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Food Derived Biostimulants Technology Revealed and Retrieved by Natural Language Processing

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Abstract

Food-derived biostimulants support sustainable agriculture; however, the scale and heterogeneity of the field hinder their synthesis. We profiled 2005–2025 innovation by mining 2,586 PATENTSCOPE filings and Web of Science articles; texts were analyzed with KH Coder and topic models, with large language models assisting in interpretation. Patent activity surged after 2018, emphasizing plant growth promotion, yield stability, and abiotic stress tolerance (amino acids, seaweed extracts, polyphenols, humic substances, and microbial consortia). In parallel, academic papers have shifted from descriptive trials to mechanism-level work on drought/salinity responses, gene expression, and metabolomics. Together, these signals outline a translation path in which deployable biological inputs converge with mechanistic evidence. Our NLP pipeline distilled heterogeneous texts into actionable indicators, yielding a reproducible map from patent/literature trends to testable hypotheses for formulation, dose, and seed stage delivery.

Keywords: Biostimulants, Sustainable agriculture, Health information science, Text mining, Patent analysis

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1. Introduction

In the context of global challenges, including food security, environmental conservation, and climate change adaptation, the imperative for sustainable agricultural practices is escalating, accompanied by a surge in interest in innovative solutions to these challenges [1–3]. Plant biostimulants have emerged as a promising approach that offers a means to enhance crop productivity and resilience while minimizing the reliance on traditional pesticides [3,4]. Biostimulants are substances or microorganisms that, when applied to plants, seeds, or the rhizosphere, stimulate natural processes to improve nutrient absorption, nutrient-use efficiency, abiotic stress tolerance, overall crop quality, and yield [5,6]. This definition has evolved from the initial concept, which sought to differentiate biostimulants from fertilizers and pesticides [1,3]. This emphasizes the functional effects of these minerals on plant physiology rather than their composition [7,8]. The European Biostimulant Industry Council (EBIC) has further elucidated that these effects are independent of the nutrient content of the product and emphasized its unique mode of action [9,10].

The global biostimulant market is undergoing substantial expansion, a trend that is projected to persist in the future. This expansion can be attributed to several factors, including the increasing demand for organic foods and foods produced using sustainable methods and the growing awareness of the environmental impact of traditional agriculture. Biostimulants encompass a diverse array of substances, including humic substances, seaweed extracts, protein hydrolysates, amino acids, beneficial

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microorganisms, chitin, and inorganic compounds [5]. In recent years, there has been increasing interest in the use for food-derived components, including amino acids, organic acids, and polyphenols, as active ingredients in biostimulants formulations [11,12]. These components can be sourced from existing food manufacturing processes or by-products, aligning with the principles of a circular economy and offering the potential to develop new, effective, and sustainable agricultural materials [13,14]. The integration of food chemistry and agricultural science has the potential to yield innovations that enhance crop yield, improve product quality, and reduce environmental impact [15].

However, the rapid increase in research and development and patent applications in the field of biostimulants, particularly those derived from food compounds, poses a significant challenge to comprehensively and quantitatively understand these technological trends [16,17]. A comprehensive analysis of the literature metrics was conducted for the entire field of biostimulant research, identifying significant research areas, active countries, and influential publications [18,19]. Moreover, the implementation of "omics" technologies (genomics, transcriptomics, proteomics, and metabolomics) is facilitating a more profound comprehension of the mechanisms underlying the actions of biostimulants, thereby propelling research from a descriptive, phenomenological level to a more mechanistic, explanatory paradigm [20,21]. However, conventional methods for reviewing and analyzing voluminous academic literature and patent information can be time-consuming, costly, and require expertise, hindering the ability to keep pace with rapidly evolving circumstances.

