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Article

Advancing genetics of agriculture and biomolecules: A BERTopic-based analysis of research evolution in leading agricultural universities

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Abstract: This study investigates the evolution of research at leading agricultural universities, with a particular focusing on genetics of agriculture and biomolecules as central themes. The objective is to identify trends, knowledge evolution pathways, and the relationship between scientific innovation and technological application. Utilizing the BERTopic model, a word-embedding-based topic extraction approach, the study analyzed data from cited articles and citing patents sourced from Web of Science and Lens databases. Key methodologies included advanced text preprocessing, topic clustering using Uniform Manifold Approximation and Projection (UMAP) and Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN), and knowledge evolution analysis based on topic heat and cosine similarity metrics. The findings indicate that research on the genetics of agriculture and biomolecules play a critical role in driving both fundamental science and application-oriented innovation. A strong correlation between cited articles and citing patents was observed, particularly at institutions such as the University of Tokyo and Kyoto University. Notably, genetics-related scientific outputs were associated with denser knowledge networks, while biomolecule-focused patents demonstrated more pronounced application trends, highlighting the translational potential of these innovations. Over time, research in genetics of agriculture and biomolecules intensified, underpinning their critical role in addressing global challenges like food security and sustainable development. This analysis offers insights into interdisciplinary convergence and the dynamic interplay between science and technology, contributing to strategic planning and policy development for agricultural innovation.

Keywords: BERTopic; knowledge evolution; research trends; genetics of agriculture; biomolecule

1. Introduction

Ensuring global food security in the face of population growth and resource limitations necessitates continuous advancements in agricultural science and technology. The 21st century presents the farm sector with unprecedented challenges. Feeding a rapidly growing global population while minimizing environmental impact necessitates significant advancements in food production practices [1–3]. In July 2023, the United Nations Food and Agriculture Organization and other agencies jointly released the "State of Food Security and Nutrition in the World" report, stressing that global food security still faces multiple challenges, and the transformation of agricultural and food systems toward sustainable development remains a daunting task [4]. Universities have increasingly emphasized their role in social service since the well-known "Wisconsin Idea" was proposed in the early 1900s.

Through multiple channels of industry-university knowledge transfer, universities have gradually formed a positive interaction with regional, industrial, and social development [5]. Today, modern universities should step out of academic isolation, integrate into society, and take on greater responsibility for promoting social development in order to achieve excellence [6]. Agricultural universities, since their inception, have been shouldering the mission of serving the nation and the people, cultivating a large number of agricultural talents, promoting the transformation of agricultural scientific and technological achievements, and balancing human nutrition, health, and sustainable development [7]. Biomechanics has also emerged as a crucial field in recent agricultural research. It plays an important role in understanding the mechanical properties of plants, soil mechanics related to agricultural machinery operation, and the physical processes involved in livestock movement. For example, studies in biomechanics have helped optimize the design of agricultural tools to reduce soil compaction and improve energy efficiency [8–11]. Therefore, analyzing the research hot topics and evolution pathways of leading agricultural universities is crucial for understanding the academic frontier in the agricultural field. Previous studies by Erndwein et al., Kolb et al., Tomobe et al., Hamza et al., and Baggs et al. [12–17] focused on the biomechanical analysis of crop root systems and their interaction with the soil environment, providing valuable insights for improving crop growth conditions. Another significant work by Arreguit et al., Fethke et al., Behnke et al., Hasahya et al., and Johansson et al. [18–22] investigated the biomechanics of animal locomotion in agricultural settings, which has implications for livestock management and welfare.

Scientific articles are typically used to assess the extent of basic scientific research, while patents are often utilized to measure the level of technological innovation in industry [23–25]. An increasing number of patents that cite scientific articles can foster innovation and promote technological progress and economic growth. The flow of knowledge between science, represented by cited articles, and technology, indicated by citing patents, emphasizes the interconnectedness of research and development [26]. However, some researchers argue that patent citations to articles may not necessarily reflect a simple linear relationship; instead, they suggest a complex interaction between the two domains [27]. Despite this complexity, analyzing such knowledge flow can provide valuable insights into research advancements and potential applications.

Traditional bibliometric methods, such as word frequency analysis co-word networks, and network communities, have been employed to analyze research trends [28–30]. However, these methods have limitations in capturing the semantic relationships between words, potentially leading to inaccurate topic identification. For instance, word frequency analysis might identify frequently occurring individual keywords but fail to capture the broader thematic context [29,31,32]. Co-word analysis, while providing a network of associated terms, can struggle to distinguish between core topics and less significant keywords with high co-occurrence [33,34]. To overcome the limitations of traditional methods and to analyze research trends and knowledge flow, topic modeling techniques have emerged. A knowledge unit refers to the smallest, indivisible, and independent basic unit used in knowledge management, which can be created by combining thematic concepts that encompass several topic terms [35]. These techniques can identify latent topics within a corpus of text data by examining the relationships between words [35,36].

This study leverages the BERTopic pre-trained model, which can fully exploit the semantic features and scientifically and efficiently identify the potential topics of research in leading agricultural universities, compared to the current mainstream models, such as the Latent Dirichlet Allocation model (LDA) [37], the Dynamic Topic model (DTM) [38], and the Biterm Topic model (BTM) [39]. By leveraging pre-trained word vectors, BERTopic can capture semantic relationships between words, resulting in more coherent and meaningful topics [40]. Additionally, BERTopic eliminates the need for manual topic number selection, a complex step in traditional topic models. This allows for a more automated and objective analysis of research trends.

Most studies on the evolution of knowledge conducted by scholars have focused on a single data source [37,41–43]. Only a few have utilized multidimensional data sources [44,45], making it challenging to establish direct connections between these sources [44]. In agriculture-related fields, several researchers have tracked the evolution of topics within specific segments. For example, Lu et al. [46] analyzed the characteristics of topic evolution and future development trends related to land degradation using the WoS core dataset and the Latent Dirichlet Allocation - Hidden Markov Model (LDA-HMM). Similarly, Wei et al. [47] employed the BERT-LDA model to explore the evolution of core technologies in agricultural machinery based on patent data. Differing from previous studies, we use data from papers and patents with citation relationships to measure the knowledge evolution between science and technology at the granularity of knowledge units. All the advances in this study will help scientific policymakers and technological managers to understand the trends of science and technology more effectively, which will provide the basis for strategic decision-making, innovation resource allocation, and development planning in agricultural universities. These insights can also potentially contribute to a more comprehensive understanding of current trends and potential breakthroughs in the agricultural field, ultimately supporting efforts to address global food security challenges.

Nevertheless, our study has some limitations. While we utilize an effective topic model to examine the evolution of knowledge and its relationship between science and technology across different periods at the level of knowledge units, we do not account for the differences between synonymous terms used in basic scientific research and technological innovation.

2. Data sets

2.1. Data sources

The research objects of this paper are the cited articles and citing patents of leading agricultural universities. The article data source is the Web of Science (WoS), and the patent data source is Lens[48]. Articles published by the top 50 global agricultural universities were retrieved from WoS, and the article data was imported into Lens to obtain information on cited articles and citing patents, spanning the period from 1998 to 2022.

