

Granular Computing: Trends, Insights, and Bibliometric Review

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Abstract

In human–computer interaction, translating information between binary and numerical representations and human concepts remains an active research area aimed at bridging the gap while preserving the core meaning of the information. The field concerned with this transition, translation, and transformation of information is known as Human-Centric Computing (HCC). In this context, adopting a human-centered approach to information representation, such as categorization, grouping, and summarization through various forms of granulation, incorporates information into the paradigm of Granular Computing (GrC). This perspective on information processing and semantics in systems and programming has experienced continuous growth in both conceptual development and methodological interest. This paper investigates GrC research from 1990 to 2026, with a particular focus on the evolution of publications in the field. It begins with an overview of GrC, including a brief history and a discussion of its main techniques. Publications since 1990 are statistically analyzed and reviewed to identify common themes and research trends. In addition, selected research papers are examined under specific categories to provide further insights and discussion. This paper aims to highlight the evolution of GrC and identify potential future research directions.

Keywords: granular computing; bibliometric analysis; systematic review; thematic analysis; fuzzy sets; rough sets; granulation; interval sets

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1. Introduction

Granular Computing is a concept that emerged in the late 1970s through the introduction of information granularity in 1979 [1]. 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 [2,3]. 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 [4] 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 [5]. Granular computing as a development is not recent but has been in use under different names across many fields of programming and theory, including the likes of cluster analysis, data compression, and chunking [3]. Among the terms that were granular computing placeholders are fuzzy sets, rough sets, interval sets, and shadowed 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 [6]. 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 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 [7]. 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.

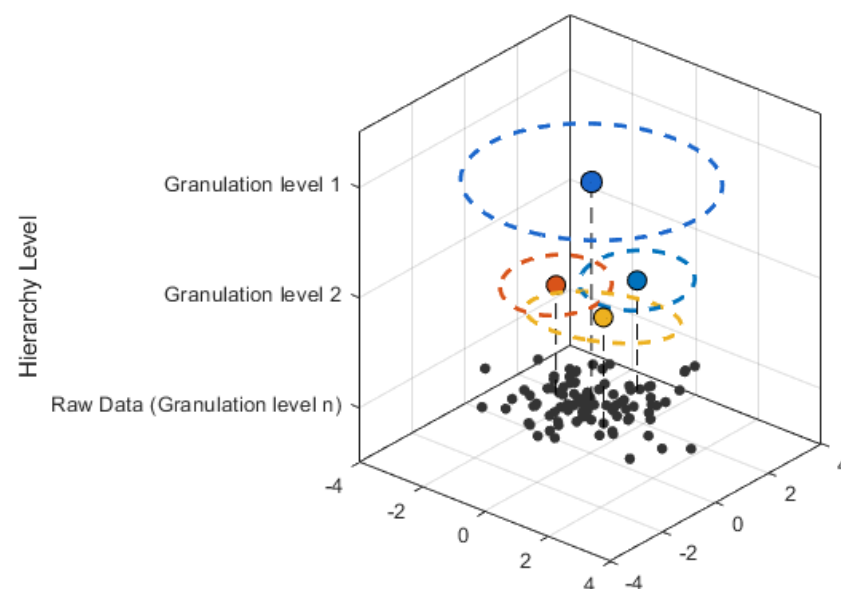


Figure 1. Information granules in terms of levels of granulation.

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 [8], as social sciences and others have been analyzed [9]. 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 2026.

The contributions of this paper can be summarized as follows:

- Conduct a comprehensive bibliometric analysis of granular computing.
- Identify the major themes and future research directions in granular computing.

The paper is structured as follows. Section 1 discusses formal approaches to granular computing, followed by the classification of research areas in Section 2. The method used to evaluate the scientific literature is detailed in Section 3. Section 4 describes the bibliographic dataset on granular computing, including statistical performance indicators such as the number of published documents, citations, the most productive authors, publishers, and journals, among others. In Section 5, a bibliometric approach is employed to examine the most prominent and recurring research areas within the collected data, allowing for hypotheses regarding thematic evolution and predictions about future research trends in the field. Finally, the paper concludes in Section 6.

2. Granular Computing

The first explicit use of the term “granular computing” occurred in the paper [10] in 1997, as confirmed by [11]. However, the concept of granular computing was first introduced by Lotfi Zadeh in the context of fuzzy sets in 1979 [1] as the “granulation” of information. This provides insight into the connection between granular computing, set theory [12], and fuzziness.