The advent of sophisticated analytical technologies, including text mining and natural language processing (NLP), has provided researchers with potent instruments to traverse this "information deluge" [22,23]. These computational approaches are being applied to increasingly complex challenges, from developing deep learning frameworks for medical diagnostics, such as COVID-19 [24], to designing hierarchical adaptive evolution frameworks for privacy-preserving data publishing [25]. Furthermore, AI-driven encryption methods are being developed to secure sensitive information in big data analysis and brain-computer interface technologies, underscoring the broad utility of intelligent data processing [26,27]. Similarly, recent studies have demonstrated the application of machine learning in detecting phishing websites by combining lexical, host, and content-based features [28], using spectrum estimation with neural networks for event extraction [29], and analyzing professional perceptions of teledentistry to balance accessibility with data security concerns [30]. In recent years, significant advancements have been made in these technologies, largely attributable to the integration of large language models (LLMs), which facilitate more precise analyses [31,32]. These computational tools facilitate the efficient and accurate processing of large volumes of text data contained in academic papers and patents, revealing underlying trends and knowledge structures through keyword extraction, co-occurrence network analysis, and topic-based clustering [33,34]. Text mining has been used to analyze research trends in various scientific fields [35]. Within the patent domain, Jiang and Goetz provide a recent survey of NLP methods for tasks such as patent text classification and retrieval, highlighting structural and terminological characteristics of patent texts that complicate tokenization and normalization [14]. Roh et al. demonstrate an NLP-based methodology for structuring and layering technological information in patent documents, illustrating how such processing can support technology roadmapping and prior-art analysis, in line with work on cross-lingual patent search [31]. However, research that utilizes natural language processing technology to analyze the technological trajectory of food-derived biostimulants across patents and academic literature is novel and timely.

This study aimed to systematically analyze patent and academic databases, primarily using text mining and natural language processing technologies, with supplementary analysis using large language models (LLMs) as needed. The primary objective of this study was to elucidate the existing technological advancements and emerging development trends in biostimulants that utilize food-derived components, such as amino acids, organic acids, and polyphenols. This study aims to provide a comprehensive overview of the current state of innovation in this area. To this end, quantitative evaluations of publication and patent activities were conducted, key researchers were identified, and the interrelationships between different food-derived components and their target applications were mapped.

2. Material and Methods

2.1. Data Collection

In this study, patent information and academic literature were independently analyzed to elucidate technological trends associated with biostimulants that use food components. Patent information was collected using PATENTSCOPE, a database provided by the World Intellectual Property Organization (WIPO). PATENTSCOPE was selected because of its extensive collection of domestic and regional patent databases, making it well-suited for a comprehensive investigation of international patent data. The Web of Science (WoS) Core Collection by Clarivate was used to collect academic literature. WoS is a comprehensive database that encompasses high-quality peer-reviewed academic information across various disciplines. It is a widely used tool for analyzing academic research trends and evaluating influence, which is why it was selected for this study.

2.2. Patent Information Analysis

In the analysis of patent information, PATENTSCOPE was utilized as the database, and the search period covered all available filings up to May 21, 2025, without specifying a lower bound on the filing year. In this patent workflow, a large language model was used only as a post-processing aid to assign human-readable labels to the LDA topics and to draft short narrative summaries of the main patent themes, while all quantitative text-mining steps were implemented with KH Coder and Python. The search strategy was developed by integrating three primary concepts: (1) terms associated with biostimulants, (2) terms associated with broad food ingredients and natural substances, and (3) related patent classifications. This integration was achieved through the implementation of an AND search, as illustrated in Table 1.

Table 1. Outline of patent search strategy (PATENTSCOPE)

Search Component	Description / Example Keywords (Conceptual)	PATENTSCOPE Search Field(s) (Targeted)
Concept 1: Biostimulants	biostimulant	Title (EN_TI), Abstract (EN_AB), Claims (EN_CL), Description (EN_DE)
Concept 2: Food Components & Natural Substances	Broad list including food component*, food-derived, amino acid*, seaweed extract*, plant extract*, humic substance*, waste*, by-product*, etc. (Refer to Appendix A for detailed list)	Title (EN_TI), Abstract (EN_AB), Claims (EN_CL), Description (EN_DE)
Concept 3: Patent Classifications	A01N*, C05G*, C05F*, A01P21/00, etc.	CPC
Boolean Logic	(Concept 1) AND (Concept 2) AND (Concept 3)	