2.2. Data statistics

2.2.1. Growth trends in cited articles and citing patents

Figure 1 illustrates the growth trends of cited articles and citing patents. Before 2010, the number of citing patents was consistently lower than that of cited articles. However, after 2010, there was a notable increase in the number of citing patents. Additionally, the count of cited articles experienced a sharp decline, approaching zero after 2017. This observation could be due to a longer citation lag for more recent publications or limitations of the specific database used. To ensure the validity of the results, the following analysis will only focus on cited articles published from 1998 to 2017.

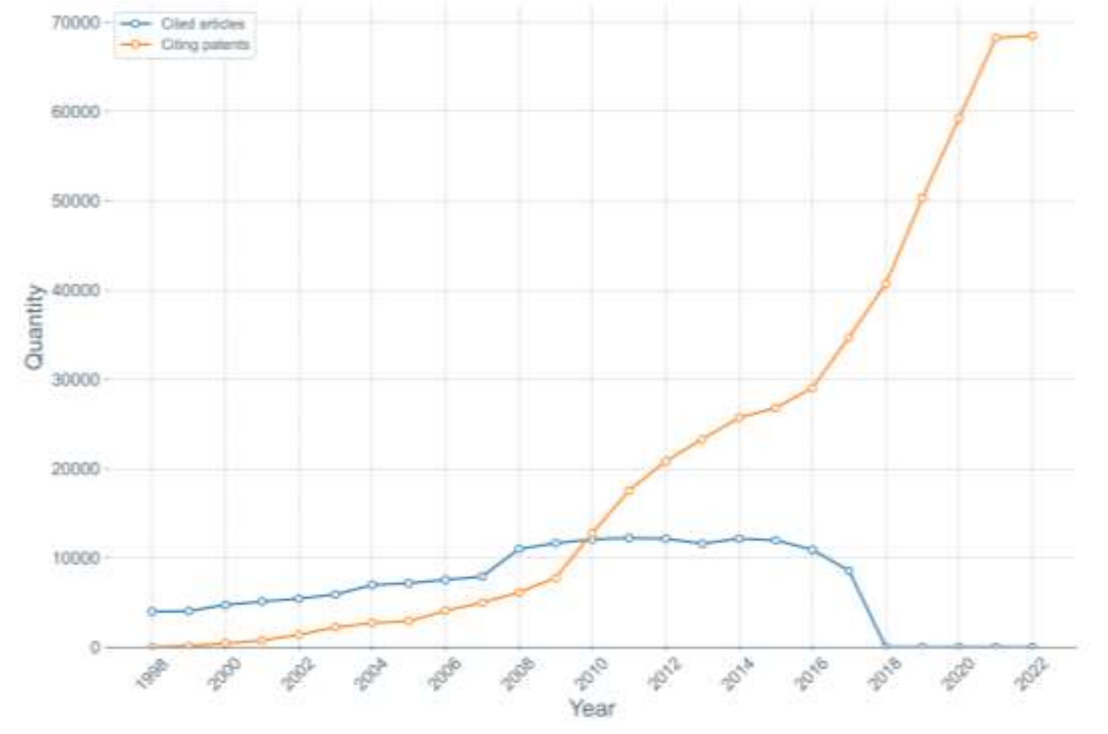

Figure 1. Growth trends of cited articles and citing patents.

2.2.2. Publishing institution analysis

Figure 2 illustrates the distribution of articles across publishing institutions. Both for cited articles and citing patents, the University of Tokyo and Kyoto University hold the top two positions, respectively. Notably, all ten leading universities for cited articles are also among the top ten for citing patents. This observation suggests a positive correlation between the rankings of leading agricultural universities based on cited articles and citing patents. In other words, universities with highly ranked cited articles tend to have highly ranked citing patents as well.

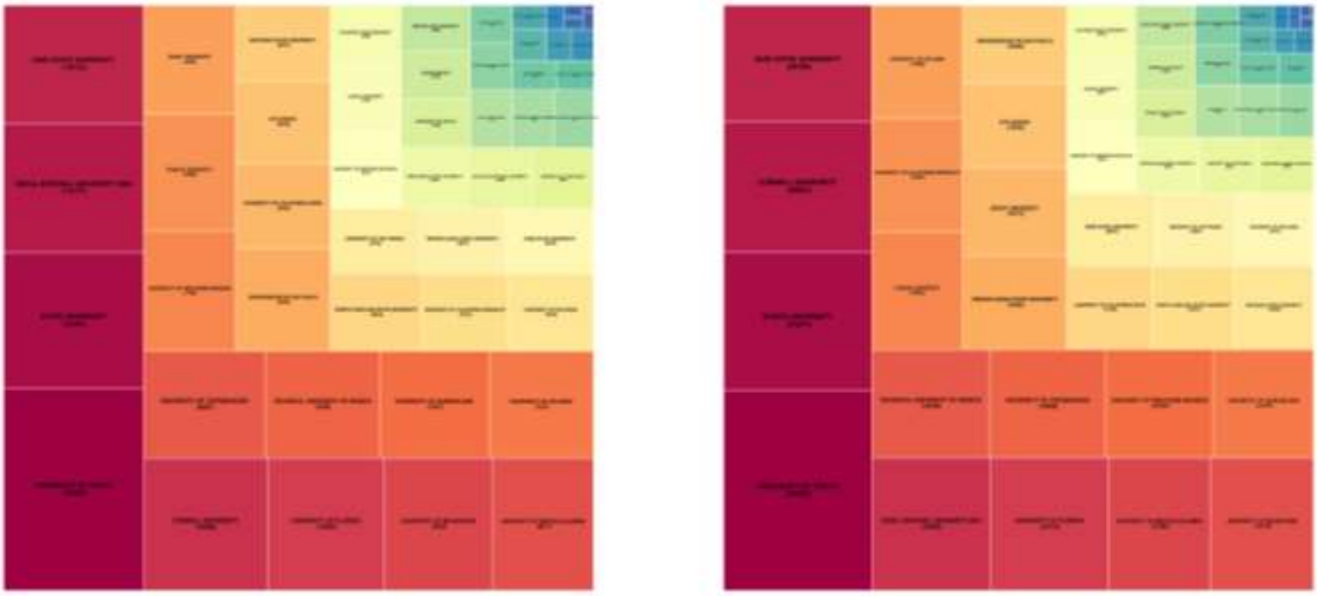

Figure 2. Comparison of publishing institutions for cited articles and citing patents.

2.2.3. Time window analysis

Based on the publication timeline, the data was divided into five stages for both cited articles and citing patents. It is important to note that cited articles are limited to the first four-time windows due to the potential citation lag. **Table 1** presents the publication counts within each time window.

Table 1. Dataset division and publication statistics.

