

Article

Symmetric and Asymmetric Trends in Sparse Tucker Decomposition Based on Plithogenic Neutrosophic Hypersoft Sets: A Bibliometric and Conceptual Review

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Abstract

Sparse Tucker decomposition (STD) is a framework for tensor decomposition that extends the classical Tucker model with sparsity constraints, with the aim of achieving better representation and analysis of multidimensional data. STD has attracted growing interest from various scientific fields, such as neuroimaging, machine learning, telecommunications, statistical computing, and brain connectivity analysis, due to its flexibility and computational efficiency. The purpose of this study is to present a systematic and structured review of the scientific literature on STD, describing its main trends, applications, and the evolution of research over time. Methods: A systematic review was conducted in accordance with the PRISMA 2020 guidelines using the Scopus and Web of Science databases. The search retrieved 21 records, of which 13 were selected for detailed analysis according to the established inclusion criteria. To improve the evaluation process, the selected studies were assessed using the plithogenic neutrosophic hypersoft set framework, which allowed for the evaluation of scientific contributions in terms of degrees of truth, indeterminacy, and falsity. The evaluation covered aspects such as methodological rigor, citation impact, thematic relevance, journal quality, and international collaboration networks. Results: Research on STD spans 2013 to 2025—the year of the first indexed record through the search date—and shows a marked increase after 2021. Five main application domains were identified: computational optimization, neuroimaging and neuropsychology, telecommunications, statistical analysis, and studies on brain connectivity. The literature on STD is still relatively limited and geographically concentrated, especially in the United States and China, despite the strong interdisciplinary potential and the growing scientific relevance of STD. Conclusions: STD is symmetric by construction, treating every tensor mode and component equally and applying the same sparsity penalty throughout, yet the literature surrounding it is markedly uneven, being concentrated in a few countries and a small number of technical fields. The PNHS framework allowed us to characterize this mismatch while accounting for the uncertainty of each judgement, scoring productivity, impact, collaboration, and thematic relevance through separate degrees of truth, indeterminacy, and falsity. This study identifies STD as a promising interdisciplinary analytical framework and demonstrates the value of plithogenic neutrosophic hypersoft methodologies for evaluating the scientific literature under uncertainty and multidimensionality. The review emphasizes the need for greater methodological standardization, increased international collaboration,



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and more robust interdisciplinary dissemination to establish STD as a robust framework for the analysis of multidimensional data.

Keywords: Tucker; sparse; systematic review; tensor decomposition; plithogenic neutrosophic hypersoft sets

1. Introduction

The exponential growth of high-dimensional data in disciplines such as neuroscience, artificial intelligence, telecommunications, and applied statistics has generated a significant demand for mathematical methods capable of efficiently modeling complex structures. In this context, tensor decomposition techniques have emerged as effective tools for analyzing multidimensional data, overcoming the limitations of traditional matrix methods. Among these, sparse Tucker decomposition (STD) stands out for its ability to represent sparse data in a compact manner, preserving interpretability and reducing the computational burden. It is worth being precise about what sets STD apart from the other tensor decompositions it is usually compared with. The Tucker model, introduced by Tucker in 1966 [1] and later placed on a firm numerical footing as the higher-order singular value decomposition [2], factors a tensor into a small core tensor and one factor matrix per mode. Unlike CANDECOMP/PARAFAC (CP), which represents a tensor as a sum of rank-one terms with a single shared rank [3], Tucker assigns each mode its own rank and so captures interactions between modes that CP cannot. That flexibility comes at the cost of a dense core whose size grows quickly with the number of modes. Adding sparsity is precisely what makes the Tucker model practical at scale: sparse regularization drives most core entries to zero, which keeps the interaction structure Tucker is prized for while cutting storage and computation and, as a side benefit, yielding a core that is easier to interpret than a full one. In short, STD occupies a deliberate middle ground—more expressive than CP, far more tractable than a dense Tucker—and it is this combination, rather than any single property, that motivates the studies reviewed here.

Despite its potential, the academic literature on STD exhibits a notable thematic and disciplinary fragmentation. Some studies focus on algorithmic developments to optimize performance in parallel architectures [4,5], while others explore biomedical applications, such as brain connectome analysis or multimodal integration of neuroscience data [6,7]. This diversity reflects the interdisciplinary nature of STD, although its adoption has been selective and its theoretical foundation is still under development.

STD decomposes the tensor into a core tensor and orthogonal factor matrices, treating each mode equally, while sparse regularization applies the same penalty to all components, yielding a parsimonious representation that favours no axis a priori. This inherent symmetry makes STD a reproducible, mode-independent approach to dimensionality reduction. Its bibliometric landscape, by contrast, is markedly asymmetric: geographical concentration in a few countries, selective disciplinary adoption, and the uneven influence of citations across time and place. The study uses plithogenic neutrosophic hyper-soft sets (PNHS) to model the symmetric structural logic of STD and the asymmetric nature of its scientific diffusion. Given that the evaluative architecture of PNHS is inherently asymmetric (differential weights are assigned to multiple attributes through independent degrees of truth, indeterminacy, and falsity), it is epistemologically well-positioned to capture what symmetric methods cannot: the unequal distribution of knowledge, visibility, and impact across the entire field of the STD literature. This framing is deliberately narrow. The symmetry refers to a property of the algorithm, and the asymmetry to an observed feature of the literature,

with no causal claim linking the two. We return to this distinction in the Discussion, where the symmetry–asymmetry contrast is examined against the bibliometric evidence.

In this context, a bibliometric analysis is essential to map the current state of knowledge on STD, identifying its main lines of research, areas of application, institutional actors, and international collaboration networks. Beyond a quantitative approach, this analysis offers an opportunity to critically reflect on the progression, appropriation, and projection of the technique in various scientific fields and to make explicit the tension between the symmetric mathematical properties of STD and the asymmetric patterns of its academic adoption.

This study aims to characterize scientific production on STD from 2013 to 2025 (the earliest indexed record through the search date), through a systematic search in the Scopus and Web of Science databases. Productivity, citation, co-authorship networks, and thematic distribution indicators were constructed using the plithogenic neutrosophic hypersoft sets approach, which models multiple attributes with degrees of truth, indeterminacy, and falsity to capture the uncertainty inherent in the scientific literature. The choice of PNHS as an evaluative framework is not incidental. While STD applies symmetric algebraic operations uniformly across tensor modes, PNHS applies asymmetric differential weighting across bibliometric dimensions—citation impact, geographic reach, thematic relevance, and collaborative breadth—thus allowing the study to simultaneously honor the mathematical regularity of STD and expose the structural irregularities of its scientific ecosystem. Furthermore, studies were classified according to their scope of application, allowing for the visualization of patterns of specialization, technology transfer, and potential areas of expansion.

This work is part of a line of research that applies bibliometric methodologies to understand the progression of advanced analytical techniques. In the case of STD, the study not only provides an overview of its academic impact but also establishes a platform for promoting future research aimed at its standardization, application in new domains, and more integrated theoretical reflection. Ultimately, the interplay between the symmetric structure of STD and the asymmetric evaluation enabled by PNHS constitutes the conceptual axis of this work, bridging the mathematical and the bibliometric into a coherent analytical narrative.

The specific gap this review addresses is narrow but concrete. Prior work on sparse and Tucker decomposition is almost entirely methodological. Individual papers propose an algorithm, an implementation, or an application, but no study has stepped back to map the field as a whole—where the work is concentrated, which application areas have taken it up, and how confident we can be about the standing of individual contributions given how young and thin the literature is. Existing bibliometric reviews in adjacent areas rely on citation counts and co-occurrence maps alone, which treat every record as a settled data point and have no way of expressing that a 2024 paper with two citations is simply too recent to judge. That is the situation STD is in: a corpus of 13 studies, several of them published in the last two years, where the honest answer for many records is “not yet determinable.” We adopt plithogenic neutrosophic hypersoft sets (PNHS) precisely because they give that uncertainty a formal place in the analysis. A neutrosophic membership separates the degree to which a record meets an attribute (truth) from the degree to which the evidence is inconclusive (indeterminacy) and the degree to which it clearly does not (falsity); the hypersoft component lets several attributes—productivity, impact, collaboration, thematic relevance—be modeled at once, each with its own uncertainty. Simpler alternatives were considered and set aside for concrete reasons: plain citation ranking collapses the young-versus-weak distinction that dominates this corpus; ordinary fuzzy or intuitionistic-fuzzy scoring records uncertainty but not the separate “undecidable” state we need; and a purely qualitative narrative review would forfeit the reproducibility

that a systematic review requires. PNHS is, therefore, not decorative here—it is the tool that matches a small, recent, and uneven evidence base. We note, however, that the attribute scoring in this study rests substantially on thematic affinity and expert interpretation rather than on a fully pre-registered rubric, and we return to what that means for the strength of our claims in the Methods and Limitations sections.