The search fields included the invention title (TI), abstract (AB), claims (CL), and descriptions (DE). PATENTSCOPE's multilingual search functionality (CLIR) was also employed. Consequently, the search conducted on May 21, 2025, yielded 2,586 patent documents for analysis. The bibliographic information and invention titles of each patent were extracted, and preprocessing was performed, including the removal of exact-duplicate and patent-family-duplicate records. Subsequently, text mining was conducted using the "invention title (TI)" of the patents as the primary analysis target. We did not perform a formal sensitivity analysis comparing title-only inputs with combined title-and-abstract inputs for the patent corpus; this choice is therefore acknowledged as a limitation of the patent text analysis. The analysis was conducted using the freely available KH Coder software. In KH Coder, we applied tokenization, removed non-informative function words using a custom stopword list, and registered key multi-word technical expressions in a user dictionary so that they were treated as single tokens. The software was employed to analyze the number of patents by filing year and to extract and frequency analyze major keywords based on morphological analysis, co-occurrence network analysis of keywords, and hierarchical cluster analysis. To further refine the insights derived from the text mining results, we employed a large-scale language model (gpt-4.1-2025-04-14) as an auxiliary tool for the analysis. The extraction of new technical perspectives was attempted, and support was provided for the interpretation of the analysis results. The objective of this study was to identify potential technological trends and unexplored research areas (white spaces). Additionally, we applied probabilistic topic modeling (latent Dirichlet allocation, LDA) to a set of invention titles (TI) to extract coherent technical themes. Topic proportions were aggregated in five-year bins to visualize longitudinal shifts, and topic labels were assigned post-hoc by inspecting the top-weighted terms. To select and estimate the LDA model, we compared solutions with different numbers of topics and chose the one in which the top-weighted terms in each topic were most interpretable and stable, and LDA was estimated using KH Coder's default symmetric Dirichlet priors for document–topic and topic–term distributions.

2.3. Academic literature Analysis

In the analysis of academic literature, the Web of Science (WoS) Core Collection was used as the database, and the same time period as the patent analysis (May 22, 2005, to May 21, 2025) was set as the target. The search strategy involved the combination of "biostimulants" with a comprehensive array of food ingredient and natural substance-related terms, including amino acids, organic acids, and polyphenols, using an AND search to identify peer-reviewed academic papers; the full list of search strings and synonym groups is summarized in Table 1. The data collected on May 21, 2025, encompassing paper titles, abstracts, keywords, and other relevant elements, were meticulously pre-processed into a format conducive to analysis using KH Coder. The analysis targeted the "Abstract" section of each paper. Following a series of preprocessing steps, including text cleaning, removal of duplicate records, and the application of a custom stopword list and a user dictionary to retain key technical expressions as single compound terms, KH Coder was used to perform the primary analysis. Specifically, we conducted a trend

analysis to track keyword frequency changes over time, a co-occurrence network analysis, a hierarchical cluster analysis to identify major research areas, and a correspondence analysis to visualize the relationship between keywords and external variables. Similar to patent analysis, we employed LLM as an auxiliary instrument to identify emerging keywords and deepen the interpretation of the analysis results.

All text-mining analyses were performed using KH Coder (version 3.02c) and Python 3.11 running on Google Colab with the following main libraries and utility packages: pandas 2.2.2, NumPy 1.26.4, gensim, scikit-learn, NLTK, pyLDAvis, networkx, matplotlib, openpyxl, and related standard dependencies, and LLM-assisted topic naming and summarization used OpenAI's GPT-4.1 model via the official Python client.

The WoS search was executed on 15 May 2025 using the query TS=(biostimulant) AND (DT==("ARTICLE" OR "REVIEW") AND LA==("ENGLISH")), restricted to publications dated 1 January 2000–14 May 2025. This query returned 3,113 records in total, of which 2,650 were classified as articles and 2,535 were in English prior to deduplication and text pre-processing.

