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Discover Food

REVIEW

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A bibliometric review for mapping synergies between life cycle assessment and industry 4.0 in the food sector

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Abstract

Purpose Exploring how Industry 4.0 (I4.0) technologies support or intersect with Life Cycle Assessment (LCA) in the food industry reveals a growing but methodologically fragmented body of research. This study aims to map the evolution, key actors, and conceptual developments of this intersection through bibliometric methods.

Methods A total of 414 peer-reviewed publications from 2010 to 2024 were retrieved from Scopus using search strings about I4.0 technologies, LCA and food sector, using the PRISMA protocol. A two-step analysis was conducted: quantitative trends (authors, journals, institutions, countries) and keyword co-occurrence using VOSviewer to detect thematic clusters.

Results and discussion Four thematic areas were identified: IoT for smart agriculture, environmental impact of food industry, AI driven food processes, and food supply chain 4.0. While research activity has intensified post-2020, conceptual integration of Industry 4.0 and Life Cycle Assessment remains limited and fragmented. Several clusters show weak connectivity, reflecting a need for interdisciplinary bridging.

Conclusions This study highlights knowledge gaps and emerging directions at the interface of digital innovation and environmental sustainability in the food sector. Findings support the development of a more cohesive research agenda and inform stakeholders seeking to align digital transformation with robust sustainability assessment tools.

Keywords Life cycle assessment, Industry 4.0, Food sector, Bibliometric analysis, Sustainability, Digital technologies

1 Introduction

The increasing integration of Industry 4.0 (I4.0) technologies in the food sector is reshaping both agricultural [1] and industrial production systems [2]. In agriculture, often referred to as "Agriculture 4.0," tools such as sensors, IoT devices, cloud computing, and remote monitoring systems are being used to reduce resource waste and improve plant health management [3], showing how I4.0 is adopted in the food sector since the input realization. In the food industry, understood as the set of processes that transform raw materials into derived products (e.g., from milk to cheese, from grain to pasta), digital transformation is already underway. In this context, technologies such as blockchain can enhance product traceability and transparency, improving consumer confidence [4]. While it is often assumed that these innovations support more sustainable production, their actual environmental impact remains poorly explored. The installation and operation of technological infrastructures (e.g., sensor networks and data systems) can themselves have an ecological footprint. Therefore, it is essential to rely on objective methods to assess the environmental trade-offs of digitalization. Life Cycle Assessment (LCA) is a widely recognized tool that measures the environmental impacts of a product or process throughout its life cycle; further, it can support data-driven decisions to guide investments toward sustainability [5]. Despite the strategic relevance of the agri-food sector and its environmental impact, from water consumption to biodiversity loss and chemical pollution, few studies have examined the intersection between technologies and environmental sustainability using an LCA perspective [6–8]. Although several reviews focus on Agriculture 4.0 or digital transformation, only rare studies were found that explicitly combine I4.0 and LCA in the food sector [9, 10].

Moreover, few reviews have explored sustainability in food systems from broader perspectives. For example [11], highlights the role of managerial practices in driving environmental, economic, and social sustainability through bibliometric and thematic analysis. However, the study focuses on supply chain (SC) management models without exploring the role of I4.0 technologies in generating environmental data or integrating LCA frameworks.

More directly related to the convergence of digitalization and LCA [12] offers a valuable classification of digital tools—such as cyber-physical systems, IoT, and simulation—as enablers of Life Cycle Inventory (LCI) generation. The paper proposes a scoring system to assess each technology's contribution to LCA phases but does not address sector-specific applications, such as food production. Similarly, some authors [13] propose a Dynamic LCA model that integrates ERP (Enterprise Resource Planning) systems, sensor networks, and business intelligence platforms. Their case study on ceramic tile manufacturing demonstrates the potential of real-time environmental monitoring, though its sectoral scope remains outside the food domain. About sustainability [14], focuses on the Water-Energy-Food (WEF) nexus in the context of I4.0, whereas this work targets specific I4.0 technologies, such as IoT, AI, and blockchain, and their role in reducing environmental impact in the food sector. Similarly [15], explores digital transformation and sustainability in a broad sense, particularly in relation to SMEs and sustainable entrepreneurship, while our approach narrows the sustainability focus to environmental indicators, using LCA and related metrics (e.g., "carbon emission", "CO2"). Further distinctions emerge when comparing the approach followed in the present study to other relevant reviews.