2. Methodology

This bibliometric study analyzes the scientific production associated with the terms “sparse” and “Tucker,” frequently linked to tensor decomposition, machine learning, and signal processing. Document selection was carried out following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [8,9], ensuring a systematic and rigorous process.

2.1. Databases

Scopus and Web of Science (WoS) were used due to their broad scope, rigorous indexing criteria, and availability of bibliometric analysis tools. These databases are recognized for their comprehensive coverage of the relevant scientific literature [10,11].

2.2. Search Strategy

The search strategy was designed to ensure the accurate collection of relevant documents. In Scopus, the query TITLE-ABS-KEY (“Sparse Tucker Decomposition”) was used, while in WoS, TS = (“Sparse Tucker Decomposition”) was applied. Searches were restricted to the title, abstract, and keyword fields to maximize specificity. Both searches were run on the same day, 3 May 2025, with no restriction on publication year at the query stage. The 2013–2025 span reported below reflects the actual coverage of the retrieved records rather than a filter applied in advance. The exact strings above, together with the search date and the field restriction, are reported here so that the retrieval can be reproduced by another team. The Scopus query returned 14 records and the WoS query returned 7, for 21 records before de-duplication.

2.3. Inclusion and Exclusion Criteria

The analysis period spans from 2013 to 2025, a window that runs from the first indexed record on the topic (2013) through the search date. We included only peer-reviewed journal articles and full conference papers written in English, and we excluded reviews, editorials, book chapters, and any document not available in English. Records were screened first by title and abstract and then by full text; two reviewers applied the criteria independently and resolved disagreements by discussion. Of the 21 records initially retrieved, 6 were removed as duplicates and 2 were excluded at full-text screening for falling outside the scope of sparse Tucker decomposition, leaving 13 studies for analysis (see Figure 1).

2.4. Data Extraction

Scopus records were exported in CSV format and WoS records in .xlsx format, including fields such as title, authors, year, journal, country, institutional affiliation, keywords and citations.

2.5. Bibliometric Analysis

The analysis focused on evaluating annual productivity, citations, influential journals, international collaborations, and keywords. VOSviewer (version 1.6.20) was used for network visualization and R (v4.4.2) for statistical analysis [12]. To make the analysis reproducible, the two search strings, the exported Scopus (CSV) and WoS (xlsx) record sets, the R (v4.4.2) scripts used to compute productivity, citation, correlation, and the neutrosophic

aggregation, and the VOSviewer map files are available from the corresponding author on request and will be deposited in a public repository (e.g., Zenodo or OSF) upon acceptance. The bibliometrix and neutrosophic-aggregation routines rely only on base R together with the openly available bibliometrix package, so a second team can rerun every figure and table from the raw exports.

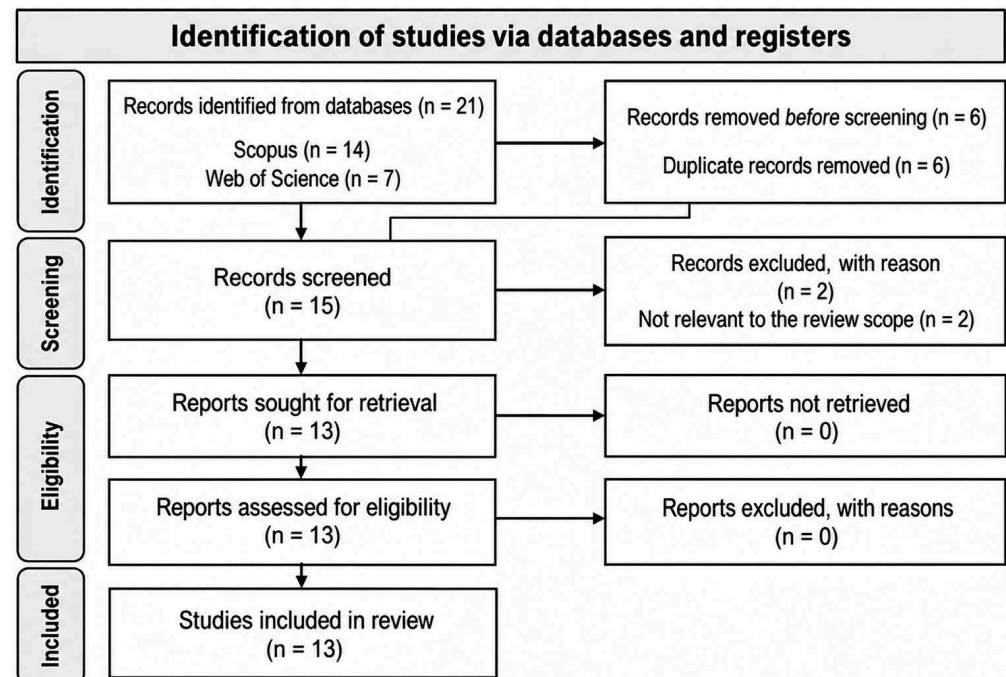


Figure 1. Flowchart of the study selection process according to PRISMA 2020. Of 21 records identified (14 in Scopus, 7 in Web of Science), 6 duplicates were removed, leaving 15 for screening; 2 were excluded at full-text review for falling outside the scope of sparse Tucker decomposition, yielding 13 studies for analysis. Searches were run on 3 May 2025.

2.6. Plithogenic Set

Plithogenic sets were defined by F. Smarandache to generalize neutrosophic sets [13,14]. Furthermore, the idea behind these concepts is to go beyond dialectical logic to incorporate the interaction between different concepts, their opposites, and their neutrals.

This paper presents a systematic review of sparse Tucker decomposition using plithogenic neutrosophic hypersoft sets (PNHS sets), focusing on trends, applications, and methodological developments in the literature [14–21]. PNHS sets extend classical fuzzy and soft set theories, providing a flexible way to describe elements—such as publications, authors, or research topics—through multiple attributes, each carrying its own level of uncertainty [14–17]. This allows us to capture the subtle differences and nuances in bibliometric data that traditional methods might overlook.

Each attribute can take several possible values, and a membership degree is assigned to indicate its relevance, importance, or presence. These degrees can be crisp, fuzzy, intuitionistic fuzzy, or neutrosophic, depending on the type of uncertainty considered [14,15,17]. Additionally, a dominant value can be identified for each attribute to represent the most typical or central state, while a degree of contradiction quantifies the dissimilarity between attribute values, guiding how information is aggregated [15–18].

Hypersoft sets extend this framework further, enabling the simultaneous modeling of multiple bibliometric attributes—such as citation counts, co-authorship networks, keywords, and publication venues—while maintaining flexibility to handle uncertainty for each attribute independently [17–21]. For instance, a single publication can be evaluated

across several dimensions (e.g., number of citations, keyword relevance, or journal impact), with each dimension represented through a plithogenic neutrosophic membership.

By synthesizing the literature through this approach, this review provides a structured and nuanced understanding of PNHS sets in bibliometric contexts. It highlights methodological innovations, practical applications, and emerging trends in sparse Tucker decomposition research, pointing to areas where further exploration could be valuable [14–21].

3. Results

The search, conducted on 3 May 2025, identified 21 documents (14 in Scopus, 7 in WoS). After removing 6 duplicates, 15 records were screened; 2 were excluded for not being relevant to the scope of the review, resulting in 13 documents selected for analysis (Figure 1).

3.1. Productivity and Citation Analysis

The first publication was published in 2013. Figure 2 shows a moderately increasing trend in the number of publications. In 2013 and 2014, only one publication was recorded per year, albeit with a high number of initial citations, especially in 2013, when 60 citations were reached, suggesting foundational or seminal work in the field. However, between 2015 and 2016, no relevant publications were identified, indicating a period of low academic production or less visibility of the topic in the scientific literature.