3. Results

We analyzed 2,586 PATENTSCOPE filings (retrieved and deduplicated on May 21, 2025) and Web of Science (WoS) articles spanning 2005–May 2025 using KH Coder for keyword/time-series/network analyses and latent Dirichlet allocation (LDA) for topic discovery. The search strategies for patents and papers are summarized in the Methods section (Table 1). The counts for 2025 are partial, by design. To ensure consistent comparability, outputs were aggregated into five-year windows and inspected against the annual filing baseline so that topic transitions could be interpreted in the context of volume dynamics rather than isolation.

3.1. Patent landscape and Thematic Shifts

Annual counts of food-derived biostimulant filings increased modestly until the mid-2010s and then rose sharply after 2018 (Figure 1).

LDA on patent titles resolves five themes: agrochemical compositions, plant growth promotion technology, plant-based products, biofertilizer technology, and microbial agricultural materials, the shares of which shift over time (Figure 2). In early windows, Agrochemical Compositions dominate; after 2010, their share steadily contracts, while Plant Growth Promotion rises through the 2000s and then plateaus. From the mid-2010s onward, Biofertilizer and Microbial themes became pre-eminent, with the 2020–2024 window and the partial 2025 counts adding further weight to this biological turn. Substantively, the post-2018 inflection (Figure 1) coincided with filings that foreground growth/yield and abiotic stress tolerance through well-established classes, including amino acids, seaweed extracts, humic substances, microbial consortia, and seed-stage delivery (Figure 2). These patterns are consistent with the transition from composition-centered disclosures to function-first claims, aligned with field performance. Agrochemical Compositions dominated early windows but waned after 2010; Plant Growth Promotion rose through the 2000s; from the mid-2010s, Biofertilizer and Microbial themes became pre-eminent. The post-2018 inflection (Figure 1) coincides with filings that foreground growth/yield and abiotic stress tolerance, often via amino acids, seaweed extracts, humic substances, and microbial consortia (Figure 2).

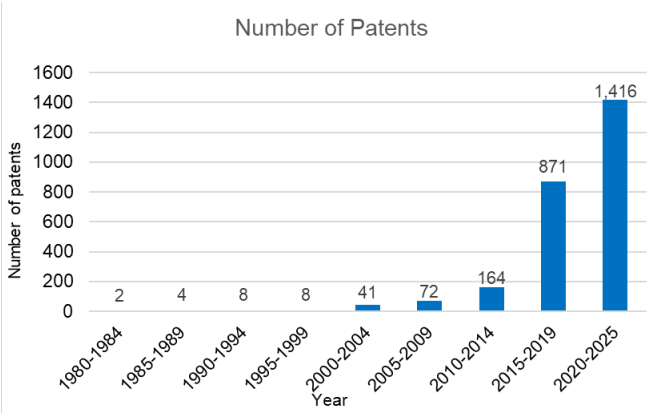

Figure 1. Annual trends in the number of patent applications

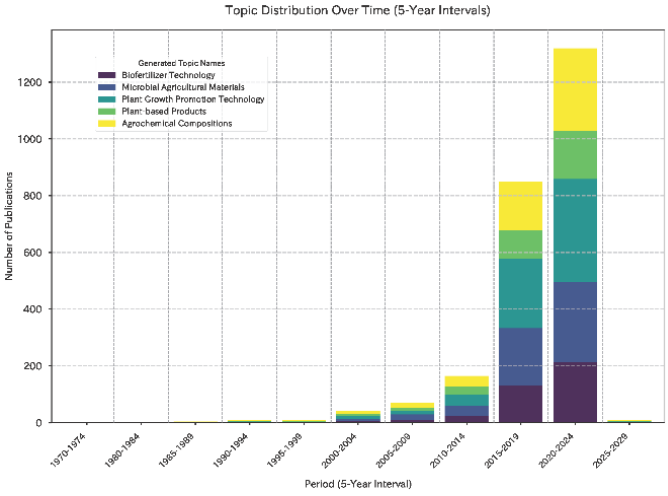

Figure 2. LDA Topic Distribution of Patent Titles Over 5 Year

3.2. Patent Keywords and Technical Content

Keyword trajectories corroborated the shift from process-centric language (processes, coating, release) to function-oriented claims (biostimulant, microbial, stress,