Time Window	Cited Articles Dataset	Number of Articles	Citing Patents Dataset	Number of Patents
First Stage	YPR0	23313	YPT0	2715
Second Stage	YPR1	35504	YPT1	16945
Third Stage	YPR2	59107	YPT2	65010
Fourth Stage	YPR3	55204	YPT3	139555
Fifth Stage			YPT4	286957

3. Methodology

3.1. Research approach

We adopted a two-step approach to uncover the development and changes in research foci:

(1) Topic Extraction with BERTopic: We utilized the BERTopic model, a word-embedding-based topic extraction method, on two sets of data: Cited articles and citing patents. This model addresses the limitations of traditional methods like Latent Dirichlet Allocation (LDA) by leveraging pre-trained word vectors to capture semantic relationships between words and improve topic coherence.

(2) Knowledge Evolution Analysis: After extracting topics, we analyzed their evolution over time. We calculated the topic strength (Support Index) to identify prominent topics in each time window and measured the cosine similarity between topics across different periods. This allowed us to determine the thematic relationships

and evolutionary pathways between research areas. The basic process flow is illustrated in **Figure 3**.

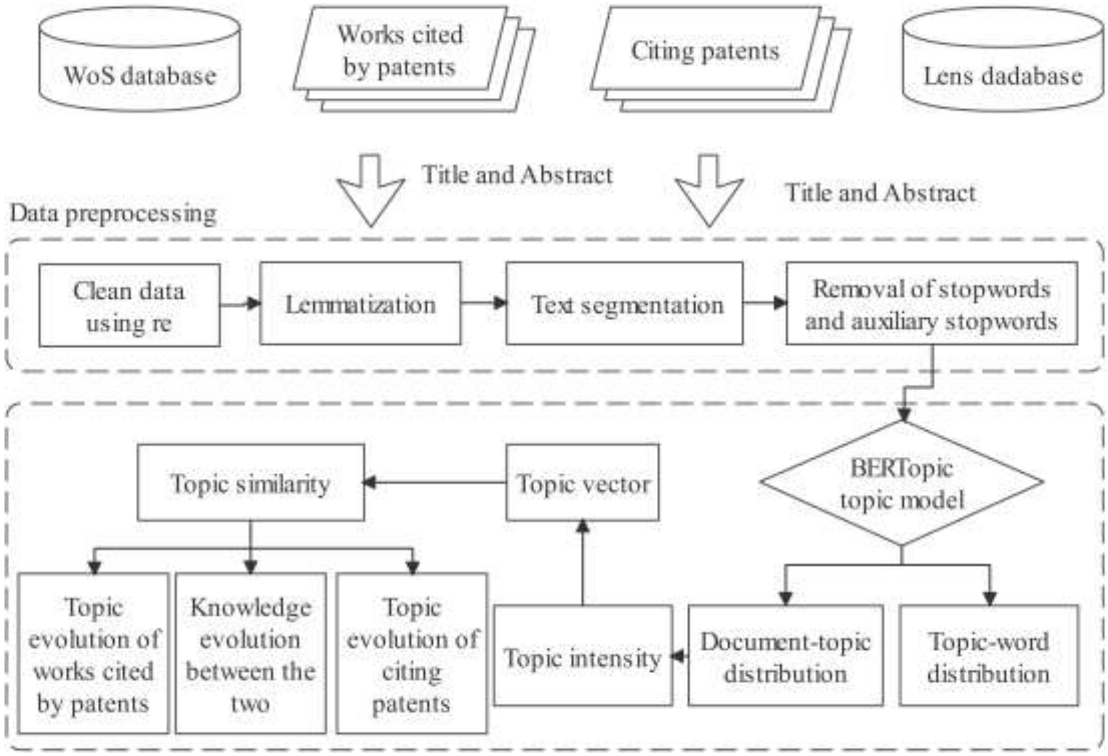

Figure 3. Basic process flow.

3.2. Key technologies

3.2.1. Text pre-processing

The corpus for this model was created by extracting titles and abstracts from the bulk-exported literature data, ensuring that any null values were removed. Irrelevant characters were eliminated using regular expressions. The English text was then tokenized and lemmatized with the help of the NLTK (Natural Language Toolkit) library in Python, while a default stopword list was utilized for filtering. Additionally, a new academic word list [49], which excludes terms like "sequence", "compounds", "energy", and "nuclear", along with a terminology list from the United States Patent and Trademark Office [50], were used as additional stopwords. These lists helped remove the most frequently used vocabulary from academic and patent contexts.

3.2.2. BERTopic model

The BERTopic model is a word-embedding-based topic extraction method designed for large-scale text data analysis [51]. It offers several advantages compared to the widely used Latent Dirichlet Allocation (LDA) model [52]. LDA assumes word independence, leading to difficulties in capturing contextual information and potentially suffering from semantic absence and word ambiguity [53]. In contrast, BERTopic leverages pre-trained word embeddings to encode semantic relationships between words, resulting in more coherent and meaningful topics [40]. Additionally, BERTopic eliminates the need for manual topic number selection, a complex parameter tuning step in traditional topic models. The key steps involved in the BERTopic model are outlined below:

a) Word Embedding: Text from the data sources (cited articles and citing patents) is embedded using the all-MiniLM-L6-v2 pre-trained Transformer-based BERT model [54]. This model offers a balance of efficiency and accuracy in word representation.
b) Dimensionality Reduction and Clustering: The high-dimensional word embeddings are then reduced in dimensionality using the Uniform Manifold Approximation and Projection (UMAP) algorithm [55]. This allows for efficient clustering of the embedded data points using the Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) algorithm [56].
c) Topic Representation Creation: Candidate topic words are identified using class-based TF-IDF (c-TF-IDF) to capture topic-specific keywords. The KeyBERT-Inspired algorithm updates topic vectors by considering the similarity between candidate keywords and existing topic vectors. Finally, Maximum Marginal Relevance (MMR) is employed to select a diverse and coherent set of topic words by minimizing redundancy within each topic. The basic process of this model is illustrated in **Figure 4**.

Among them, UMAP is a non-linear dimensionality reduction algorithm that allows for adjustments in its final low-dimensional data structure through several key parameters. The number of neighboring data points (n_neighbors) determines how many neighboring data points are used in the manifold approximation process, and the minimum distance (min_dist) defines the minimum distance between two points in the embedding. Its workflow includes four steps:

1) Neighborhood Graph Construction: The k-nearest neighbor algorithm is employed to identify the local neighbors of the data points, which helps in forming the fuzzy topological structure of the high-dimensional data.
2) Low-Dimensional Graph Initialization: The initial positions of the data points are set in a low-dimensional space.
3) Optimization: The low-dimensional graph is refined through gradient descent to minimize the difference between the high-dimensional and low-dimensional representations.
4) Output of Low-Dimensional Representation: A low-dimensional data representation is generated for further analysis.

The HDBSCAN algorithm's main parameters include the minimum cluster size (min_cluster_size), which controls the granularity of clusters, and the minimum number of neighbors (min_samples), used to calculate the core distance from samples. Its workflow includes four steps:

1) Density Estimation: Estimate the local density around each data point to identify regions of high and low density.
2) Calculation of Mutual Reachability Distance: Determine the local density of two points and the distance between them. This approach better reflects the density structure of the data.
3) Constructing a Hierarchical Structure: Create a minimum spanning tree and then transform this tree into a hierarchical clustering structure.