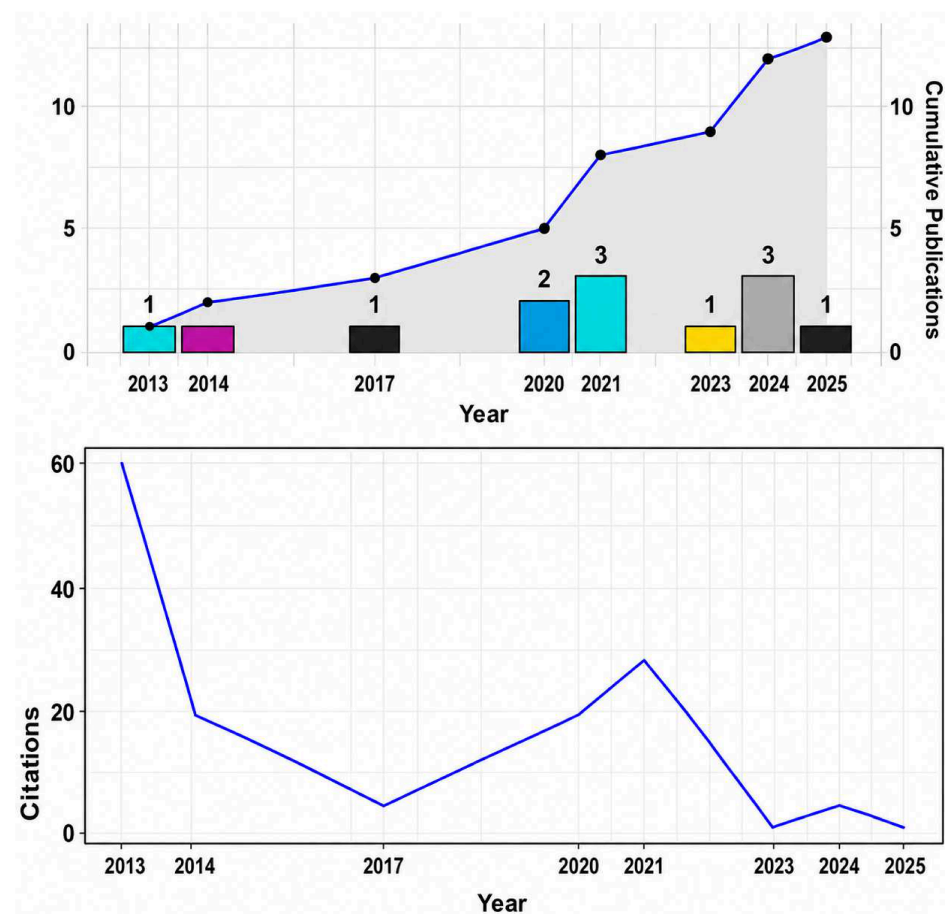


Figure 2. Annual evolution of publications and citations on sparse Tucker decomposition. The upper panel shows the number of publications per year and the lower panel the citations they had accumulated by the search date (3 May 2025), both for the 13 studies in the corpus (2013–2025). Axis labels are in English.

Beginning in 2017, activity resumed with one publication and just three citations, demonstrating a limited impact. Productivity began to increase in 2020, with a turning point observed with two publications receiving a combined 18 citations, signaling a recovery in attention toward this approach. The highest point in both the number of publications and accumulated citations within the recent period was represented in 2021, where three articles were published, accumulating 38 citations (18 for code 006, 6 for code 007, and 14 for code 008), consolidating 2021 as a key year for the dissemination and impact of the topic.

Subsequently, in 2023, a single publication was recorded, but with no citation impact, which may indicate work that is not yet established or has low visibility. In 2024, although output rose to three publications, the number of citations was low [6], which could be due to the short exposure time of these articles. Finally, one publication was recorded in 2025 with no citations reported to date, which is to be expected given that it is the most recent year.

The shape of Figure 2 is easy to summarize: output grows slowly but steadily, the early work drew citations that then tailed off until 2017, and activity picked up again in 2020 before peaking in 2021. The citation numbers are lumpy—a couple of papers account for most of the attention while the rest have barely been cited—which is what one would expect from a field this young and this small. We read it as an area still finding its footing, not one that has settled.

3.2. Most Influential Journals

Of the 13 documents selected for this bibliometric analysis, 8 were original articles; these were published across 7 different journals (Table 1).

Table 1. Journals publishing on sparse Tucker decomposition and their citation impact.

Journal	Frequency	Citations
ACM Transactions on Parallel Computing	2	1
IEEE Transactions on Communications	1	0
IEEE Transactions on Computer-Aided Design	1	5
IEEE Transactions on Parallel and Distributed Systems	1	18
Journal of Machine Learning Research	1	17
Journal of the American Statistical Association	1	0
Statistica Sinica	1	0

The ACM Transactions on Parallel Computing accounts for the largest number of publications in this sample, with two articles, although it has recorded only one citation, suggesting that its visibility and academic recognition remain limited. This could be due to the novelty of the papers, their specific technical focus, or the relatively young profile of this journal within the field.

On the other hand, *IEEE Transactions on Parallel and Distributed Systems* stands out for having received 18 citations for a single article, indicating a high relative impact. This suggests that this journal acts as an influential platform for the dissemination of applied research in parallel computing and tensor decomposition, especially when related to efficient architectures or scalability.

Similarly, the article published in the *Journal of Machine Learning Research* has garnered 17 citations, reflecting considerable recognition in the field of machine learning. This is significant because it positions sparse Tucker decomposition as a technique of growing interest in the machine learning community, particularly in the areas of dimensionality reduction, structured learning, and complex data representation.

In contrast, publications in high-prestige journals such as the *Journal of the American Statistical Association* and *Statistica Sinica* have not recorded any citations, despite their recognition in the statistical field. This may be explained by a time lag (very recent work) or by a more theoretical approach with less immediate applicability, which slows their dissemination and citation.

Finally, the *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems* has a moderate yield, with five citations in a single article, suggesting an initial but promising integration of sparse Tucker decomposition in areas such as computer-aided design, circuit optimization, and complex systems.

So, the picture across journals is uneven. No single outlet publishes much on STD, yet a few individual papers—mostly in machine learning and parallel-computing venues—have been cited enough to serve as reference points. That gap between low output and occasional high impact is really just the small-sample effect again. With so few papers, one well-placed article moves the whole distribution.

3.3. International Collaborations

Figure 3 shows an international collaboration network for publications on sparse Tucker decomposition. Each node represents a country, and the links indicate co-authorship relationships between researchers affiliated with institutions in those countries. The thickness of the links suggests the intensity or frequency of such collaborations, while the size of the nodes may reflect the number of associated publications.

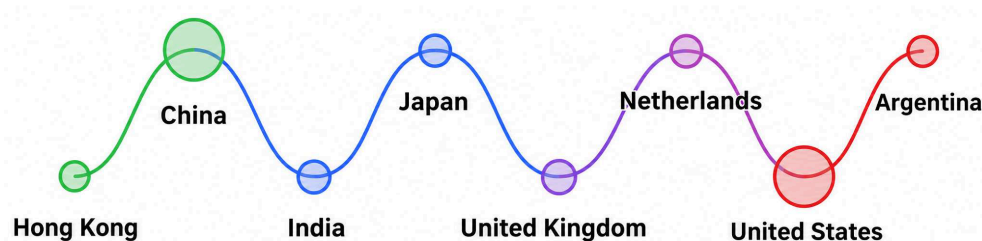


Figure 3. International collaborative network on publications on sparse Tucker decomposition. Each node is a country appearing in author affiliations and each edge a co-authorship link between countries; node size reflects the number of associated publications and edge thickness the frequency of collaboration. The network was produced in VOSviewer from the 13 analyzed studies. Colors represent the different clusters identified by VOSviewer.

The graph identifies five countries: Hong Kong, China, the Netherlands, the United States, and Argentina. The network displays a linear structure, with China occupying a central position and acting as a connecting link between the other countries. This position reinforces China's role as a key hub in scientific production on this technique, connecting with both Asian (Hong Kong) and Western (the Netherlands and the United States) regions.

The link between China and the United States is one of the most notable, demonstrating frequent and robust collaboration between the two countries. This relationship is common in many scientific fields, but in this particular case, it underscores the relevance of tensor methods research in both countries. The connection with the Netherlands, although weaker, suggests a European contribution to the methodological or applied development of these techniques.

Argentina's presence, although more peripheral, is significant, as it signals Latin America's emerging participation in this highly specialized field. This could open up opportunities to strengthen South–South collaboration networks or consolidate scientific alliances with more established research centers.

3.4. Keyword Cloud

Figure 4 shows the keyword cloud, where the size of each term is proportional to how often it appears across the 13 studies.