protection, nitrification). Rapidly expanding tokens, such as Bacillus, seed/seedling, nutrition/nutrient, strain, and

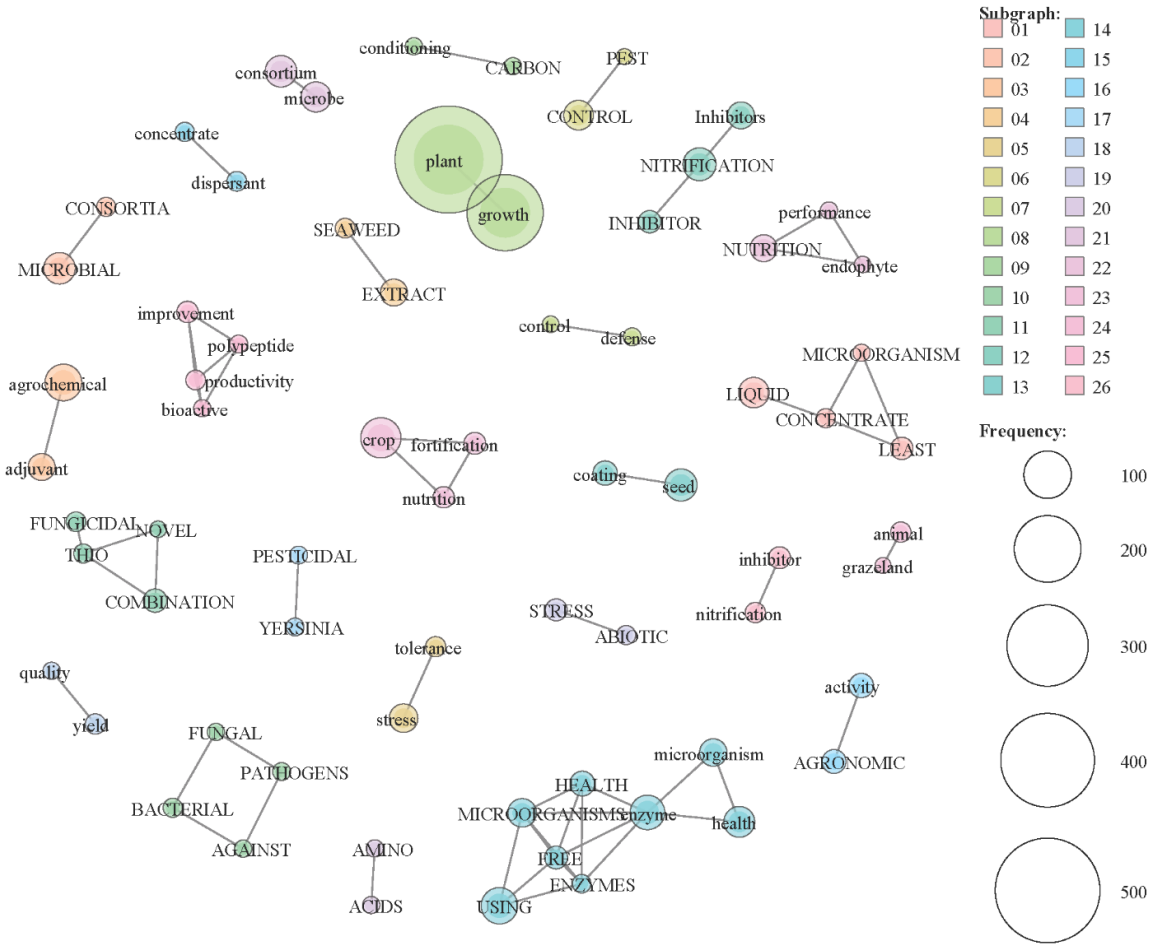

Figure 3. Co-occurrence network of major keywords appearing in patent titles

consortia, indicate scalable routes, including spore-forming taxa compatible with industrial manufacture, seed treatments as a controllable application point, and nutrient-use-efficiency technologies relevant to variable field conditions. Notably, nitrification-related language appears alongside nutrient terms, implying attention to nitrogen loss and soil function within the same functional frame. Table 2 reports representative growth rates and counts for 2014–2023, showing that general-purpose tokens (e.g., novel, producing, organic) have risen in tandem with more targeted technical terms. Together with the LDA results (Figure 2), these trajectories suggest maturation from "delivery of actives" to "engineered biological function" with stress mitigation and nutrient efficiency as anchors.

3.3. Network Structure of Patent Information

The patent co-occurrence network shows a hub-and-spoke architecture centered on plants, composition, and growth, with relatively low inter-cluster connectivity (Figure 3). Distinct modules, microbial utilization, seaweed extracts, humic substances, amino acids, evolve semi-autonomously. Bridge terms such as consortia, formulation, and seed connect otherwise separate modules, indicating the beginning of their integration. This modularity explains the concurrent rapid productization in niches (e.g., Bacillus-based seed
treatments) alongside exploratory development in other niches (e.g., polyphenol co-formulations). It also highlights an actionable opportunity space at the interfaces of microbes, small molecules, and delivery systems, where targeted combinations can convert parallel progress into compounded effects.

Table 2. Patent: Top emerging keywords (2014–2023)

keyword	Growth rate (%)	Count(2014-2023)

novel	6300	64
bacillus	6200	63
nutrition	4500	46
seed	4300	44
application	3900	40
control	3800	39
treating	3800	39
agriculture	3600	37
nutrient	3500	36