4) Extracting Stable Clusters: Obtain the final clustering results by evaluating the stability of the clusters.

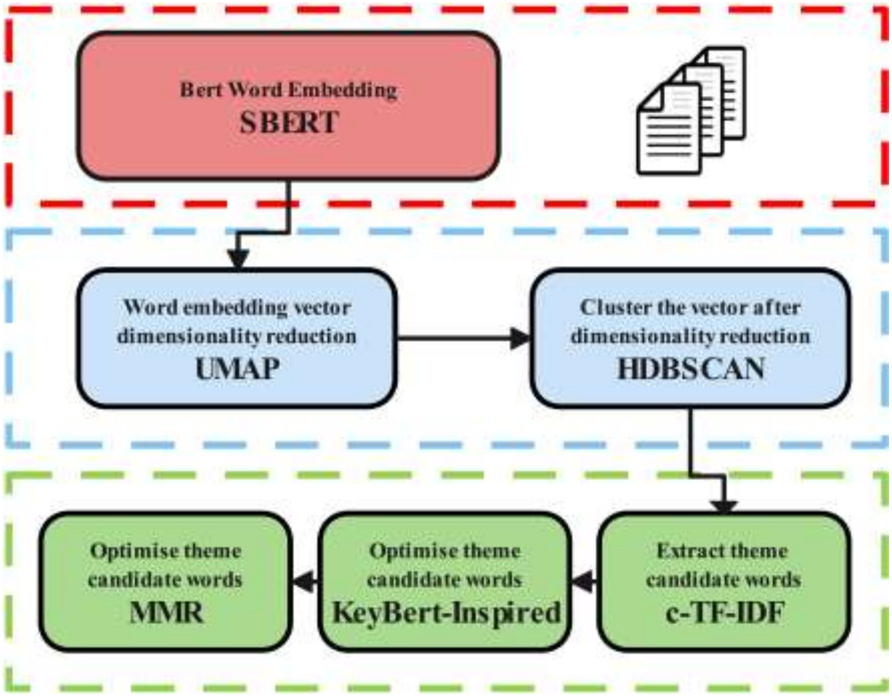

Figure 4. Basic process of BERTopic model.

3.2.3. Topic heat calculation based on BERTopic

The support index is a metric used to quantify the strength of a topic within a specific time window [57]. It reflects the level of attention a particular topic receives in the corpus during that period. The BERTopic model generates a document-topic $\theta(t)$ matrix for different time windows, obtaining the probability distribution of topics in documents, providing a set of supporting documents for each topic. The criterion for evaluating supporting documents is that the probability value generated by a topic is greater than or equal to 10% [58]. The topic intensity can be calculated using the support index, as shown in Equation (1):

$$HT(t) = \frac{S_{T_i}(t)}{n(t)} \tag{1}$$

where $S_{T_i}(t)$ is the total number of documents for topic T_i in time window t, and $n(t)$ is the total number of documents in time window t. The larger the $HT(t)$ value, the larger the proportion of supporting documents for the topic among the total documents, indicating stronger topic strength.

3.2.4. Topic similarity

This paper uses cosine similarity to measure the similarity between hot topics across different time windows, thereby determining the evolutionary relationships and paths between related topics. Cosine similarity measures the difference between two vectors by calculating the cosine value of the angle between them in the vector space. Assuming in an n dimensional vector space, the topic vectors of topics T_i and T_j can be represented as $\{x_1, x_2, \ldots, x_n\}$ and $\{y_1, y_2, \ldots, y_n\}$, the calculation formula is as follows:

$$\cos(\theta) = \frac{\sum_{i=1}^{n}(x_i y_j)}{\sqrt{\sum_{i=1}^{n}(x_i)^2}\sqrt{\sum_{i=1}^{n}(y_i)^2} \tag{2}$$

In the formula, the closer the cosine value of x_i and y_i is to 1, the higher the similarity between the two vectors. We determine the correlation among topics by calculating the cosine values between the topic vectors.

4. Results

4.1. Topic identification based on BERTopic

The pre-processed corpus from the previous steps was input into the BERTopic model for training, and the distribution of topics was obtained for each time window. By calling the visualize_documents() function, each color cluster represents documents belonging to the same topic. Taking the first stage result of cited articles as an example (**Figure 5**), the boundaries between different colored clusters are distinct, indicating a good clustering effect.

In the topic identification process, it was noticed that although not as prominent as genetics and molecular biology related topics, there were some emerging trends related to biomechanics. For instance, in a few clusters, terms related to the mechanical properties of plants and the interaction of agricultural machinery with the soil were sporadically present. However, these were not yet well-developed topics compared to the mainstream ones.

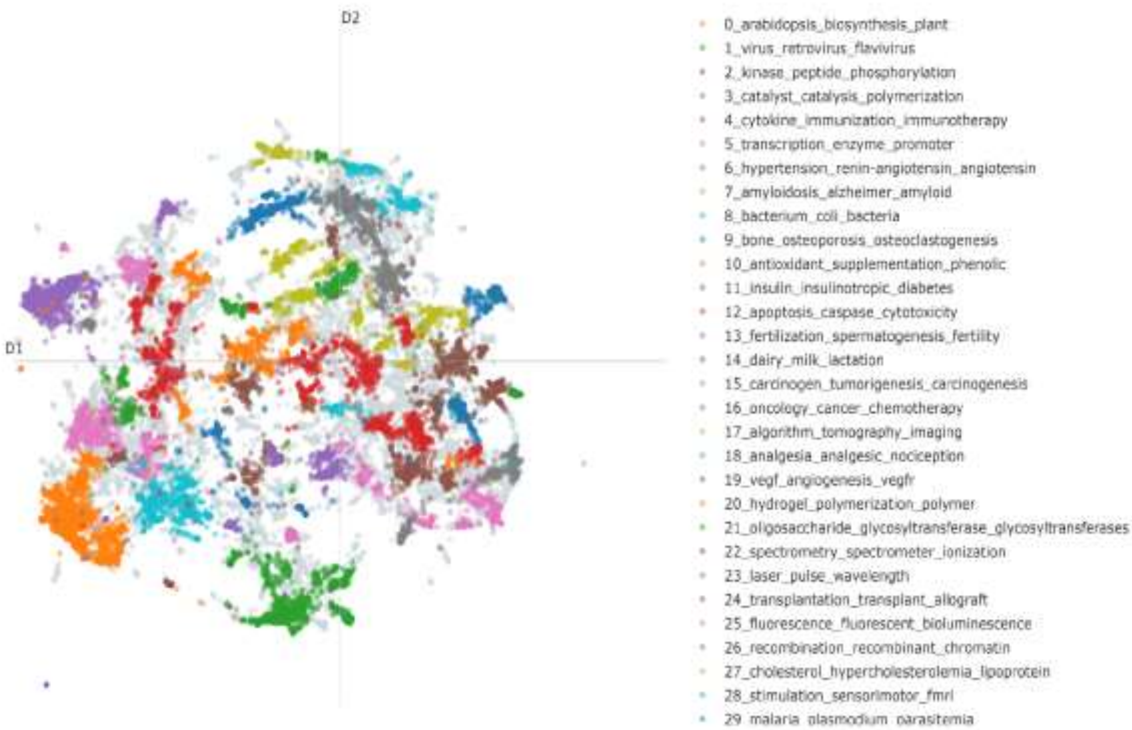

Figure 5. Topic distribution of cited articles in the first stage dataset.