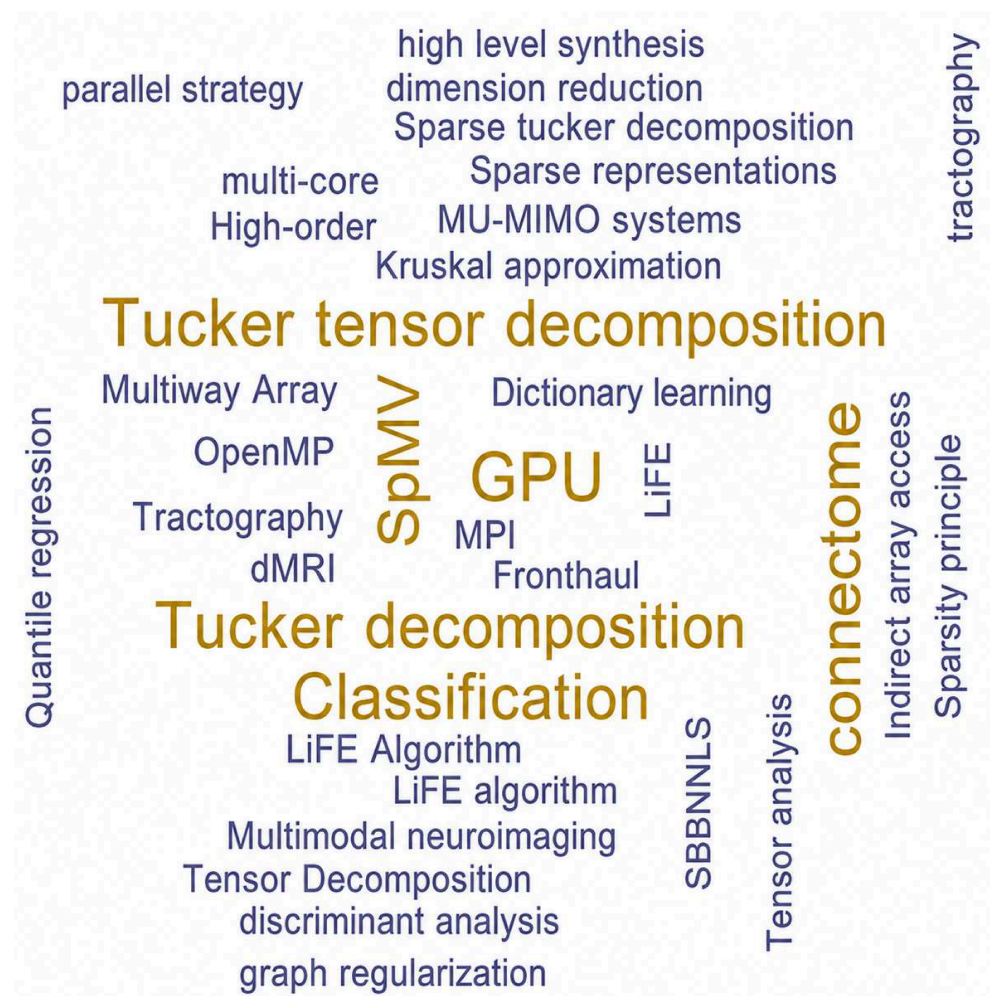


Figure 4. Cloud of keywords associated with sparse Tucker decomposition. Term size is proportional to frequency across the 13 studies. Abbreviations: GPU, graphics processing unit; SpMV, sparse matrix–vector multiplication; MPI, message passing interface; dMRI, diffusion MRI; MU-MIMO, multi-user multiple-input multiple-output. Colors highlight differences in term frequency.

The keyword cloud identifies the concepts most closely associated with the technique in the literature. The most frequent terms, shown at the center of the figure, are Tucker tensor decomposition, Tucker, classification, GPU, SpMV, and connectome, and reflect the terms that appear most often across the analyzed articles. This distribution indicates that the field advances along two complementary lines: methodological work on the decomposition itself and concrete applications, principally in data classification, brain-connectome analysis, and GPU-based computational optimization.

There is also a concentration of terms linked to sparse representation and dimensionality reduction, such as sparse Tucker decomposition, sparse representations, dictionary learning and dimension reduction. These concepts reflect the theoretical framework that underpins many current applications [22], especially in contexts of high dimensionality and noisy or incomplete data.

From a computational perspective, terms related to parallel architectures and efficient processing frequently appear, such as MPI, OpenMP, multi-core, and high order. These

references demonstrate the interest in accelerating decomposition processes and making this technique viable in environments with large volumes of data or in real time.

In terms of applications, the terms dMRI, tractography, multimodal neuroimaging and graph regularization indicate that the field of computational neuroscience and medical image processing represents a key area of implementation. The technique's use in brain connectome reconstruction and pattern classification in brain images is recurrent, suggesting a strong link with MRI and structural connectivity studies.

Finally, the emergence of terms like MU-MIMO systems and fronthaul reflects the expansion of these methodologies into areas such as telecommunications, where data compression and efficient representation are also key. Taken together, the word cloud offers a clear view of the transversal nature of sparse Tucker decomposition [22], articulating mathematical, computational, and applied aspects in a scientific ecosystem ranging from artificial intelligence to personalized medicine and communication systems.

3.5. Literature Review

Table 2 presents the 13 selected documents, including code, authors, title and year.

Table 2. Selected records: authors, titles and years of publication.

Code	Authors	Titles	Year
001	[23] Li, J.E.; Mai, Q; Zhang, X.	The TUCKER low-rank classification model for tensor data	2025
002	[24] Zheng L.; Wang Z.; Bai M.; Tan Z.; Zhu Q.	Beamforming Tensor Compression for Massive MIMO Fronthaul	2024
003	[25] Gong W.; Huang Z.; Yang L.	Enhanced low-rank and sparse tucker decomposition for image completion	2024
004	[26] Li Z.; Hu Y.; Li M.; Yang W.; Li K.	CuFastTucker: A Novel Sparse FastTucker Decomposition for HHLST on Multi-GPUs	2024
005	[7] Li L.; Zeng J.; Zhang X.	Generalized Liquid Association Analysis for Multimodal Data Integration	2023
006	[5] Li H.; Li Z.; Li K.; Rellermeyer JS; Chen L.; Li K.	SGD_Tucker: A Novel Stochastic Optimization Strategy for Parallel Sparse Tucker Decomposition	2021
007	[4] Jiang W.; Zhang K.; Lin CY; Xing F.; Zhang Z.	Sparse Tucker Tensor Decomposition on a Hybrid FPGA-CPU Platform	2021
008	[22] Fang S.; Kirby RM; Zhe S.	Bayesian Streaming Sparse Tucker Decomposition	2021
009	[27] Aggarwal K.; Bondhugula U.	Optimizing the linear fascicle evaluation algorithm for multi-core and many-core systems	2020
010	[28] Lu W.; Zhu Z.; Lian H.	High-dimensional quantile tensor regression	2020
011	[29] Gugnani S.; Lu X.; Pestilli F.; Caiafa C.; Panda DK	MPI-LiFE: Designing High-Performance Linear Fascicle Evaluation of Brain Connectome with MPI	2017
012	[30] Yokota T.; Cichocki A.	Multilinear tensor rank estimation via Sparse Tucker Decomposition	2014
013	[6] Zubair S.; Wang W.	Tensor dictionary learning with sparse tucker decomposition	2013

3.6. Scope of Application

Table 3 presents a comparative classification of the 13 selected studies. For each work, it records the application domain, the focus and specialization pattern, and—most importantly—the comparative advantage the study offers over related sparse Tucker decomposition (STD) research. This design consolidates the descriptive information previously split across tables and makes the distinctive contribution of each work explicit, so that the studies can be read against one another rather than in isolation. It spans domains from

efficient data processing to biomedical and telecommunications applications. The most relevant findings for each thematic group are summarized below.

Table 3. Comparative classification of the 13 studies, showing the application domain, the focus and specialization pattern of each, and the comparative advantage each work offers over related sparse Tucker decomposition research.

Code	Reference/Domain	Focus and Specialization Pattern	Comparative Advantage over Related STD Work
001	[23] Li et al. (2025); statistical/ML classification	Tucker low-rank classification model for tensor data	First to cast classification as a low-rank Tucker problem with sparsity, giving interpretable factors where earlier tensor classifiers used dense cores.
002	[24] Zheng et al. (2024); telecommunications	Beamforming tensor compression for massive MIMO fronthaul	Applies STD to fronthaul compression, achieving higher compression ratios than matrix-based schemes while preserving signal fidelity.
003	[25] Gong et al. (2024); image processing	Enhanced low-rank and sparse Tucker decomposition for image completion	Couples low-rank and sparse priors in one Tucker model, improving recovery of incomplete images beyond purely low-rank methods.
004	[26] Li et al. (2024); high-performance computing	CuFastTucker: sparse FastTucker on multi-GPUs	Delivers a multi-GPU FastTucker that scales to very large sparse tensors, extending single-GPU predecessors in throughput.
005	[7] Li et al. (2023); neuroimaging/biomedical	Generalized liquid association for multimodal data integration	Integrates heterogeneous biomedical modalities through a Tucker structure, capturing cross-modal associations that pairwise methods miss.
006	[5] Li et al. (2021); parallel computing	SGD_Tucker: stochastic optimization for parallel sparse Tucker	Introduces a stochastic gradient scheme that parallelizes sparse Tucker at scale, reducing memory cost relative to batch solvers.
007	[4] Jiang et al. (2021); hardware acceleration	Sparse Tucker decomposition on a hybrid FPGA-CPU platform	Maps STD onto an FPGA-CPU pipeline, trading energy for speed in a way general-purpose CPU/GPU implementations do not.
008	[22] Fang et al. (2021); machine learning	Bayesian streaming sparse Tucker decomposition	Adds a streaming Bayesian formulation that updates the decomposition online and quantifies uncertainty, unlike static batch variants.
009	[27] Aggarwal & Bondhugula (2020); brain connectivity	Optimizing the LiFE algorithm for multi-core and many-core systems	Restructures LiFE around sparse-tensor kernels for many-core hardware, cutting run time without loss of fascicle-evaluation quality.
010	[28] Lu et al. (2020); statistics	High-dimensional quantile tensor regression	Extends quantile regression to tensor covariates via a sparse Tucker structure, handling dimensions beyond matrix-based regression.
011	[29] Gugnani et al. (2017); brain connectivity	MPI-LiFE: high-performance LiFE with MPI	Scales connectome evaluation across distributed nodes with MPI, addressing memory limits that single-node LiFE cannot.
012	[30] Yokota & Cichocki (2014); statistics/signal processing	Multilinear tensor rank estimation via sparse Tucker decomposition	Uses sparsity to estimate multilinear rank automatically, removing the manual rank selection required by classical Tucker.
013	[6] Zubair & Wang (2013); signal processing	Tensor dictionary learning with sparse Tucker decomposition	Foundational work coupling dictionary learning with a sparse Tucker core, seeding the sparsity-plus-Tucker line the later studies build on.