Taken together, these contributions indicate growing interest in the synergies between I4.0 and LCA. Nonetheless, much of the current research is either conceptual in nature, focused on non-food sectors, or lacks bibliometric insights into the structural evolution of this interdisciplinary field. This fragmentation underscores the need for a systematic investigation. Accordingly, the present study aims to address this gap by offering a bibliometric review specifically focused on the intersection of LCA and I4.0 in the food industry, identifying the most frequently studied technologies, revealing key research trends, and uncovering persistent knowledge gaps.

This gap in the literature provided the primary motivation for executing the current analysis. Relying on a well-established bibliometric methodology [16–18], this paper aims to provide an original and timely contribution. By systematically mapping the existing literature, it seeks to clarify which research areas have been thoroughly explored and which remain under-investigated, offering theoretical insights and guiding future research directions.

To this end, the following research questions have been formulated:

RQ1: What is the current state of research on the intersection between I4.0 and LCA in the food industry?

RQ2: Which I4.0 technologies are most frequently studied in relation to sustainability and carbon footprint reduction?

RQ3: What are the main research gaps and future directions in this field?

The paper is organized as follows. Section 2 describes the bibliometric methodology adopted, while Sect. 3 illustrates the results of the Scopus filtering process, including a quantitative analysis of publications by year, country, affiliation, journal source, and subject area. Section 4 presents the keyword analysis conducted with VOSviewer, focusing on the identification of thematic clusters, their interconnections, and the temporal evolution of key terms. Section 5 discusses the main findings, highlighting both theoretical and practical implications, and outlines promising directions for future research. Finally, Sect. 6 concludes the paper.

2 Methodology

The paper is based on a bibliometric analysis, which is increasingly used in different fields [19]. In fact, due its objectivity [20], it can correctly identify the status of literature [18]. The methodology followed in this research is based on the one presented in [16–18] and depicted in Fig. 1.

The first step consists in the definition of the domain and the goals of the study. Nowadays, sustainability is a key characteristic in every field, including the food industry, which is well-known for its significant environmental impact and thus requires specific attention. On the other side, I4.0 is the current innovation wave. As LCA is an instrument to evaluate the impact of a product or process on environment, it was included as methodology in this research. Therefore, the links between I4.0 and environmental impact of food industry requires more studies, and it was chosen for this research. Despite the contributions already presented in Sect. 1, most existing research is either conceptual, focused on other sectors, or lacks bibliometric insight into the evolution of this interdisciplinary field.

The second step of the methodology involves the choice of important papers. In Table 1 the selection of the appropriate keywords is reported, a crucial process that enables the identification of relevant studies for the research. As for the source of the papers, we utilized the Scopus database, one of the largest bibliographic and scientific article databases worldwide, which specializes in scientific, technical, and multidisciplinary research [21]. The search was performed by applying the query to titles, abstracts, and keywords only, in line with common practice in bibliometric analyses to ensure relevance and replicability.