2.1. Granular Computing Categorization

Within the scope of granular computing, there are several subcategories focused on the techniques of decomposition, clustering, granulation, and handling imprecise data [13]. For the purposes of this paper, the relevant techniques are formalized into rough sets, interval sets, shadowed sets, and fuzzy sets [14]. Sets refer to any totality of a definite number, a theory dating to the late 1800s [15]. A classical set has crisp boundaries [16], a definition that was sufficient until data variety and purpose became unavoidable, leading to multiple techniques as follows:

2.1.1. 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 [14]. 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:

$$A = [a^-, a^+], \quad (1)$$

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

Addition:

$$A + B = [a^- + b^-, a^+ + b^+] \quad (2)$$

Multiplication:

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

Intersection:

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

Union:

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

f non-decreasing function:

$$f([a, b]) = [f(a), f(b)] \quad (6)$$

f non-increasing function:

$$f([a, b]) = [f(b), f(a)] \quad (7)$$

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 [17–19]. Data and model parameters are represented as intervals (or hyperboxes), enabling uncertainty propagation, error control, and multiresolution analysis [18,20]. 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 [19,21–26]. 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 [18,20,23,26].

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.

2.1.2. Rough Sets

Rough sets were first introduced through rough set theory [27] 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 bounds [28]. 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:

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

Upper Approximation:

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

Boundary Region:

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

The rough set framework introduces the concepts of lower and upper approximations to model uncertainty arising from indiscernibility. Recent developments have extended this framework into three-way decision theory, which goes beyond binary classification by enabling deferment or abstention under uncertainty. The work presented in [29] has been pivotal in this area, demonstrating how three-way approximations can 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 [30–32]. Objects are grouped into granules (e.g., equivalence classes, neighborhoods, fuzzy relations), and rough approximations are generalized for probabilistic and fuzzy uncertainty modeling [31,33]. 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 [32,34,35]. Entropy and granulation-based measures guide uncertainty quantification and attribute selection in incomplete systems [36]. Applications include classification, rule extraction, feature reduction, multiscale knowledge representation, and engineering tasks like sensor fusion and pattern analysis [33,35–37].

2.1.3. 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 [4], 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 [38], 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:

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

Intersection:

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

Complement:

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

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 [39,40]. Their integration happens via fuzzy granulation, fuzzy-rough hybrid models, granular ball representations, and granule-based preprocessing, enabling interpretable, efficient learning [41,42]. Fuzzy-rough systems combine graded membership, boundary approximations, and entropy-based measures to boost

robustness and rule extraction [41,43], while granular ball fuzzy models enhance scalability and noise tolerance in classification tasks like Support Vector Machines (SVMs) [42]. Applications include classification, pattern recognition, data mining, and control systems, where granule compression, multilevel reasoning, and uncertainty quantification improve robustness, interpretability, and efficiency [42,44,45].

2.1.4. Shadowed Sets

Shadowed sets, also known as shadow sets, were first introduced in 1998 [46]. They are a development of fuzzy sets that build upon the idea of continuous boundaries found in fuzzy sets [47], by providing a mapping with set mapping values [48]. When capturing vagueness, the use of fuzzy tools and gradual membership was an effective descriptive method, but it introduced a burden of computational overhead [48]. The adoption of shadowed 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 shadowed 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. shadowed 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 shadowed width (uncertainty parameter).

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

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

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

Full Membership Region (Certain Inclusion):

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

Full Exclusion Region (Certain Non-membership):

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

Shadowed Region (Uncertainty Region):

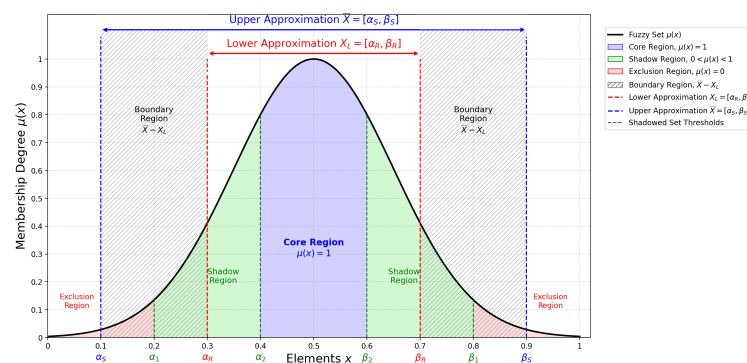
$$x \in X \quad \text{such that} \quad \alpha < \mu_A(x) < 1 - \alpha \quad (17)$$