4.2. Analysis of research focus through topic heat

Given the diverse research focus areas within global agricultural universities, this study employs Equation (1) to calculate the topic heat for each identified topic within cited articles and citing patents across different stages. The results are visualized as heatmaps in **Figure 6**, where deeper colors represent hotter (more prevalent) topics, and lighter colors represent cooler (less prevalent) topics.

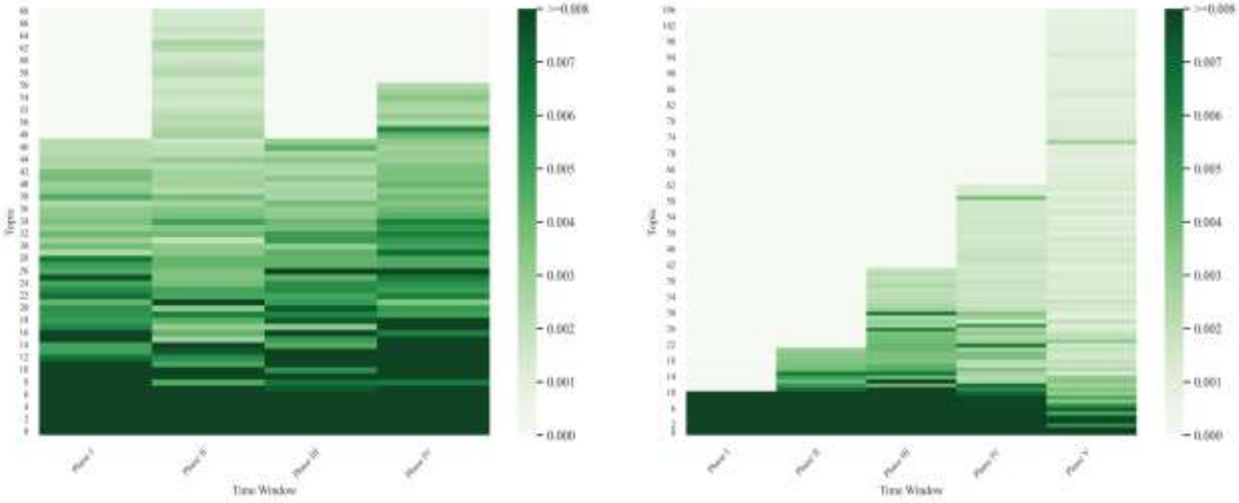

Figure 6. Heatmaps of topics for cited articles and citing patents.

The content analysis of cited articles revealed a focus on research areas such as malaria, insecticides, retinal degeneration, glycosylation, diabetes, analgesia, vaccination, exercise, transplantation, ferritin, bioinformatics, dairy products, arabidopsis genome, quantum technologies, tuberculosis, spectral analysis, hypercholesterolemia, medical imaging, porphyrin, waveguides, and cancer. The contents analysis of citing patents revealed a focus on research areas such as fertilization, nucleotide, diabetes, converter, electrode, immunity, biofuel, biosensor, malaria, skin complaint, glycosylation modification of proteins, protease, and cartilage Regeneration. Notably, while these research topics are not strictly confined to traditional agriculture, they demonstrate a strong connection to fields like genetics and molecular biology. This highlights the increasingly interdisciplinary nature of research within leading agricultural universities.

The content analysis of cited articles and citing patents revealed that while traditional agricultural topics dominated, there were some underlying connections to biomechanics. For example, in the area of plant research, there were occasional mentions of studies on the mechanical strength of plant structures in relation to growth conditions. In the citing patents related to agricultural machinery, a few patents hinted at the consideration of biomechanical principles in design to improve efficiency. However, these biomechanics-related topics did not reach the level of "hot" topics based on our defined thresholds.

The average heat value across all topics served as the threshold for defining "hot" topics. Based on this criterion, the threshold for cited article topic heat was 0.0130, and the threshold for citing patent topic heat was 0.0221. As a result, 30 hot topics were identified in cited articles, while 31 hot topics were identified in citing patents. Notably, the hot topics found in citing patents showed a stronger emphasis on practical applications compared to those in cited articles.

4.3. Knowledge evolution path identification

This section explores the evolution of knowledge within leading agricultural universities by analyzing the relationships between topics in cited articles and citing patents. Cosine similarity (Equation (2)), a metric for measuring the similarity between two vectors, is employed to quantify the relatedness of topics derived from both data sources. Topics exceeding a specific similarity threshold are deemed to share a degree of inheritance and continuity, suggesting an evolutionary relationship.

Topics with a cosine similarity greater than 0.7 between adjacent time windows were determined to have an evolutionary relationship and belong to the same topic evolution path. The cosine similarity function from the sklearn library was used to calculate the cosine similarity, and the open-source pyecharts visualization library was employed to plot Sankey diagrams to illustrate the knowledge evolution relationships, as shown in **Figures 7–9**. In these figures, each node represents a topic, the lines between nodes indicate the direction and connection of topic flow, the thickness of the lines represents the strength of topic similarity, and nodes with similarities to multiple topics have larger label blocks.

Figure 7 presents the topic evolution and development of leading agricultural universities across the four-time windows for cited articles. In the first stage, the topics were YPR0T4_immune factor, YPR0T8_bacterium, YPR0T5_transcription, YPR0T2_protein kinase, YPR0T15_cancer, and YPR0T9_osteoporosis. In the second stage, the topics were YPR1T0_vaccine, YPR1T12_bioinformatics, YPR1T1_cancer, YPR1T4_alzheimer, and YPR1T5_analgesia. In the third stage, the topics were YPR2T1_Arabidopsis genome, YPR2T2_imaging, YPR2T0_cancer, YPR2T22_fertility, and YPR2T4_diabetes. In the fourth stage, the topics were YPR3T6_semiconductor, YPR3T0_Arabidopsis genome, YPR3T11_autoimmunity, YPR3T16_embryo, and YPR3T33_dystrophy, which had higher similarities with multiple other topics, indicating that the domain knowledge represented by these topics received inheritance or derived development from multiple topics.

On the other hand, if a topic performs prominently within a certain period, its evolution has a longer duration, such as YPR0T15_cancer, YPR0T14_dairy, YPR0T29_malaria, YPR0T21_glycosylation, and YPR0T37_thromboembolism in the first stage, which had related research in each subsequent time window. However, these topics were not all the most frequently associated with other topic knowledge. Meanwhile, some new topics emerged in the second and third stages, such as YPR1T38_quantum, YPR1T30_prostatic cancer, YPR1T25_nutritional supplement in the second stage, and YPR2T12_semiconductor nanomaterial, YPR2T7_polymer, YPR2T37_microfluidics in the third stage. These new topics persisted on the timeline, maintaining good domain knowledge inheritance and continuity. Furthermore, in the second stage, many topics became extinct, such as YPR1T62_antibiotic, YPR1T31_cytoskeleton, and YPR1T47_neurotoxin, which did not continue and showed discontinuity.