strain	3100	32
producing	3050	63
organic	2950	61
fungicidal	2900	30
improved	2500	26
compound	2500	26

3.4. Academic literature Trends and Mechanistic Deepening

The WoS volume expanded markedly after 2010. LDA indicates a shift from application-oriented biostimulants in Agriculture to Abiotic Stress Tolerance as the leading theme from the mid-2010s onward. Early vocabulary emphasized extracts, activity, seaweed, and quality, whereas recent years have concentrated on stress, drought, antioxidants, sustainability, and mechanistic terms (salinity, genes/gene expression, metabolites, proline, and chitosan). The persistence of these mechanistic tokens points to a field that has moved beyond phenomenological screenings towards causal explanations of stress resilience, with seed-stage targets and redox/osmotic regulation as recurring foci. The longitudinal persistence of "new" terms first appearing in 2013–2022 and their frequencies in 2023–2025 is summarized, confirming the consolidation of abiotic stress mechanisms and seed-stage targets in the literature. This consolidation provides a mechanistic substrate against which patentable claims of stress protection and plant health can be framed.

4. Discussion

4.1. Interpretation of Quantitative Results

Taken together, the quantitative patterns (Figures 1–3; Table 2) show a field pivoting from synthetic actives and process language to biologically derived inputs and mechanism-aware and field-relevant functions. The thematic rise of biofertilizer/microbial materials (Figure 2) and vocabulary centered on stress, protection, and nutrient efficiency (Table 2) aligns with the surge in filings after 2018 (Figure 1). Importantly, the keyword mix indicates not only interest in microbes per se but also attention to delivery points (seed/seedling) and soil-process modulation (nitrification), which are coherent with the claims of yield stability under abiotic stress. In parallel, the literature's move from phenomenology to gene/metabolite-level explanations provides a mechanistic substrate for targeted product claims, tightening the link between discovery science and deployable functionalities.