Shadowed sets are three-valued abstractions of fuzzy sets classifying elements into full membership, nonmembership, and an intermediate shadowed (uncertainty) region [48,49]. 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 [49,50]. Extensions such as entropy-based approximations and complex shadowed sets expand decision-making and clustering applications [51,52]. Shadowed sets facilitate three-way decision models, fuzzy clustering, preprocessing, and hybrid fuzzy systems, providing efficient, uncertainty-aware granular computing applications [48,53].

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

Table 1. Granular Computing Formal Models Summary.

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

**Figure 2.** Relation between a fuzzy set, its shadowed set approximation, and the induced rough set approximations.

2.2. 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 computing [54] 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 computational [11], 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.
- **Human-Centered Computing:** Human Centric Computing (HCC), in simple terms, is an area studying the link between 2 values logic (binary) and human information [4], 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 [27,46,47].
- **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 more [55–60].

2.3. 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 [61], 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 semantics [62,63]. The author discusses the contradictory relationship between specificity and coverage at the core of this concept in [61]. 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 technique [64] that bases the solution on three questions or levels of analysis [54]. 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 [65], among others [58]. By taking this 3-way approach, decision-making applications gain a reduction in ambiguity, particularly that of classification [66], 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 similarity [67]. This process utilizes boundaries defined by membership functions, such as those used in Fuzzy C-Means (FCM). While *K*-means is a clustering technique (*K* here refers to the number of clusters) 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 membership [68,69]. The goal of an FCM algorithm is to generate optimal partitions of the known data cluster centers [70–72].
- **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 problem [73]. The order in which aspects of the data are handled changes the method. For data that have 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 [74], 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 [75,76]. An IVF is defined by a membership function that assigns intervals. Atanassov [77] 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” [78], though its foundational idea differs from IVFs.

- Type-2 fuzzy sets: extend traditional fuzzy sets by allowing the membership degree itself to be fuzzy [76]. 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 [79]. 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 [80].
- 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” [81], 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.

GrC 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 [82].

2.4. 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 [11]. Definitions also maintain that granules provide an approximation to incomplete, vague, imprecise, or uncertain data, providing deeper comprehension and facilitating better pattern recognition [83], 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 [84]. Furthermore, granulation can face and sometimes produce overlap and uncertainty of classes, particularly in iterative situations [85]. Another major issue faced is the lack of standardization in the field of GrC, resulting in systems that lack interoperability and regulation [86].

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 [40]. 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 [87], 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 [88,89], 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 [87]. 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 methods [90]. 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 to [91], 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 groups [92]. Specifically, the centrality examined here measures the influence of a theme on a scale of 0–1. It is calculated using Equation (18), where e refers to the number of occurrences of k , a keyword belonging to the theme, and h belongs to other themes.

$$c = 10 \times \sum e_{kh} \quad (18)$$

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.

$$d = 100 \sum \frac{e_{ij}}{T} \quad (19)$$

The themes produced were analyzed using centrality and density [93] to categorize them into quadrants as follows (refer to Figure 3):

- QI: Representing the Motor themes of the field, themes within this quadrant can be labeled as “mainstream” [94] 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 isolation and specialty) 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.