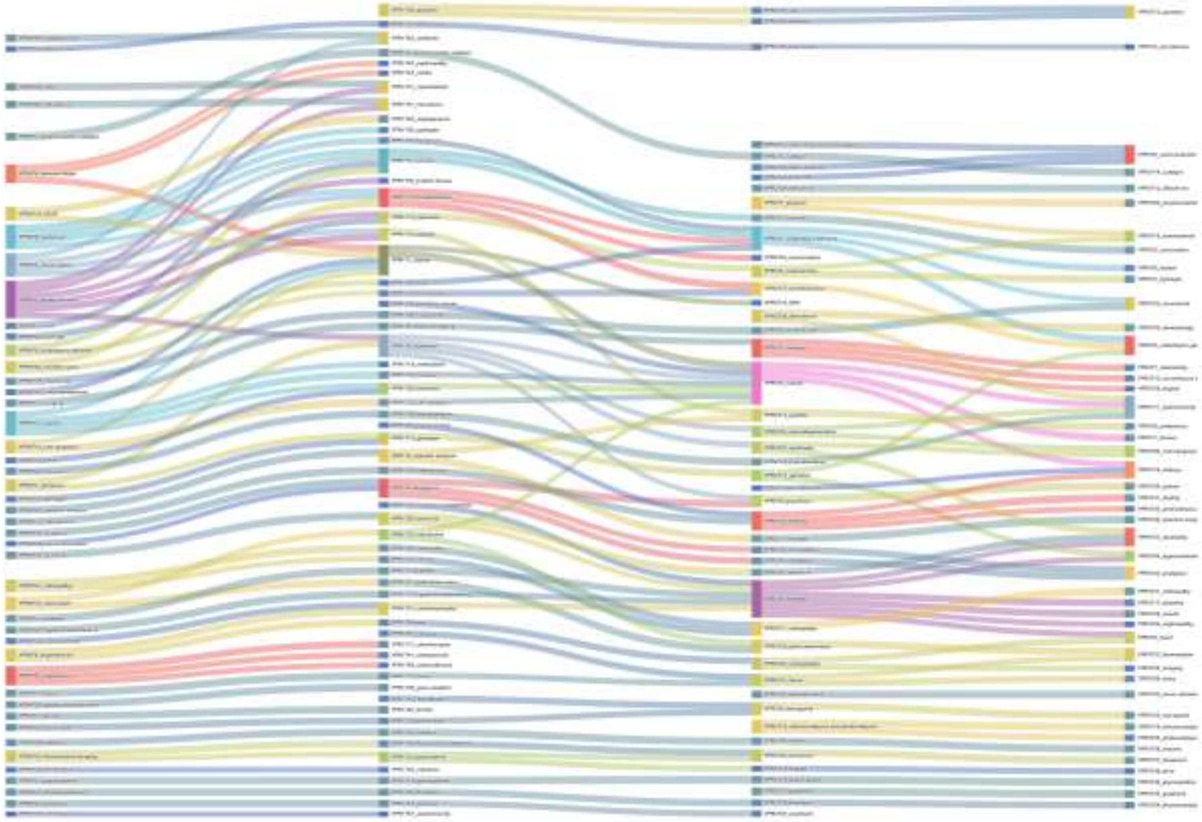

Figure 7. Knowledge evolution of cited articles.

Figure 8 presents the topic evolution and development of leading agricultural universities across the five-time windows for citing patents. In the first and second stages, only one topic exhibited a high degree of knowledge association, namely YPR0T0_cancer chemotherapy, and YPR1T0_nucleotide, respectively. After the second stage, the connections between topics increased, and a large number of new topics emerged starting from the third stage, such as YPR2T14_skin complaint and YPR2T37_gel, most of which maintained good knowledge inheritance and continuity. Among them, YPR2T0_immunity and YPR2T1_sensor in the third stage, YPR3T62_transmethylase, YPR3T0_biochemical indexes, YPR3T9_anti-microbico, YPR3T4_electrostimulation, YPR3T7_video segmentation, YPR3T3_sensing strategy, and YPR3T17_analytical instrument in the fourth stage, and YPR4T32_methylation and YPR4T0_immunotherapy in the fifth stage had higher similarities with multiple other topics. Furthermore, topic extinction began to occur from the third stage, such as YPR2T3_Arabidopsis genome and YPR2T8_genome, where the evolution process was truncated and unable to maintain good continuity.

The knowledge association between domain topics in the citing patent data source showed an increasing trend over time, while the domain topics in the four stages of the cited article data source maintained a relatively stable knowledge association. From an overall perspective, the knowledge association between domain topics in the cited article data source was closer than that in the citing patent data source. The new topics in both data sources maintained a good inheritance and continuity of domain knowledge, but the citing patent data source showed topic extinction later than the cited article data source.

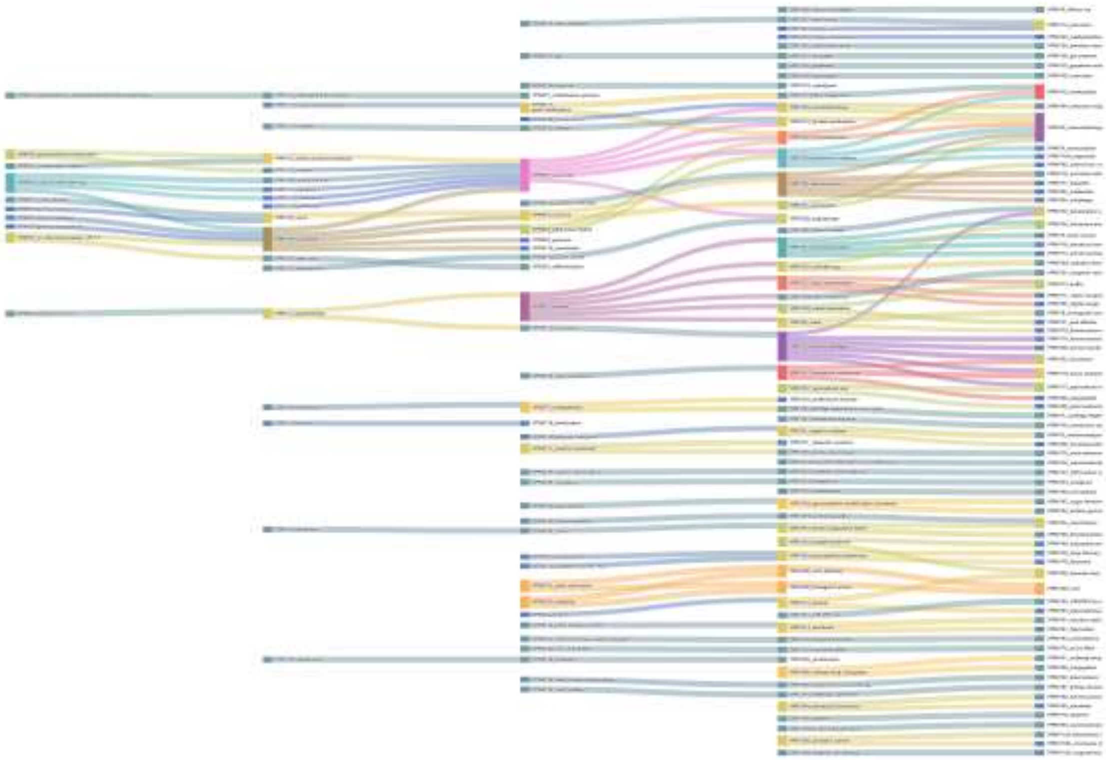

Figure 8. Knowledge evolution of citing patents.