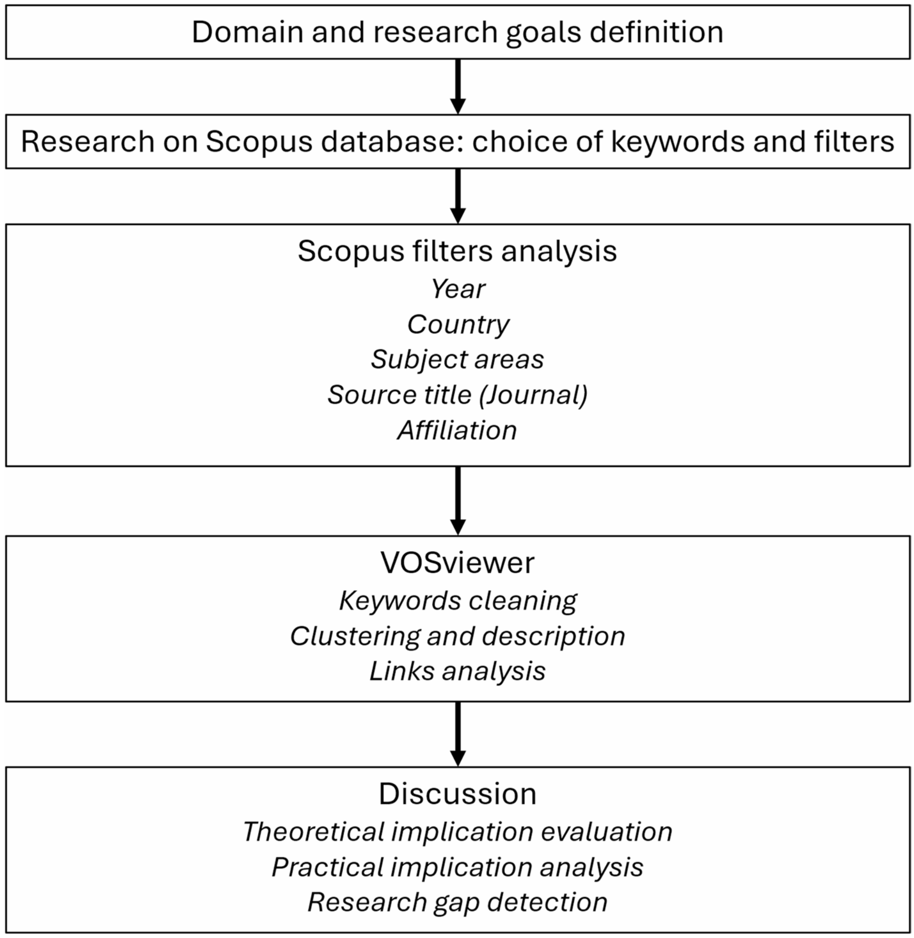

Fig. 1 Followed methodology

Table 1 Keywords strings used

String	Description	*N*°
"LCA" OR "life cycle*" OR "carbon emission*" OR "CO2" OR "footprint*"	This string focuses on Life Cycle Assessment and carbon emissions. The asterisk expands the search to variations of the term.	1.117.897
"Industry 4.0" OR "iot" OR "internet of things" OR "edge computing" OR "fog computing" OR "cloud computing" OR "digital twin" OR "smart manufacturing" OR "digital transformation" OR "cyber physical system" OR "artificial intelligence" OR "machine learning" OR "neural network" OR "deep learning" OR "blockchain"	The choice of the string is motivated by the need to comprehensively cover all the components and enabling technologies of I4.0. The inclusion of concepts such as "IoT," "Digital Twin," and "Artificial Intelligence" allows for a focus on advanced technologies.	36.725
"food*"	The choice of the term "food" allows for the selection of works in which I4.0 enabling technologies and environmental impact assessment are applied to the food sector. The asterisk expands the search to variations of the term.	800

The Scopus search was conducted on January 20, 2025, and provided over a million records Therefore, the research was refined, as shown in Fig. 2, to improve the quality of the papers and better focus on the desired domain. To ensure that the selected documents were relevant, high-quality, and specifically related to the intersection of Industry 4.0, LCA, and the food sector, cascade of exclusion criteria was applied.

- Keyword: the 2nd string was searched only within keywords in the Scopus research bar, excluding "Article Title" and "Abstract". This strategy helps capture documents where the technological component (i.e., I4.0 technologies) is a central rather than peripheral topic. It reduced the number to 598 articles.
- Subject Area refinement: the selection was limited to relevant disciplinary areas (Computer Science, Engineering, Environmental Science, Energy, Decision Sciences, Social Sciences, Business, Management and Accounting, Chemical Engineering, Chemistry, Multidisciplinary, Economics, Econometrics and Finance), reducing the number to 500 articles ensuring thematic consistency with the study's focus and granting a higher quality of results.
- Document type limitation: only articles published in journals or presented at conferences were retained to ensure academic rigor and peer-reviewed quality. This step reduced the dataset to 424 articles.
- Limitation on language: only articles written in English were chosen, reaching 414 records, to guarantee consistent analysis and international accessibility.