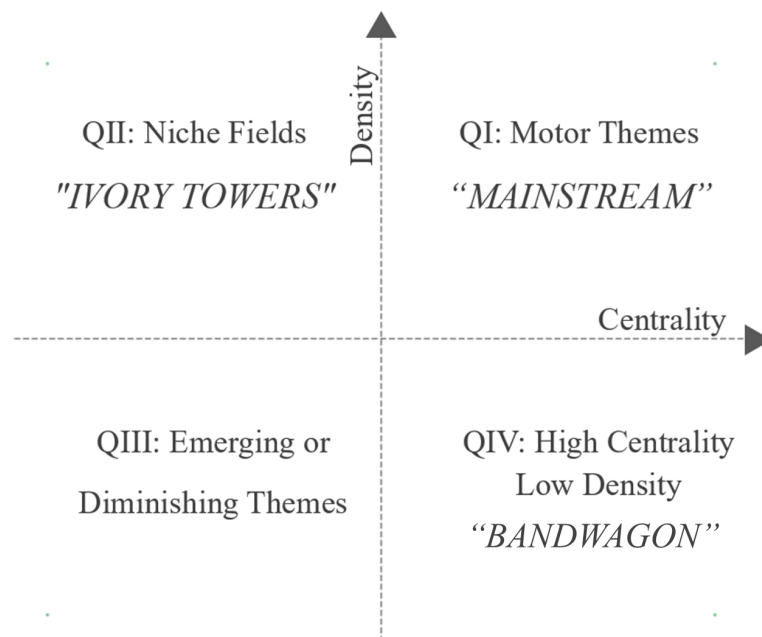


Figure 3. Interpretation of quadrants as dictated by the centrality vs. the density (i.e., strategic diagram).

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.

4. Granular Computing Bibliographic Dataset

To begin exploring the world of publications, data were collected for studies. The data were collected as of March 2026, 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 2026. 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 “shadowed set” were also used as keywords.

As the year 2026 is incomplete as of the writing of this paper, and significantly, the availability of the full year's data is needed (i.e., trend of keyword occurrence in publications, number of publications per year in the topic of granular computing, references recorded to each year of literature on the subject of granular computing, average citations of publications per year in the topic of granular computing), the year 2026 is excluded from the comparisons, and information is considered from 1990 to 2025. On other metrics

unrelated to the year (i.e., granular computing papers and citations, top cited papers, most productive authors, journals with the highest numbers of publications, most occurring keywords, major reoccurring themes, thematic analysis), information up to march of 2026 will be included.

In cases of duplicate or incomplete information, the data were cleaned and refined manually. Several challenges were encountered during the data acquisition process. One challenge was the limitation on the number of coded queries that could be executed before security measures restricted further collection, which required part of the data to be collected manually from HTML pages. Another issue was the limited and sometimes incomplete information returned by the search function, particularly for older publications.

An additional limitation involved missing author information and incomplete author profiles in some cases. Considering the impact of the missing data, the required information was manually completed whenever necessary.

The raw data was extracted and processed using Python version 3.11 programming, and key information was collected in an Excel sheet. Table 2 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 source, (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 16,948 entries from an initial 18,501 records (refer to Table 3).

Table 2. Sample of Collected Bibliometric Dataset (Metadata and Publication Attributes of Selected Studies).

Title	Abstract/ Document Snippet	Keywords	Authors	Journal	Year	Publisher Link (accessed on 31 March 2026)	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://ieeexplore.ieee.org/abstract/document/9858107/	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://link.springer.com/article/10.1007/s40815-023-01577-z	18
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://link.springer.com/article/10.1007/s41066-023-00372-3	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://link.springer.com/article/10.1007/s10462-022-10327-w	24

Table 3. Granular Computing Papers and Citations (1990 to 2026).

No. of papers (Raw data)	16,948
No. of citations	436,702
Average citation per item	25.76

Analyzing the collected data, occurrences of the keywords “rough set”, “fuzzy set”, “interval set”, and “shadowed set” were examined to illustrate Figure 4.

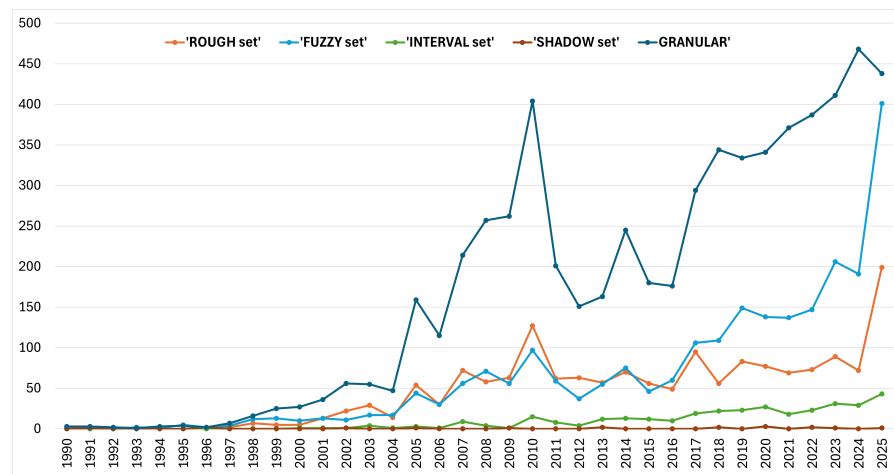


Figure 4. Trend of keyword occurrence in publications (1990 to 2025).