Figure 9 illustrates the knowledge evolution and development between science and technology. In the four stages, there were 16, 28, 35, and 41 evolution paths, respectively, between the domain topics of the cited article and citing patent data sources. It is evident that as the time window progressed, the number of knowledge evolution paths between the domain topics of the cited article and citing patent data sources gradually increased, indicating more frequent and closer knowledge evolution between science and technology.

Among leading agricultural universities, cutting-edge disciplines such as genetics and molecular biology are shown to be prominent research areas due to their multiple appearances in the domain topics and their maintenance of good knowledge inheritance in the evolution of the topics. From **Figure 6**, we notice that these leading agricultural universities do not focus all their research on traditional agricultural aspects, such as bioinformatics, biofuel, quantum technologies, and immunity, although the cited papers and citing patents cover topics related to traditional agriculture. It may be attributed to the fact that the new scientific and technological revolution has led to new demands on the traditional disciplinary system of agricultural sciences, and the crossing and seeping of agricultural and non-agricultural science majors has become a trend in today's higher education to serve the development of society [59,60]. Especially in the 21st century, with breakthroughs and developments in the life sciences, agricultural universities must utilize new biotechnology to transform and upgrade traditional agricultural majors to strengthen interdisciplinary intersection, penetration, and integration [61]. In **Figures 7** and **8**, we can also notice that these emerging disciplines have also maintained a relatively active performance in the process of knowledge evolution, deriving or developing multiple topics. Active performance and technological advances in emerging disciplines offer new solutions for food security and the production of novel biomaterials under changing environmental conditions [62], and the beneficial and complementary relationship between the disciplines will accelerate the achievement of stable and adequate food production [63].

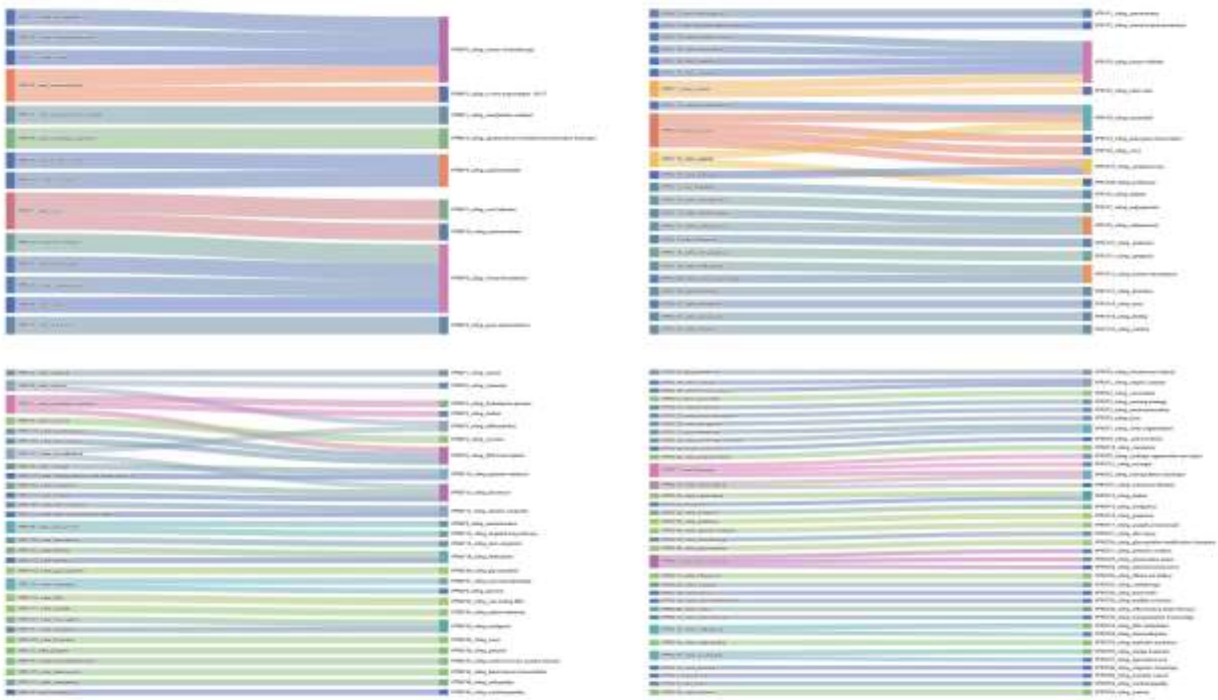

Figure 9. Knowledge evolution of science and technology.

The knowledge evolution of the domain topics for cited papers and citing patents becomes increasingly frequent, the trend of interdisciplinarity is obvious, and the discipline fields involved show high similarities, revealing that the research between science and technology exhibits a high correlation. From **Figure 9**, we can observe that there are fewer knowledge evolution paths for cited papers and citing patents in the early stages, while the knowledge evolution paths are more complex in the later stages.

In the knowledge evolution paths, it was observed that there were some weak connections between certain topics and biomechanics-related concepts. For example, in the evolution of topics related to crop growth, there were intermittent links to the mechanical aspects of plant development. However, these connections were not as strong or continuous as those in other fields like genetics. This indicates that while there is potential for the growth of biomechanics in agricultural research, it is still in an early stage of development.

5. Discussion

Articles are the primary outputs of fundamental scientific research, while patents represent key outcomes of technological innovation. The citation of patents in articles can, to some extent, represent the conversion of scientific knowledge into technological knowledge [64,65]. Accordingly, some scholars have utilized “cited papers-citing patents” data to explore the relationship between fundamental scientific research and technological innovation. For instance, Sun et al. (2023) [66] conducted a trend analysis of SCI-cited papers and citing patents derived from projects funded by the National Natural Science Foundation of China (NSFC) between 2012 and 2021. Their findings revealed that the number of cited papers initially increased and then declined, whereas the number of citing patents exhibited a sustained upward trend. Certainly, this is in line with the trends identified in this study. Patents citing academic articles and the subsequent public disclosure of these patents necessitate a certain period of accumulation [67]. Moreover, similar trends have been observed in other fields. For example, the number of citing patents in graphene technology [68] and biomedicine [69] has experienced rapid annual growth.