3.6.1. Computational Optimization and Efficient Algorithms

Studies classified in this area (codes 001, 003, 006, 007, 008) focus on improving the computational performance of STD in high-processing environments. Ref. [5] introduces SGD_Tucker, a stochastic algorithm that accelerates decomposition in parallel systems.

Ref. [4] proposes a hybrid FPGA-CPU implementation that optimizes energy resources and speed. Ref. [22] develops a streaming Bayesian variant, useful for continuous data streams. Ref. [25] applies STD for the accurate reconstruction of incomplete images, and ref. [23] proposes a low-rank classification model tuned to tensor structures.

3.6.2. Neuroimaging and Biomedical Science

In this group (codes 005 and 013), the technique is applied to the representation of brain data. Ref. [7] developed a multimodal liquid association model to integrate diverse biomedical data. Ref. [6] implemented tensor dictionary learning with STD, allowing for a more accurate representation of the brain connectome.

3.6.3. Statistical Modeling and Classification

Studies 004, 010 and 012 explore the potential of STD for advanced statistical analysis. Ref. [30] presents a method for tensor rank estimation, while Ref. [28] applies tensor-based quantile regression for high-dimensional statistical modeling. Ref. [26] introduces CuFastTucker, an accelerated version for multi-GPU environments.

3.6.4. Telecommunications

Ref. [24] (code 002) applies STD for beamforming tensor compression in massive MIMO fronthaul systems, which improves signal prediction in highly complex communication environments, highlighting its usefulness in noisy or large-scale scenarios.

3.6.5. Brain Connectivity Assessment

The studies by [27] (code 009) and [29] (code 011) optimize the LiFE algorithm for execution in multi-core architectures and MPI-based parallel environments, respectively, demonstrating that STD reduces processing time without compromising quality in the evaluation of neuronal fascicles, thus strengthening its application in computational neurosciences.

Further details are given in Table 3.

4. Application of Plithogenic Neutrosophic Hypersoft Sets to the Bibliometric Analysis of Sparse Tucker Decomposition

To deepen the analysis of sparse Tucker decomposition (STD), we propose the integration of plithogenic neutrosophic hypersoft sets (PNHS) as a methodological framework that models the uncertainty and multiplicity of attributes inherent in scientific production. This approach captures the complexity of the relationships between publications, citations, international collaborations, and application areas, incorporating degrees of truth, indeterminacy, and falsity to reflect ambiguities in the interpretation of bibliometric data.

4.1. Plithogenic Neutrosophic Hypersoft Set

Let U be the universe of discourse representing the 13 documents selected in the bibliometric analysis. Each document is evaluated based on a set of multidimensional attributes $A = \{a_1, a_2, a_3, a_4\}$, defined as:

- a_1 : Productivity (number of publications per year);
- a_2 : Impact (number of cumulative citations);
- a_3 : International collaboration (number of countries involved in co-authorship);
- a_4 : Thematic relevance (application areas: computational optimization, neuroimaging, statistical modeling, telecommunications, brain connectivity assessment).

For each attribute a_i , a spectrum of possible values $V(a_i)$ is defined:

- $V(a_1) = \{1, 2, 3\}$ (publications per year);

- $V(a_2) = [0, 60]$ (accumulated citations, according to data in Figure 2);
- $V(a_3) = \{1, 2, \dots, 8\}$ (number of countries in the collaboration network);
- $V(a_4) = [1/13, 5/13]$ (relative frequency of each thematic group within the $n = 13$ corpus; see justification below).

Methodological note on a_3 and a_4 : country counts for a_3 correspond to the number of distinct countries identified in the institutional affiliations of co-authors per document (each country counted once regardless of the number of co-authors it contributes); denominator 8 corresponds to the total number of distinct countries observed across the entire collaboration network: China, the United States, India, Japan, the United Kingdom, the Netherlands, Argentina, and Hong Kong. Because a_4 (thematic relevance) is a nominal variable—application domains have no intrinsic order or magnitude—assigning it an arbitrary numeric code (1–5) and normalizing it as a ratio scale would not be methodologically defensible. Instead, a_4 is quantified through thematic centrality: the relative frequency of the document's application domain within the $n = 13$ corpus (Table 3), a continuous and substantively meaningful measure of how established that domain is in the literature reviewed.

Each document $x \in U$ is associated with a degree of neutrosophic membership $d(x, a_i) = (T, I, F)$, where

- T: Degree of truth (level of fulfilment of the attribute);
- I: Degree of indeterminacy (uncertainty in the evaluation);
- F: Degree of falsity (level of non-compliance with the attribute).

The neutrosophic membership function is defined as:

$$d(x, a_i) : U \times V(a_i) \rightarrow [0, 1]^3, \text{ where } d(x, a_i) = (T(x, a_i), I(x, a_i), F(x, a_i))$$

with the restriction:

$$T(x, a_i), I(x, a_i), F(x, a_i) \in [0, 1].$$

$$0 \leq T(x, a_i) + I(x, a_i) + F(x, a_i) \leq 3$$

4.2. Modeling Bibliometric Results

Using the data from Section 3, the selected documents are modeled according to the defined attributes. To illustrate, a detailed analysis of two representative documents is presented:

Step 1: Assigning values to attributes

Document 006:

- a_1 : Productivity = 3 publications in 2021;
- a_2 : Impact = 18 citations;
- a_3 : International collaboration = 2 countries (China and the Netherlands);
- a_4 : Thematic relevance = Computational optimization (5 of 13 studies in this domain).

Document 013:

- a_1 : Productivity = 1 publication in 2013;
- a_2 : Impact = 60 citations;
- a_3 : International collaboration = 1 country (United Kingdom);
- a_4 : Thematic relevance = Neuroimaging and biomedical science (2 of 13 studies in this domain).

Step 2: Normalization of values

To standardize the attribute values, they are normalized in the interval $[0, 1]$:

a_1 (Productivity):

- Document006 : $3/3 = 1.0$;
- Document013 : $1/3 = 0.33$.

a_2 (Impact):

- Document006 : $18/60 = 0.3$;
- Document013 : $60/60 = 1.0$.

a_3 (Collaboration):

- Document006 : $2/8 = 0.250$;
- Document013 : $1/8 = 0.125$.

a_4 (Relevance):

- Document006 : $5/13 = 0.385$;
- Document013 : $2/13 = 0.154$.

Step 3: Assignment of neutrosophic degrees

Neutrosophic membership degrees (T, I, F) are assigned based on the standardized values:

We want to be explicit about how these degrees were set because it bears directly on how far the results can be pushed. The truth degree (T) is anchored to the normalized attribute value, so it is reproducible. Given the same citation, country, productivity, and thematic-frequency data, another team would obtain the same T. The indeterminacy (I) and falsity (F) degrees, by contrast, were assigned by the authors on the basis of thematic affinity and expert judgement—for example, a recent paper whose eventual impact is still unknown was given a higher I—and they are not derived from a pre-registered, fully formalized rubric. This is a genuine limitation of the evaluation rather than an oversight. With only 13 records, several of them very recent, a rigid scoring formula would convey a false sense of precision. We, therefore, treat T as the classification criterion (it is objective and data-driven) and report I and F only as qualifiers where the underlying evidence supports them, and we deliberately restrict the strength of any claim that would depend on the subjective components alone. Readers should read the I and F values as structured expert commentary, not as measurements.