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” [1].

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 2025 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.

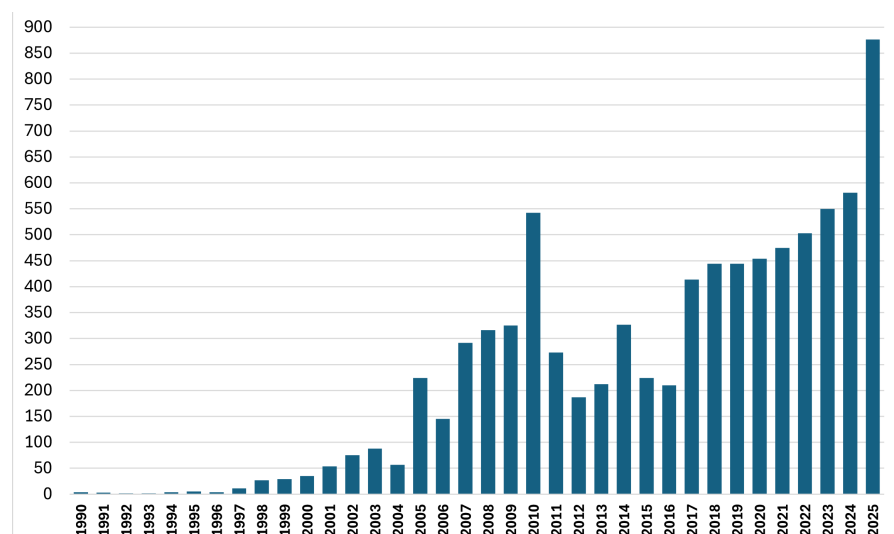


Figure 5. Number of publications per year in the topic of granular computing (1990 to 2025).

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 [95]. Examining the most cited year for publications (see Figure 6), 2008 stands out as the year with the highest total citations accumulated by publications issued in that year. However, when considering the average citations per publication across each year (see Figure 7), the most cited publications, on average, were produced in 1990. This interpretation reveals the lasting influence of the paper [96] on the evolution of literature in GrC for years to come, an influence unmatched to date within this time frame. The high overall citation counts linked to 2020 indicate that the significant growth spurt in publication volume during that year also contributed substantially to the subsequent accumulation of citations across later publications in the field, whereas 1991 shows no recorded publications in the dataset and therefore does not contribute to the citation trends.

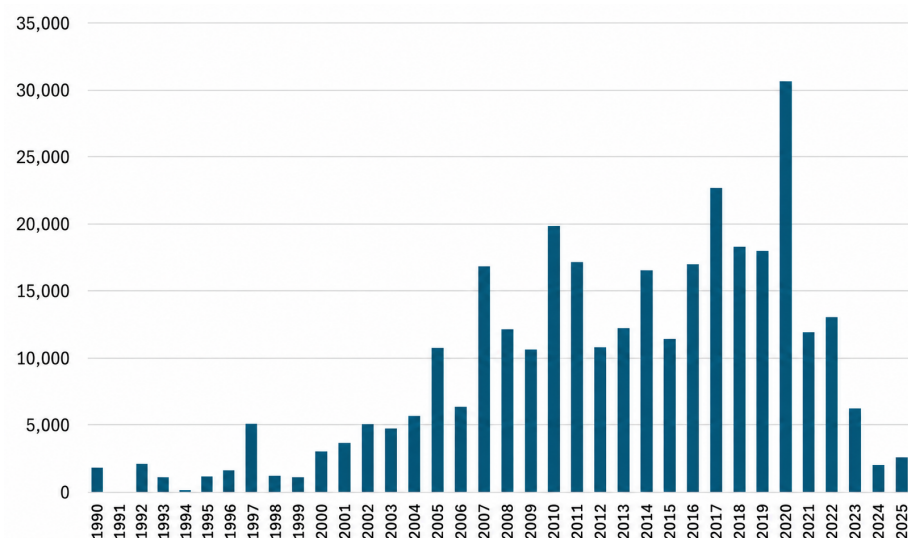


Figure 6. References recorded to each year of literature on the subject of granular computing (1990 to 2025).