In recent years, significant studies related to biomechanics in agriculture have emerged. For example, research on the biomechanics of plant roots has shown that understanding the mechanical forces exerted by roots during growth can help optimize soil conditions and nutrient uptake. Studies have found that by analyzing the root penetration ability and anchoring force in different soil textures, it is possible to develop more effective soil management strategies [14,70–72]. Another area of focus has been on the biomechanics of agricultural machinery operation. By applying biomechanical principles to the design of tractor tires and plowing tools, researchers have been able to improve energy efficiency and reduce soil compaction [73–75].

University rankings are firmly associated with knowledge impact and productivity [76]. Compared to lesser-known agricultural institutions, leading agricultural universities possess higher research platforms and more resources to generate a substantial number of research papers and innovative patents [77]. For instance, both the University of Tokyo and Kyoto University enjoy high reputations in the field of agriculture, with significant research outputs that reflect their capabilities in conducting basic scientific research and technological innovation.

However, the exponential growth in publications, such as papers and patents, renders it increasingly challenging for researchers to read and comprehend this vast array of literature. Amidst the swift progression of artificial intelligence and natural language processing technologies, topic modeling techniques are capable of effectively extracting pivotal information and topics from textual data. This capability allows researchers to continuously monitor the evolution of specific issues over time, thereby capturing the vanguard dynamics within their field of study [35,36]. In policy analysis, these models have been widely used to identify the thematic distribution and developmental trends of policies [78,79]. Specifically in the field of graphene, Teng et al. (2023) [45] tracked the evolution of knowledge using multidimensional data. Their findings revealed that the topics in patents are often more focused on practical applications, with some overlapping topics observed between academic papers and patents. This is highly congruent with the findings of this study, further suggesting that there is a significant knowledge correlation between inventive innovation and theoretical research. Meanwhile, with the continuous development of academic research and the intensification of cross-fusion of disciplines, the research topics of cited papers and citing patents have gone through the process of inheritance, splitting, merging, and extinction. Research topics and knowledge evolution pathways are becoming more complex. Similarly, related studies have observed similar results [43,45], demonstrating a generalized tendency of this phenomenon.

This study has been of great potential to shed light on agricultural policymaking. It can provide policymakers with an accurate basis for decision-making and help them be aware of the research dynamics and cutting-edge directions in the field of agriculture, identifying the current research topics and knowledge evolution pathways of the leading agricultural university through the topic model [80]. Specifically, policymakers can optimize the allocation of research funding for frontier topics of academia revealed in cited papers and assign priority to supporting basic research in these crucial fields to stimulate knowledge innovation and technological breakthroughs in the field of agriculture; Policymakers can encourage the industrialization and application of relevant technologies for cutting-edge topics in citing patents and promoting the efficient transformation of scientific research results. In addition, the robust knowledge evolution path between cited papers and citing patents illustrates that there is a tight synergistic relationship between basic science research and technological innovation and that leading agricultural universities play a pivotal role in the process of knowledge creation and translation. Policymakers have the opportunity to foster deeper collaboration between agricultural universities and enterprises, thereby further enhancing the rate of technology transfer and commercialization [81]. As an example, the establishment of joint research laboratories and technology integration platforms will facilitate the industrialization of university scientific achievements [82]. The adoption of cutting-edge research and technological innovations can be effectively facilitated through these agricultural policies, which, in turn, may offer practical solutions to key challenges related to global food security, sustainable agricultural development, and other pressing issues.

Biomechanics, which has a rich historical background and a solid knowledge foundation, has continuously evolved and identified novel applications within agricultural research. The integration of biomechanics with genetics and molecular biology has unveiled new vistas. For example, by grasping the biomechanical factors that impact gene expression in plants, a more comprehensive understanding for crop improvement can be achieved. The development of biomechanics-related technologies also holds the potential to augment the efficiency and sustainability of agricultural production. The findings of this study demonstrate that sustained research endeavors and investments in this area are of utmost importance for unlocking additional potential benefits and fueling innovation in agriculture. This not only reaffirms the crucial status of biomechanics as an essential discipline but also underlines the necessity for agricultural researchers and policymakers to place greater emphasis on its role in resolving current agricultural challenges and fostering sustainable development.

6. Research conclusions

This comprehensive study investigated the evolution of knowledge within leading agricultural universities by conducting an in-depth analysis of the relationships between topics in cited academic articles and citing patents. The research approach involved a multi-faceted examination of the literature trends, publication characteristics, and thematic developments within this domain.

Firstly, our finding revealed a steady increase in the overall volume of cited articles and citing patents, with a notable inflection point observed after 2010 when the number of citing patents surpassed that of cited articles, indicating an accelerating rate of technological innovation. Further investigation into the institutional rankings highlighted the consistent leadership of the University of Tokyo and Kyoto University, which ranked among the top publishing entities for both cited articles and citing patents. Interestingly, a positive correlation was identified between the publication rankings of these universities' cited articles and citing patents, suggesting a strong alignment between their scientific research and technological development.

Building upon this foundation, the study then employed advanced topic modeling techniques, specifically the BERTopic algorithm, to uncover the domain-specific topics that characterized the knowledge landscapes of the cited articles and citing patents. The analysis revealed that while agricultural sciences were certainly represented, the primary research foci of these leading agricultural universities extended well beyond this traditional domain, delving into cutting-edge disciplines such as genetics, molecular biology, and other interdisciplinary fields. Notably, the hot topics identified within the citing patent data tended to be more application-oriented, reflecting the translational nature of technological innovation.

Delving deeper into the thematic evolution, the study examined the knowledge associations and continuity within the cited article and citing patent datasets separately, as well as the interrelationships between science and technology. The cited article dataset exhibited a rich tapestry of diverse domain topics, which maintained strong knowledge associations and were accompanied by the continuous emergence of new topics, indicative of robust domain knowledge inheritance and continuity. However, the analysis also identified instances of topic extinction during the second stage, suggesting occasional disruptions in the knowledge evolution process. In contrast, the citing patent dataset initially displayed a relatively lower number of domain topics with weaker knowledge associations, but these connections gradually strengthened over time. Starting from the third stage, a proliferation of new topics was observed, although topic extinction also began to occur. Importantly, the study tracked the increasing number of knowledge evolution pathways between the domain topics of cited articles and citing patents, highlighting the growing frequency and depth of knowledge exchange between scientific research and technological innovation.

In conclusion, this study provides a comprehensive and nuanced understanding of the evolving knowledge landscape within leading agricultural universities, illuminating the dynamic interplay between scientific research and technological development. The findings contribute to the broader literature on knowledge flows, interdisciplinary convergence, and the complex relationships between academia and industry in the context oFf agricultural innovation. The insights generated by this research can inform strategic planning, resource allocation, and collaborative initiatives aimed at fostering knowledge-driven progress within the agricultural domain and beyond.

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Supplemental online material: The partial data, the code for implementing the algorithms, and the complete experiment results have been released on GitHub at: https://github.com/lucgyn/BERTopic-paper.

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