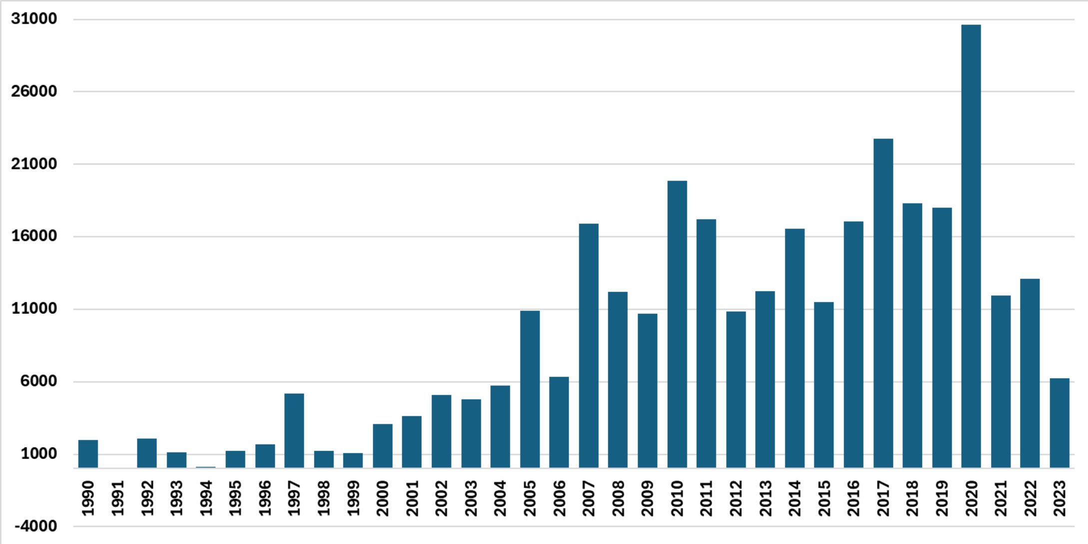

Figure 6: References recorded to each year of literature on the subject of granular computing (1990 to 2024).

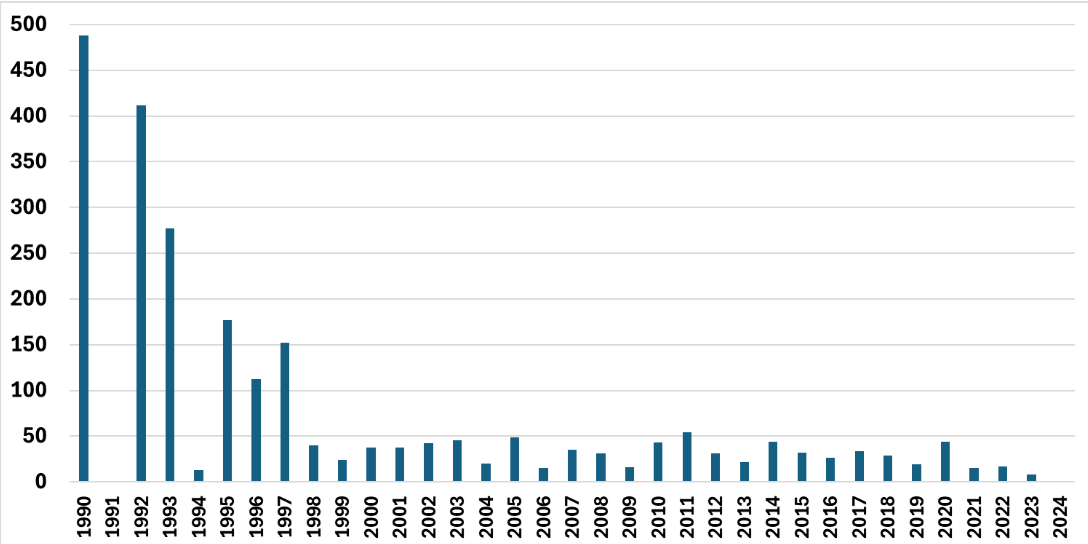

Figure 7: Average citations of publications per year in the topic of granular computing (1990 to 2024).

High centrality indicates a strong relationship between the thematic cluster and surrounding themes, while high density reflects the robust inner development of the theme. The Rough-Set-related cluster displayed similar behavior, likely due to the theoretical connections the keywords have with several themes. The fuzzy cluster fluctuated between two quadrants, mostly because of its density. Although fuzzy sets exhibited high centrality, indicating frequent occurrence alongside other terms, the low density suggests a lack of co-occurrence within the keyword group. The movement between quadrants may result from the high threshold influenced by the surrounding themes.

Overall, themes of theoretical investigation and innovation dominated the mainstream representation of this research field. Areas of application in granular computing showed a growing interest, as reflected by the trend of representing clusters toward quadrants with higher density and/or centrality over the period of interest. This indicates an increasing interest in applying granular computing to various fields of information while continuing theoretical development. Furthermore, the steady rise in centrality suggests that application-oriented studies are increasing in number and becoming more influential in shaping the future direction of research. This evolution shows a dynamic interplay between conceptual growth and domain-specific adaptation, highlighting the relevance of granular computing in various contexts.