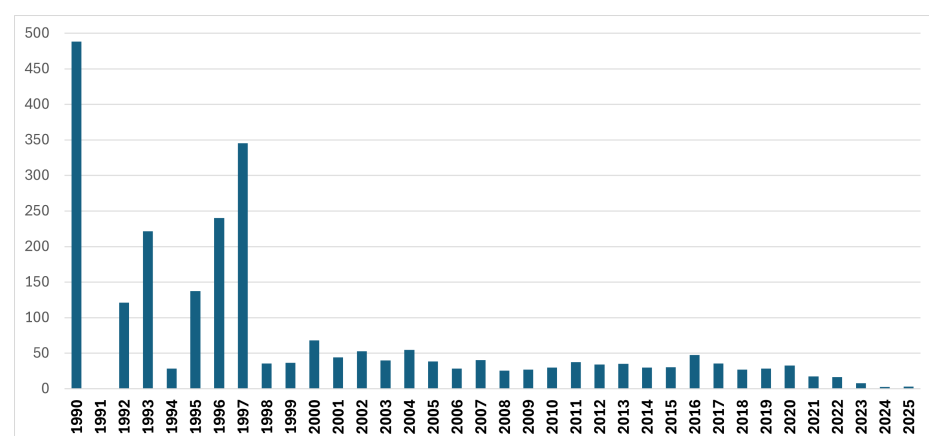


Figure 7. Average citations of publications per year in the topic of granular computing (1990 to 2025).

The top 10 most cited papers are listed in Table 4, 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 2026, 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.

Table 4. Top cited papers (as of March 2026).

Rank	Paper	Authors	No. of Citations
1	Data-intensive applications, challenges, techniques and technologies: A survey on Big Data [55]	CLP Chen & CY Zhang	4481
2	Toward a theory of fuzzy information granulation and its centrality in human reasoning and fuzzy logic [40]	LA Zadeh	3866
3	Ensemble-based classifiers [97]	L Rokach	3463
4	Measurement of situation awareness in dynamic systems [98]	MR Endsley	2956
5	Rudiments of rough sets [99]	Z Pawlak & A Skowron	2787
6	Is there a need for fuzzy logic? [100]	LA Zadeh	1983
7	Soft sets and soft groups [101]	Hacı Aktaş & Naim Çağman	1944
8	Tabu Search: A Tutorial [96]	F Glover	1935
9	Digital twin: Values, challenges and enablers from a modeling perspective [102]	A Rasheed, O San, and T Kvamsdal	1651
10	Three-way decisions with probabilistic rough sets [29]	S Maldonado & R Weber	1650

Table 5. Most Productive and Most Cited Authors (as of March 2026).

Author	Publications	Author	Citations
Witold Pedrycz	828	Witold Pedrycz	36,285
Yiyu Yao	218	Yiyu Yao	16,635
T Li	211	Lotfi Zadeh	12,252
Andrzej Skowron	195	Andrzej Skowron	10,388

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.

5.3. Publishers and Publications

The following table shows the sources with the highest number of publications produced (see Table 6). These sources include conference proceedings, books, journals, and periodicals. During data collection, no academic literature was found for the year 1991 that satisfied the search criteria or was available through the Google Scholar search engine. This may be due to limitations of the search tool, as it is possible that relevant studies from 1991 exist that fall under the scope of Granular Computing when interpreted more broadly. It may also be related to the applied filters and how they are implemented by the search engine.

Table 6. Journals With the Highest Numbers of Publications (1990–2026).

Name	Publications
Journal of Intelligent and Fuzzy Systems	650
Information Sciences	428
Soft Computing	355
Journal of Business Research	294
IEEE Trans. Fuzzy Systems	284
Applied Intelligence	289
Granular Computing	277
IEEE Access	272
Sustainability	252
Neurocomputing	207

Starting in 1990, the oldest paper in our collected data is a tutorial on Tabu-search [96], 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 [103–105]. 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. The paper [96] 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, including the likes of:

- Uncertain Rule-Based Fuzzy Systems by Jerry M. Mendel, published in 2017 [106].
- Granular Computing: An Introduction by Witold Pedrycz and Andrzej Bargiela, published in 2000 [88].
- Handbook of Granular Computing by Witold Pedrycz, Andrzej Skowron, and Vladik Kreinovich, published in 2003 [107].
- Novel Developments in Granular Computing: Applications for Advanced Human Reasoning and Soft Computation by JingTao Yao, published in 2010 [56].
- Granular Computing and Decision-Making by Witold Pedrycz and Shyi-Ming Chen, published in 2015 [108].