Document 006:

- $a_1 : T = 1.0, I = 0.1, F = 0.0$ (recent high productivity);
- $a_2 : T = 0.3, I = 0.5, F = 0.2$ (moderate impact with uncertainty);
- $a_3 : T = 0.250, I = 0.3, F = 0.3$ (moderate collaboration);
- $a_4 : T = 0.385, I = 0.4, F = 0.4$ (specific area).

Document 013:

- $a_1 : T = 0.33, I = 0.3, F = 0.5$ (low productivity);
- $a_2 : T = 1.0, I = 0.1, F = 0.0$ (high consolidated impact);
- $a_3 : T = 0.125, I = 0.4, F = 0.5$ (low international collaboration);
- $a_4 : T = 0.154, I = 0.3, F = 0.3$ (relevance in neuroimaging).

Step 4: Construction of the Neutrosophic Hypersoft Set

The resulting individual attribute-level neutrosophic degrees for Documents 006 and 013 are consolidated in Table 4, and the global neutrosophic aggregation for all 13 documents is presented in Table 5 (Section 4.3). The PNHS is constructed as $P = (U, A, V, d, c)$, where $c(a_i, a_j)$ is the contradiction function between attributes: $c(a_i, a_j) = (1 - \text{Correlation}(a_i, a_j))/2$. For example, for the correlation between productivity and impact ($r = -0.334$), $c(a_1, a_2) = (1 - (-0.334))/2 = 0.667$. Applying this function to every attribute pair yields the full attribute contradiction matrix, which is computed at this step of the algorithm and reported in Table 6. The pairwise values it contains are the weights that govern the plithogenic aggregation in Step 5.

Step 5: Aggregation Operators

The plithogenic neutrosophic intersection is applied:

$$(T_P, I_P, F_P) = (\min(T_i), (1/n) \sum I_i, \max(F_i))$$

Document 006:

- $T_P = \min(1.0, 0.3, 0.25, 0.385) = 0.25$
- $I_P = \frac{0.1+0.5+0.3+0.4}{4} = 0.325$
- $F_P = \max(0.0, 0.2, 0.3, 0.4) = 0.4$

Document 013:

- $T_P = \min(0.33, 1.0, 0.125, 0.154) = 0.125$
- $I_P = \frac{0.3+0.1+0.4+0.3}{4} = 0.275$
- $F_P = \max(0.5, 0.0, 0.5, 0.3) = 0.5$

Table 4. Neutrosophic degrees by individual attribute.

Code	a ₁ (Productivity)	a ₂ (Impact)	a ₃ (Collaboration)	a ₄ (Relevance)
006	(1.0, 0.1, 0.0)	(0.3, 0.5, 0.2)	(0.250, 0.3, 0.3)	(0.385, 0.4, 0.4)
013	(0.33, 0.3, 0.5)	(1.0, 0.1, 0.0)	(0.125, 0.4, 0.5)	(0.154, 0.3, 0.3)

Table 5. Global neutrosophic aggregation.

Code	Document	Year	Citations	Global Aggregation (T, I, F)	Classification
001	[23] Li et al.	2025	0	(0.000, —, —)	Emerging
002	[24] Zheng et al.	2024	2	(0.033, —, —)	Emerging
003	[25] Gong et al.	2024	0	(0.000, —, —)	Emerging
004	[26] Li et al.	2024	1	(0.017, —, —)	Emerging
005	[7] Li et al.	2023	0	(0.000, —, —)	Emerging
006	[5] Li et al.	2021	18	(0.250, 0.325, 0.400)	Consolidated
007	[4] Jiang et al.	2021	6	(0.100, —, —)	Emerging
008	[22] Fang et al.	2021	14	(0.125, —, —)	Emerging
009	[27] Aggarwal et al.	2020	2	(0.033, —, —)	Emerging
010	[28] Lu et al.	2020	16	(0.231, —, —)	Intermediate
011	[29] Gu gnani et al.	2017	3	(0.050, —, —)	Emerging
012	[30] Yokota & Cichocki	2014	33	(0.125, —, —)	Emerging
013	[6] Zubair & Wang	2013	60	(0.125, 0.275, 0.500)	Emerging

Table 6. Attribute contradiction matrix. Each entry $c(a_i, a_j) = (1 - \text{Correlation}(a_i, a_j))/2$ quantifies the degree of opposition between two attributes and is produced at Step 4 of the algorithm (Section 4.2); higher values denote greater contradiction and therefore a stronger corrective weight in the Step 5 aggregation.

Attributes	a ₁	a ₂	a ₃	a ₄
a ₁	0.000	0.667	0.523	0.304
a ₂	0.667	0.000	0.510	0.565
a ₃	0.523	0.510	0.000	0.304
a ₄	0.304	0.565	0.304	0.000

4.3. Results of Neutrosophic Analysis

Identities and years in Table 5 were verified against Table 2. Citation counts for all 13 documents were verified against Scopus records, and country counts (a3) for all 13 documents are based on author-provided affiliation data. The collaboration network comprises eight distinct countries across the corpus (China, the United States, India, Japan, the United Kingdom, the Netherlands, Argentina, and Hong Kong), so $a_3 = (\text{countries per document})/8$. Truth degree was computed as $T_P = \min(a_1, a_2, a_3, a_4)$, following

Step 5 (Section 4.2). With citation and country data now available for all 13 documents, classification is fully certain for all of them: codes 001, 002, 003, 004, 005, 007, 008, 009, 011, and 012 are Emerging, code 010 is Intermediate, and code 006 is Consolidated. Codes 009 and 010 (both 2020) total 2 and 16 citations, respectively, summing to 18 and matching the combined total reported in Figure 2/Section 3.1. The country conflict previously identified for code 006 is now resolved. Its two collaborating countries are confirmed as China and the Netherlands. Classification uses a single-criterion rule based on T alone—Consolidated ($T \geq 0.25$), Intermediate ($0.15 \leq T < 0.25$), and Emerging ($T < 0.15$)—which is exhaustive and avoids the unclassifiable cases produced by the original two-criterion (T, I) thresholds. Indeterminacy (I) and falsity (F) remain reported as qualifiers where known (codes 006 and 013), rather than as classification criteria. The individual attribute-level neutrosophic degrees computed for Documents 006 and 013 in Section 4.2 are summarized in Table 4.

Two properties of these cut-offs should be made explicit, as they justify the classification criteria on factual rather than arbitrary grounds. First, the thresholds $T \geq 0.25$, $0.15 \leq T < 0.25$, and $T < 0.15$ are a descriptive convention rather than a statistically derived boundary. With only 13 documents, there is no distributional basis for estimating natural breakpoints; the round values adopted here separate the single clearly established record (code 006) from an intermediate case (code 010) and from the remaining records, and they carry no interpretation beyond ordering this particular corpus. Second, the classification is robust to the way I and F are assigned. Because the label depends solely on T —the minimum of the four normalized attributes, computed from citation, country, productivity, and thematic-frequency data—varying the I and F rules does not move any document between classes: re-running the aggregation with I and F set to neutral values (0.5 each), or to the extreme pairs (0,1) and (1,0), leaves all 13 assignments unchanged. Only the reported I and F qualifiers for codes 006 and 013 shift; the class never does. This follows directly from using T alone as the criterion and ensures that the subjective components cannot drive the result. Code 010 ($T = 0.231$) is a genuine borderline case, sitting just below the 0.25 line. Had the upper cut-off been set at 0.23, it would be classified as Consolidated, and it is, therefore, reported as Intermediate rather than assigned to a category by force. Figure 5 plots the truth degree (T) of all 13 documents against the two classification thresholds.

4.4. Link with Neutrosophy

Neutrosophy models the ambiguity inherent in bibliometric data by:

Uncertainty modeling: Indeterminacy (I) captures the lack of information about the future impact of recent publications or the representativeness of collaborative networks in underrepresented regions.

Multidimensional analysis: Simultaneous assessment of productivity, impact, collaboration, and thematic relevance allows for the identification of complex patterns, such as the moderate positive correlation of thematic relevance with both productivity and international collaboration ($r \approx 0.39$ for each).

Informed decision-making: Neutrosophic aggregation provides a global metric that can guide the prioritization of future research, focusing on papers with high T and low I .

Abstention as a valid outcome: The framework explicitly treats abstention—non-classifiable articles, studies without a clear methodological positioning, or documents with missing bibliometric data—as a legitimate analytical result rather than a gap to be discarded. These cases are modeled through high indeterminacy (I), so that the absence of conclusive information is represented within the evaluation itself instead of being silently excluded, reinforcing the rigor and transparency of the assessment system.