Name	Publications
Journal of Intellignet and Fuzzy Systems	647
Information Scinces	390
Soft Computing	341
Journal of Business Research	287
Granular Computing	277
IEEE Trans. Fuzzy Systems	277
IEEE Access	272
Applied Intelligence	265
Sustainability	252
Neurocomputing	199

Table 6: Journals with the highest numbers of publications (1990-2024)

Keyword	No. of recorded occurrences
GRANULAR COMPUTING	1232
SETS	997
FUZZY	991
INFORMATION	725
ROUGH	714
SYSTEM	617
ROUGH SET	604
MODEL	549
DECISION	428
NETWORK	366
CLASSIFICATION	286
ALGORITHM	275
KNOWLEDGE	235
RULES	229
CLUSTERING	224
INFORMATION GRANULE	206
DATA MINING	187
GRANULATION	185
FUZZY SET	183
IMAGE	182

Table 7: Most occurring Keywords.

6 Conclusions

The growing field of granular computing has taken many shapes and undergone several stages of evolution to reach its current state. This evolution and reshaping show no signs of stopping. In this endeavor, the sum of 15605 published pieces of literature has been collected and analyzed. The literature considered the occurrence of core keywords to develop several hypotheses. The field has demonstrated growth, evidenced by statistical data on the continuously rising number of publications per year and the variety of sources publishing papers on the subject. Thematically, core concepts strongly related to granularity and set theories dominated the trends, and this expanded into forms of abstraction such as rough sets and fuzzy sets. Interestingly, thematically separating keywords into nuanced clusters revealed a need for granular analysis techniques to address the vagueness and unclear boundaries. The lack of established metrics and guidelines also presented a challenge. Hybrid methods of applying granular concepts, which suggest potential growth in the future, are of constant interest. Relative to conceptually inclined papers, applications of granular computing concepts have a smaller number of publications but a notable presence, particularly in collaboration with other disciplines, and have shown promising growth over the years. This growth in application can be expected to continue spreading into a wider range of disciplines in the near future. A closer examination of the subsections and various facets of granular computing is necessary for further understanding of this field. To better comprehend the rapid changes it undergoes, an in-depth look at recent papers could provide essential insights.

Author Contribution Inas Shadoul: Methodology, Implementation, Data Analysis, Writing original draft. Rami Al-Hmouz: Conceptualization, Validation, Writing Original Draft, Supervision. Majdi Mansouri, Mostefa Mesbah: Visualization, Writing, Review, and Editing.

Data availability datasets will be available upon request and analysed during the current study.

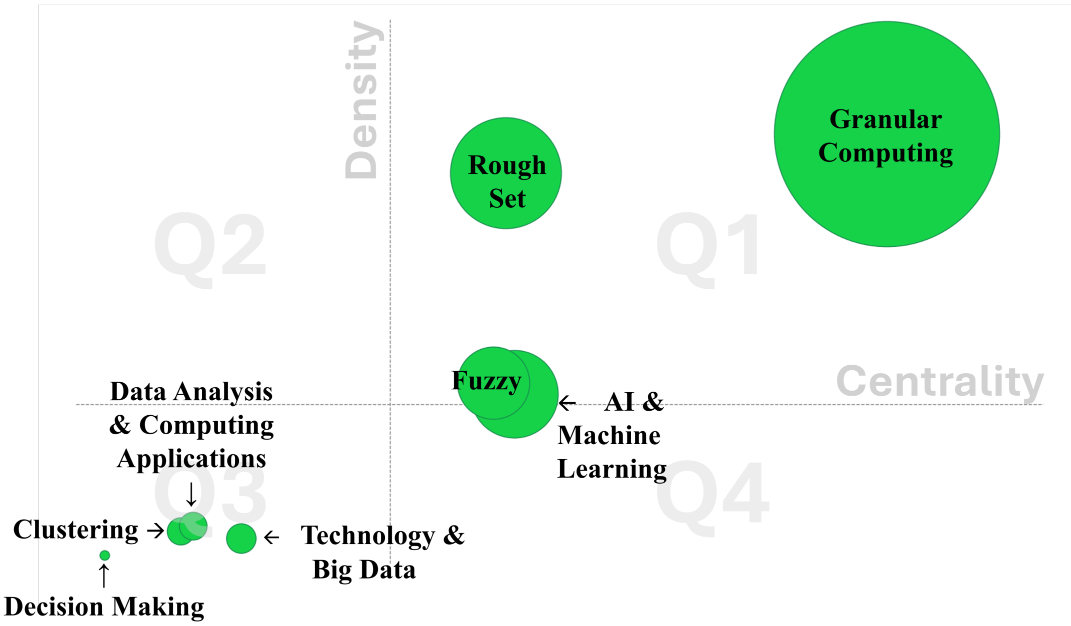

Figure 8: Strategic diagram of the time period (1990 to 2024).

Figure 9: Strategic diagrams across four time periods: (a) 1990–2005, (b) 2006–2014, (c) 2015–2020, and (d) 2020–2024.

Theme	Quadrant	No. of Keyword	Documents
Granular Computing	Q1	43	10440
Rough / Rough set	Q1	20	3284
Fuzzy / Fuzzy set	Q1	29	4182
AI and Machine Learning	Q1-Q2	38	5 564
Data Analytics and Computing	Q3	21	2418
Technology and Big Data	Q3	20	15598
Clustering	Q3	8	1292
Decision Making	Q3	6	333

Table 8: Major reoccurring themes throughout the analysis from 1990 to 2024

Declarations

Competing interests The authors declare no competing interests.

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