Although granular computing was initially rooted in theory, it has matured into a multidisciplinary research paradigm with broad applications across diverse scientific and engineering domains.

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 2026. 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.

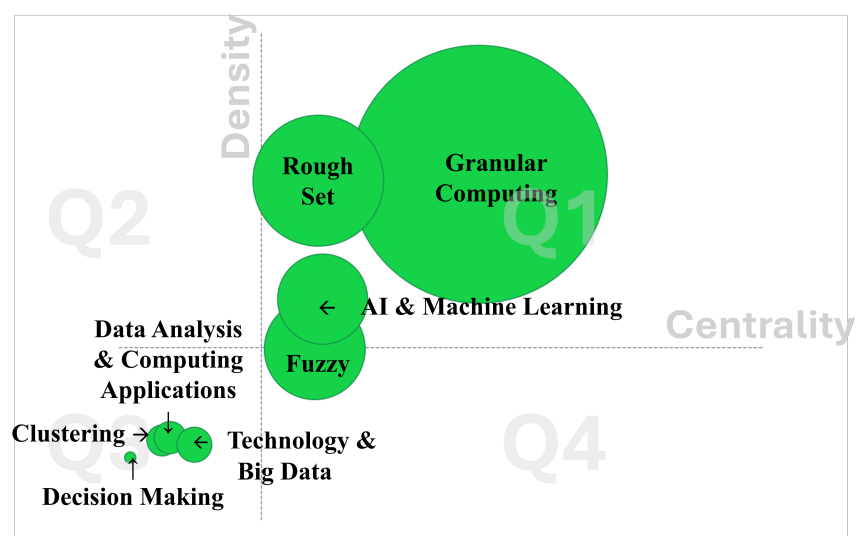
Grouped thematic clusters (refer to Table 8) represent closely related keywords. The keyword with the most occurrences in each cluster encapsulates it. Some of the most recurring keywords are shown in Table 7. The thematic structure can also be visualized in the strategic diagram shown in Figure 8.

Table 7. Most Occurring Keywords.

Keyword	No. of Recorded Occurrences
SETS	5481
FUZZY	5310
GRANULAR COMPUTING	4725
ROUGH	3085
INFORMATION	2933
ROUGH SET	2744
SYSTEM	2551
MODEL	2517
DECISION	2302
FUZZY SET	1950
NETWORK	1608
ALGORITHM	1251
CLASSIFICATION	1059
KNOWLEDGE	998
CLUSTERING	920
SELECTION	904
INFORMATION GRANULE	856
RULES	782
NEURAL NETWORKS	776
FRAMEWORK	748
TIME	730
IMAGE	707

Table 8. Major Reoccurring Themes Throughout the Analysis from 1990 to 2026.

Theme	Quadrant	No. of Keyword	Documents
Granular Computing	Q1	43	10,440
Rough/Rough set	Q1	20	3284
Fuzzy/Fuzzy set	Q1	29	4182
AI and Machine Learning	Q1–Q2	38	5564
Data Analytics and Computing	Q3	21	2418
Technology and Big Data	Q3	20	15,598
Clustering	Q3	8	1292
Decision Making	Q3	6	333

**Figure 8.** Strategic diagram of the time period (1990 to 2026).

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 Figure 9). Granular terms, such as “granularity” and “granulation”, have maintained a position of mainstream relevance throughout the years. 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.