4.2. Industry, Academia Coupling and Translation Timing

Patents emphasize deployable functionality, including microbial inputs, formulations, and yield stability, whereas academic work focuses on drought/salinity responses and redox/osmolyte regulation. This time-lagged coupling suggests that mechanistic consolidation in the literature precedes and likely catalyzes patent surges, claiming stress protection and plant health. The prominence of Bacillus in filings (Table 2) mirrors the manufacturability and efficacy demonstrated in plant–microbe research; seed-stage interventions visible in both corpora (Table 2) are natural convergence points for precision delivery. Programmatically, aligning crop × stage × environment prescriptions with formulation choices can compress translation timelines and improve field reproducibility without increasing the input complexity.

4.3. Methodological Considerations

The KH Coder + LDA pipeline efficiently surfaces macro-level trends and structures from heterogeneous corpora, and LLM-assisted reading aids topic labeling and sparse network interpretation. However, results depend on search/query design and stopwording summarized in the Methods section (Table 1) and on the use of patent titles and paper abstracts rather than full texts; the 2025 patent counts are partial and are tied to a single retrieval date. These factors should temper the interpretation of apparent inflections (Figure 1). Additionally, exogenous factors such as updates to patent and literature classification schemes, delays between filing, publication, and database indexing, and gradual changes in PATENTSCOPE and WoS coverage may modulate the apparent timing and magnitude of these inflections. These processes can shift counts between adjacent years or five-year windows without corresponding changes in the underlying innovation intensity.

Nonetheless, the convergence across independent lenses, time series, topic shares, keyword growth, and co-occurrence structure, supports the robustness of the main inferences and makes it unlikely that classification or coverage changes alone explain the post-2018 acceleration and thematic consolidation.

4.4. Implications and Outlook

Evidence supports four near-term priorities: (i) mechanism-informed consortia design combining microbes with small molecules (amino acids, polyphenols)

against defined abiotic stresses; (ii) stabilization and precision application, aligning formulation, dose, and timing with crop × stage × environment; (iii) discovery from circular biomass with standardized, biomarker-anchored evaluation to accelerate triage; and (iv) life-cycle/co-benefit assessment to quantify economic and environmental/health impacts and support its adoption. Advancing these will connect the patent-observed push towards deployable biological inputs with the literature's mechanistic depth, accelerating the translation from resilient production to broader health outcomes. In practical terms, prioritizing seed-stage delivery for drought/salinity contexts and pairing it with nutrient-efficiency levers identified in Table 2 could offer immediate, testable pathways while longer-horizon integrations across the network modules (Figure 3) are being developed. To further support reuse of the NLP pipeline in adjacent agri-tech domains, we will, within the licensing constraints of Web of Science and WIPO PATENTSCOPE, provide as supplementary material (i) complete search strategies, (ii) detailed summary statistics of the patent and literature corpora.

5. Conclusion

This study comprehensively analyzed the technological development trends of biostimulants derived from food ingredients over the past two decades. The analysis was conducted from both patent and academic literature perspectives, with the complementary use of text mining and large language models (LLMs). The analysis confirmed that interest in research and development activities in this field has increased dramatically since the late 2010s. Patent information revealed the active practical application of the characteristics of major components such as amino acids, seaweed extracts, and humic acids. Concurrently, academic literature has focused on fundamental mechanistic studies, including the elucidation of abiotic stress response mechanisms. These studies suggest that research trends are evolving towards a molecular-level understanding. The objective of the text-mining process, facilitated by KH Coder, was to provide a comprehensive visualization of key technical themes. The use of an LLM not only supported the interpretation process but also yielded additional insights, including the identification of novel prospects for technological collaboration and exploration of research areas that had not yet been investigated. The analytical approach adopted in this study is effective in efficiently extracting important trends from the vast amount of information in this rapidly developing field and providing basic knowledge that will contribute to future research and development strategies and policymaking. Food component biostimulants are key technologies for sustainable agricultural production, and the trends and insights revealed in this study are expected to contribute to their development.

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