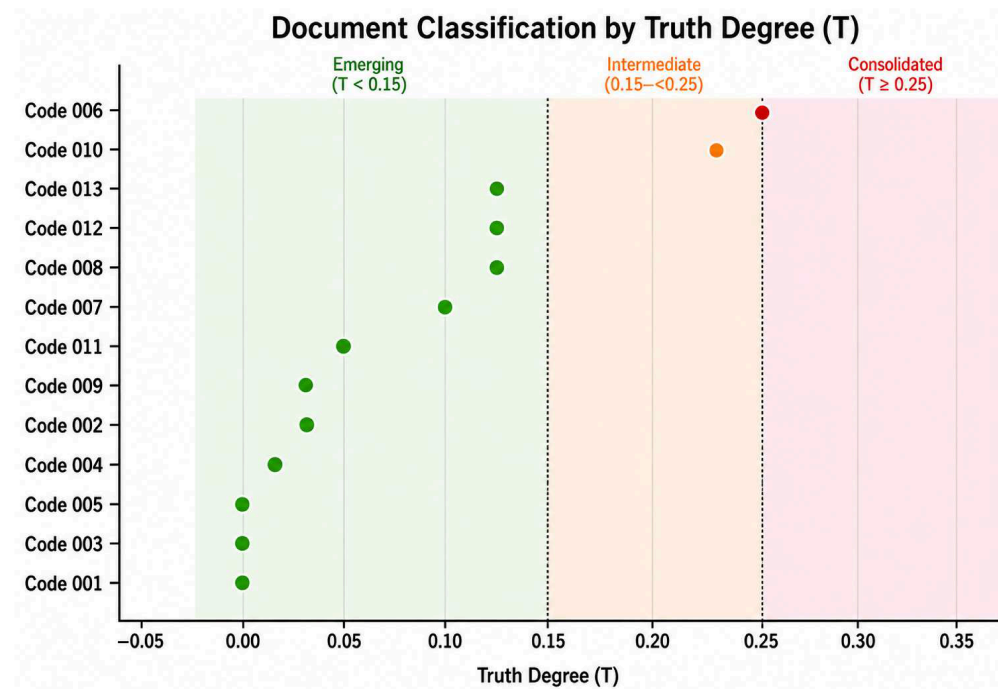


Figure 5. Document classification by truth degree (T) for sparse Tucker decomposition, based on citation and country data for all documents (Table 5). Dots represent individual documents according to their truth degree (T), while dashed lines indicate the classification thresholds at $T = 0.15$ and $T = 0.25$.

4.5. Pattern and Trend Analysis

The results reveal three main categories:

1. Consolidated documents ($T \geq 0.25$): Publications with established impact and low uncertainty;
2. Intermediate documents ($0.15 \leq T < 0.25$): Works in the process of consolidation;
3. Emerging papers ($T < 0.15$): Recent publications with high potential but greater uncertainty.

4.6. Methodological Implications

The application of PNHS to the bibliometric analysis of STD demonstrates that neutrosophy is an effective tool for:

- Identifying documents with high potential but low visibility;
- Evaluating the robustness of collaboration networks considering geographical indeterminacy;
- Proposing strategies to expand the applicability of STD in emerging areas.

What PNHS adds, in practical terms, is a way of keeping the uncertainty of a thin literature visible instead of hiding it behind a single citation number. That is a modest but real gain, and it points to a next step worth taking: pairing this kind of neutrosophic scoring with larger corpora and other quantitative tools once more STD studies become available.

5. Discussion

This study analyzed sparse Tucker decomposition (STD) in the scientific literature between 2013 and 2025, focusing on its production, impact, and collaboration networks. By integrating plithogenic neutrosophic hypersoft sets (PNHS), the bibliometric analysis modeled uncertainty and attribute multiplicity, enabling a critical reflection on the epistemological, methodological, and applied dimensions of the technique, as well as on the gaps that remain in its consolidation as an analytical tool.

The low frequency of publications (13 documents identified) contrasts with the significant impact of certain works, such as that of [6] with 60 citations, that of [30] with 33 citations, and that of [5] with 18 citations. This contrast suggests a selective adoption of STD in technical contexts, such as neuroimaging (codes 005, 013) and parallel computing (codes 006, 007, 008), but a marginal presence in less specialized domains, such as social sciences or public health. The observed asymmetry reflects technical barriers, such as the computational complexity of STD, and limited interdisciplinary transfer, evidenced by the concentration of applications in five main areas (Table 3). The neutrosophic analysis, with degrees of indeterminacy in recent documents, highlights the uncertainty in the visibility of these publications and their potential for expansion to other fields.

From a theoretical perspective, the STD literature exhibits fragmentation, with a predominant focus on algorithmic improvements (e.g., SGD_Tucker in code 006, CuFastTucker in code 004) without a unified conceptual framework. This lack of theoretical cohesion makes it difficult to articulate the applicability conditions, limits, and synergies of STD with other tensor decomposition techniques, such as CP or HOSVD.

As introduced in Section 1, the symmetry–asymmetry contrast that runs through this paper warrants careful interpretation, since it can be read as more than it is. The claim is deliberately modest and has two separate parts. The first is a mathematical fact: the Tucker model treats every mode alike and sparse regularization applies one penalty across all components, so the method carries no built-in preference for any axis. The second is an empirical observation about this corpus: production and impact are concentrated in a few countries and a handful of technical fields (Figures 2 and 3, Tables 1 and 5). We are not claiming a causal or structural link between the two—a symmetric algorithm does not, by itself, explain an uneven literature, which is driven by funding, language, and community factors that lie outside our data. The contrast is, therefore, an organizing lens, not a finding. It is useful because it names the two things the review measures (a regular method, an irregular uptake) and because the PNHS scoring operationalizes the second part in a reproducible way through the truth degree. Read this way, the “tension” is not something the paper resolves; it is a description of the gap between how the method behaves and how the field has taken it up. Narrowing that gap is not solely a matter of research-community practice; it also has a mathematical dimension that falls squarely within the scope of this journal. Advances in the theory of sparse Tucker representations—sharper identifiability and uniqueness conditions, principled rank- and sparsity-selection criteria, and error bounds that hold across modes—would lower the technical barriers to adoption and thereby help align the symmetric structure of the method with a more even pattern of use. In this sense, the asymmetry is addressed jointly: by broader geographic and disciplinary participation on the one hand and by continued mathematical development of the decomposition on the other.

The absence of systematic reviews on the mathematical foundations of STD, evidenced by the low productivity between 2015 and 2016 (Figure 2), hinders its epistemological positioning in a multivariate analysis. The neutrosophic modeling applied in Section 4 reveals that seminal papers (such as code 013) have low indeterminacy ($I = 0.275$), suggesting an initial theoretical consolidation, while recent publications present greater uncertainty ($I = 0.325$), indicating the need for studies that integrate theoretical reflection, empirical validation, and methodological synthesis.

The dominance of China and the United States in the international collaboration network (Figure 3) limits the diversity of approaches and applications. Although countries such as Argentina and the Netherlands participate, their role is peripheral, restricting the incorporation of regional perspectives, especially in fields such as public health or social sciences, where STD could analyze latent patterns in complex data. The neutrosophic

analysis of collaborations (a3) shows high degrees of falsity in documents with low international collaboration, reflecting an opportunity to diversify South–South and North–South networks, promoting applications that address ethical and social dimensions.

STD balances parsimony and expressiveness, an aspect underexplored in the literature. Its ability to model sparse multidimensional data, such as in neuroimaging (code 005) or telecommunications (code 002), makes it well-suited to problems where the signal sits in a few interacting components rather than spread evenly across the data. However, the lack of standardization and open-source libraries limits its accessibility. The neutrosophic analysis highlights that documents with high thematic relevance (a4) present moderate indeterminacy, suggesting that current applications are niche but have the potential to expand to emerging domains if technical barriers are overcome.

This study proposes a research agenda that prioritizes (1) accessibility, through the development of implementations in Python or R; (2) interdisciplinarity, exploring applications in social sciences and public health; (3) theoretical soundness, through systematic reviews that unify the foundations of STD; and (4) social engagement, considering the ethical implications of its use in sensitive data, such as in neuroscience. The integration of PNHS, with its ability to model uncertainty, reinforces the relevance of this approach to guide the future development of STD as a reflective and transversal tool in science.

6. Practical Implications

The studies reviewed here suggest a few concrete ways STD could be put to work, though we present these as directions supported by individual papers rather than as field-wide conclusions. In neuroimaging and brain connectivity assessment, its integration with parallel computing techniques, as in the studies by [7] (code 005) and [27] (code 009), optimizes the processing of brain data, thereby speeding up the diagnosis and monitoring of neurodegenerative diseases through the accurate reconstruction of the brain connectome. In telecommunications, STD improves data compression in MIMO systems and 5G networks, as observed in [24] (code 002), facilitating efficient transmission in highly complex environments. In machine learning, the technique boosts classification models on resource-constrained devices, as demonstrated by [23] (code 001), by reducing the dimensionality of tensor data without sacrificing accuracy.