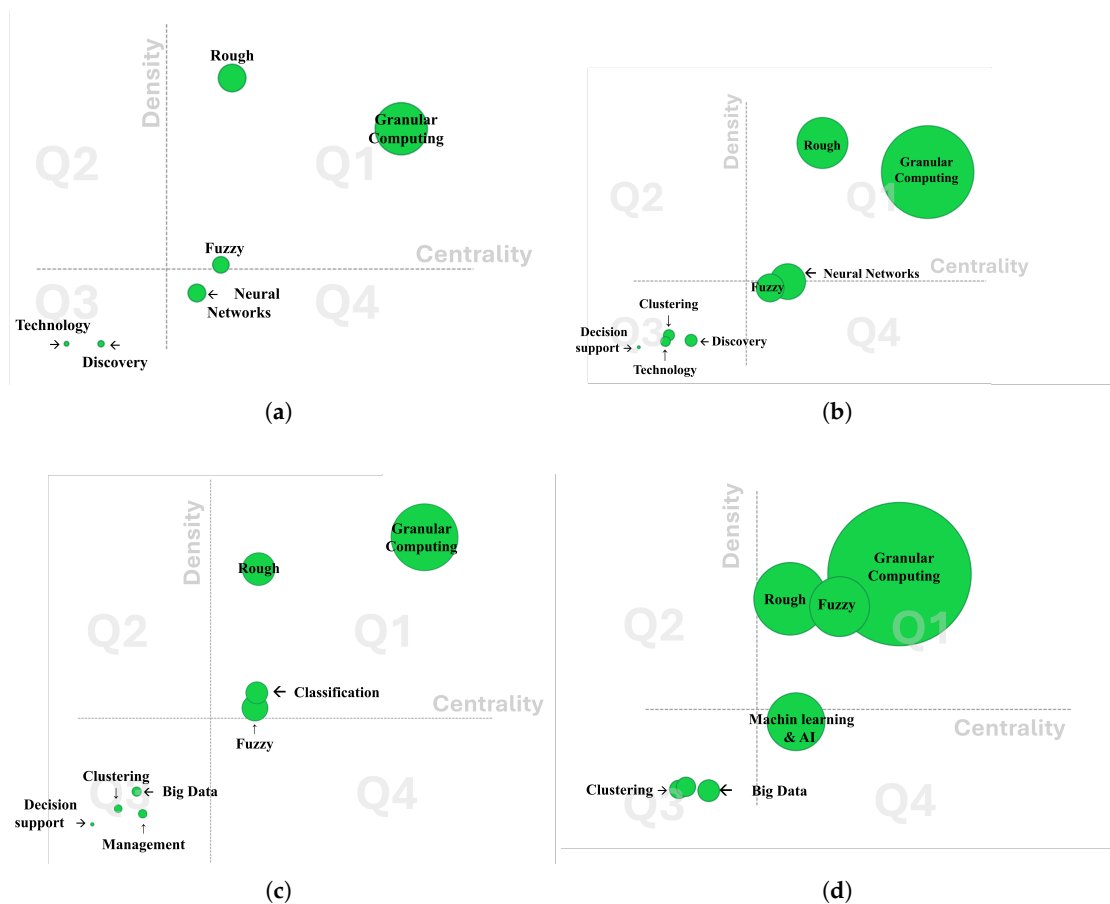


Figure 9. Strategic diagrams across four time periods: (a) 1990–2005, (b) 2006–2014, (c) 2015–2020, and (d) 2020–2026.

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.

6. Conclusions and Future Works

The rapidly growing field of Granular Computing has undergone several stages of evolution to reach its current state. An analysis of over 16,000 publications shows sustained annual growth in research output, as well as an increasingly diverse set of publication venues. The literature analysis considers the occurrence of core keywords to develop several hypotheses.

Thematically, core concepts strongly related to granularity and set theory dominate the research trends and remain central to the field. These have expanded into abstraction frameworks such as rough sets and fuzzy sets. Furthermore, thematic clustering reveals increasingly nuanced subfields that address vagueness and unclear conceptual boundaries.

Interestingly, separating keywords into finer thematic clusters highlights the need for granular analysis techniques to better handle such vagueness and boundary ambiguity.

High-centrality clusters that bridge multiple topics (e.g., rough sets and fuzzy approaches) indicate fertile ground for hybrid methods that combine the strengths of multiple paradigms. In contrast, themes with high centrality but low internal density suggest opportunities for consolidation through standardized metrics, benchmarks, and shared datasets to facilitate integration.

Although application-oriented studies are currently fewer than conceptual contributions, they are increasing in centrality and are expected to play a growing role in shaping research agendas by requiring scalable, interpretable, and domain-ready solutions.

To accelerate progress, priority directions include unifying theory and terminology, developing and benchmarking hybrid models, validating methods in high-impact domains such as bioinformatics and explainable artificial intelligence, curating shared datasets and evaluation protocols, and promoting interdisciplinary collaboration to translate granular concepts into practical systems.

Future work can benefit from applied case studies, open-source code and data sharing to enable reproducibility, comparative studies against standard baselines, and the use of surveys or focused field studies to validate the interest shifts suggested by bibliometric clustering. Together, these steps can help the field transition from conceptual consolidation toward application-centered growth driven by improved theory, standardized evaluation, and stronger connections to real-world needs.

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