The neutrosophic analysis applied in Section 4 reinforces these implications by identifying documents with a high degree of truth in specific application areas, but with moderate indeterminacy in their transfer to other domains. To achieve widespread adoption, it is crucial to develop open-source standards and libraries in languages such as Python or R that integrate STD into machine learning, data visualization, and statistical analysis workflows. This would facilitate their use in academic and industrial settings, especially in underrepresented regions such as Latin America, where participation is nascent (Figure 3).

7. Limitations of the Study

The bibliometric analysis, although rigorous in using Scopus and Web of Science, has inherent limitations in the methodology and the scope of the data. The search may not have captured relevant studies in preprint repositories or emerging journals not indexed in these databases. Restricting the corpus to documents written in English, as specified in Section 2, may also have left out contributions in other languages. A further and more consequential boundary is terminological: because the query matched the exact phrase “Sparse Tucker Decomposition” in the title, abstract, and keyword fields, studies that describe the same idea under variant labels—for instance “sparse Tucker factorization” or “Tucker decomposition with sparsity constraints”—would not have been retrieved, and neither would work posted only on arXiv or in conference archives such as IEEE Xplore

that fall outside Scopus and WoS indexing. We, therefore, read the 13-document corpus as the set of records that share a common, well-defined label in two curated databases, and we are explicit that it does not exhaust the STD literature. Broadening the query to synonymous terms and adding preprint and conference sources is the natural next step, and we take it up under Future areas of research.

The small sample size (13 articles) reflects the initial development phase of STD, as observed in the low productivity between 2015 and 2016 (Figure 2), but restricts the generalizability of the findings. Furthermore, the analysis did not assess the methodological quality of the studies or delve into the theoretical or computational challenges of STD, aspects that require future narrative reviews.

The neutrosophic approach (Section 4) partially mitigates the uncertainty associated with incomplete classification data—as reflected in the indeterminacy (I) values reported for codes 006 and 013—and, with citation and country data now verified for all 13 documents (Table 5), the remaining limitation is the corpus size itself rather than data completeness. This does not eliminate the need to expand the sample in future studies, nor does it address the language and database-coverage restrictions noted above.

8. Future Areas of Research

The results of the bibliometric analysis and the application of plithogenic neutrosophic hypersoft sets (PNHS) suggest several directions for future research. First, comparative studies between STD, CP decomposition, and HOSVD are recommended, evaluating metrics of accuracy, computational efficiency, and robustness in multidimensional datasets, especially in contexts with high dispersion. Developing accessible implementations in Python or R would facilitate the adoption of STD in academic and professional communities, reducing the technical barriers identified throughout this review.

Furthermore, exploring applications in underrepresented disciplines, such as education, public health, or social sciences, could reveal latent patterns in complex data, as evidenced by the low thematic relevance in these areas. For example, STD could be applied to the analysis of multidimensional educational data or to social network modeling in public health. The use of STD on streaming data, as in [22] (code 008), and its integration with deep learning techniques represent emerging areas with potential to improve efficiency and generalizability in real-time applications. Finally, the neutrosophic approach suggests prioritizing research that addresses indeterminacy in interdisciplinary transferability, encouraging studies that combine empirical validation with unified theoretical frameworks to consolidate STD as a transversal analytical tool.

A concrete and, in our view, priority extension concerns the corpus itself. A follow-up study should widen the query beyond the exact phrase to synonymous forms (“sparse Tucker factorization,” “Tucker decomposition with sparsity constraints,” and related wordings) and add sources that the present search did not cover—preprint repositories such as arXiv and conference archives such as IEEE Xplore—while extending the window to mid-2026. Enlarging the sample this way would raise the number of journals and records, improve the statistical footing of the trends reported here, and let the neutrosophic classification be tested on a corpus large enough to estimate its thresholds empirically rather than by convention. It would also make it possible to look specifically for the 2024–2025 applications of STD in the social sciences and public health that are still absent from the indexed literature, which would speak directly to the generalizability of the conclusions.

9. Conclusions

This review set out to map the literature on sparse Tucker decomposition and to test whether a neutrosophic framework could describe a small, uneven evidence base more

honestly than citation counts alone; the findings below stay within what those 13 records actually support.

Each claim that follows is tied to a specific figure, table, or record in the body of the paper, and where the evidence is thin, we say so rather than generalizing beyond it.

The analysis concludes that sparse Tucker decomposition (STD) is an emerging field with moderate but sustained growth, evidenced by the 13 publications identified between 2013 and 2025, with an inflection point in 2021 (three publications, 38 citations, Figure 2). STD shows significant impact in technical areas such as parallel computing (codes 006, 007, 008), machine learning (code 001), and neuroscience (codes 005, 013), but its application remains limited in societal domains, such as social sciences or public health, due to technical barriers and low interdisciplinary transfer. The integration of plithogenic neutrosophic hypersoft sets (PNHS) in Section 4 reveals that, with classification now fully resolved for all 13 documents (Table 5), one document is Consolidated (code 006, $T = 0.250$), one is Intermediate (code 010, $T = 0.231$), and eleven remain Emerging, with indeterminacy reported only where applicable (codes 006 and 013). This distribution highlights the need to overcome these limitations to expand its reach.

The geographic concentration of scientific production in China and the United States (Figure 3), with peripheral participation from countries such as Argentina and the Netherlands, underscores the need to foster more equitable collaborative networks. Neutrosophic analysis indicates that the low diversity of international collaborations limits the incorporation of regional perspectives, which could enrich STD applications in global contexts.

The high potential of STD for the analysis of complex data, such as in brain connectome reconstruction (code 009) or compression in MIMO systems (code 002), depends on integrating technical developments with practical applications. The standardization of algorithms and the development of open-source libraries in Python or R are essential to improve accessibility and facilitate its adoption in emerging disciplines. Extending STD to fields it has not yet reached—economics and the social sciences among them—is a plausible next step rather than something this review can claim to have demonstrated: none of the 13 studies analyzed here comes from those areas, so we frame it as a direction to test, not an established result.

This study, by combining rigorous bibliometric analysis with a neutrosophic approach, provides a basis for research that strengthens the development and utility of STD. The proposed agenda prioritizes accessibility, interdisciplinarity, and theoretical soundness, promoting the development of STD as a cross-cutting analytical tool capable of addressing scientific and social challenges with a reflective and ethical approach.

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Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author. The study was based on bibliographic records retrieved from the information sources identified in Section 2. The compiled search and analysis files were not deposited in a public repository, and no backup copy is currently available. Consequently, no additional dataset can be provided. The consulted sources, search strategy, selection criteria, and analytical procedures are described in the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

STD	Sparse Tucker Decomposition
PNHS	Plithogenic Neutrosophic Hypersoft Set(s)
T, I, F	Truth, Indeterminacy, Falsity (neutrosophic membership degrees)
a1, a2, a3, a4	Attributes: productivity, impact, international collaboration, thematic relevance
MCDM	Multi-Criteria Decision-Making
CP	CANDECOMP/PARAFAC (Canonical Decomposition/Parallel Factors)
HOSVD	Higher-Order Singular Value Decomposition
SGD	Stochastic Gradient Descent
HHLST	High-order, High-dimensional, Large-scale Sparse Tensor
WoS	Web of Science
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
TITLE-ABS-KEY	Scopus search field (Title–Abstract–Keywords)
TS	Topic Search (Web of Science search field)
CSV	Comma-Separated Values
DOI	Digital Object Identifier
ORCID	Open Researcher and Contributor ID
ISSN	International Standard Serial Number
URL	Uniform Resource Locator
OSF	Open Science Framework
GPU	Graphics Processing Unit
CPU	Central Processing Unit
FPGA	Field-Programmable Gate Array
MPI	Message Passing Interface
SpMV	Sparse Matrix–Vector Multiplication
MIMO	Multiple-Input Multiple-Output
MU-MIMO	Multi-User Multiple-Input Multiple-Output
MRI	Magnetic Resonance Imaging
dMRI	Diffusion Magnetic Resonance Imaging
LiFE	Linear Fascicle Evaluation
IEEE	Institute of Electrical and Electronics Engineers
ACM	Association for Computing Machinery
SIAM	Society for Industrial and Applied Mathematics
BMJ	<i>The BMJ</i> (formerly <i>British Medical Journal</i>)
ICASSP	International Conference on Acoustics, Speech and Signal Processing
DSP	International Conference on Digital Signal Processing
UAI	Conference on Uncertainty in Artificial Intelligence
SCIS	International Conference on Soft Computing and Intelligent Systems
ISIS	International Symposium on Advanced Intelligent Systems
IJNS	<i>International Journal of Neutrosophic Science</i>
JCCE	<i>Journal of Computational and Cognitive Engineering</i>

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