As the focus of this paper is to conduct a bibliometric analysis, and given the substantial number of records retrieved, the authors have chosen not to perform a full-text

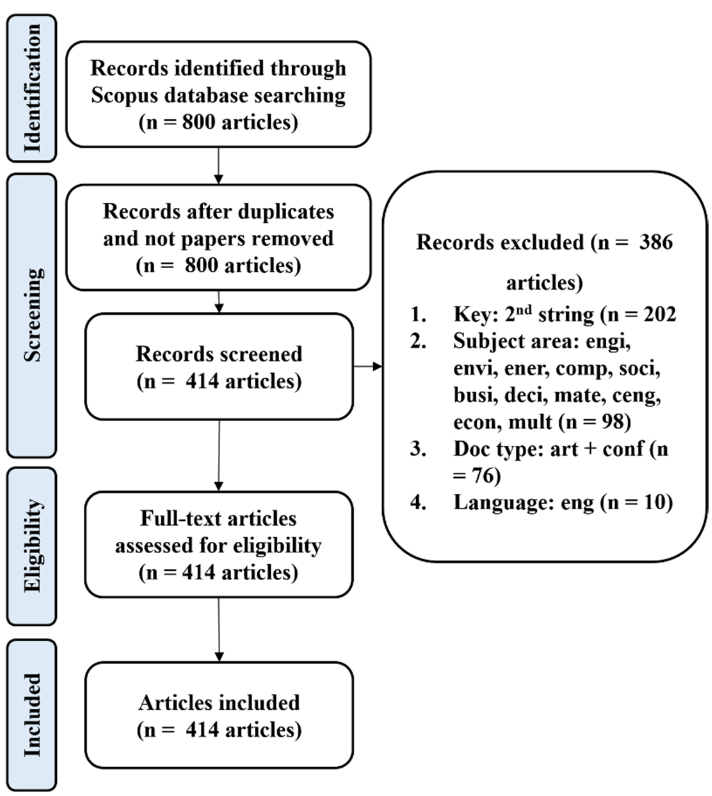

Fig. 2 PRISMA Protocol [22, 23]

reading at this stage of the study. A subsequent study will delve into content analysis, further developing the findings presented here. Figure 2 depicts the first three steps of the PRISMA protocol methodology described.

The third step corresponds with the bibliometric analysis itself; it was conducted on the Scopus filters, focusing on examining the years with the highest publication rates, the Countries most active in terms of publications, the Subject Areas with the highest citation counts, the journals most suitable for publishing articles on the topic, and finally, the universities most involved.

The fourth step was the keyword analysis, clustering them with the VOSviewer software (ver. 1.6.20). As for the use of the software, a thorough analysis was carried out on the most relevant keywords (i.e., those appearing most frequently), the creation of clusters with an in-depth study of their content, and, finally, the analysis of correlations between the clusters.

The fifth and final step consists of the extraction of knowledge from results, dividing it into theoretical and practical implications, and highlighting current research gaps, translating them into possible future research directions.

3 Scopus filters analysis

3.1 Year

Figure 3 illustrates the trend in the number of publications over time, showing a significant increase in research activity in recent years. Until 2017, the number of published papers remained low and stable, with only a few contributions per year (from 1 to 6). However, starting from 2018 (18 papers, 4.35%), the number of publications began to rise steadily, reflecting a growing interest in the topic. A sharp increase is evident from 2020 onwards, with the number of articles more than doubling between 2020 (37 papers, 8.94%) and 2021 (47 papers, 11.35%). The trend continued with a notable peak in 2023 (100 papers, 24.15%), where the highest number of publications was recorded. Although the number of publications slightly decreased in 2024 (94 papers, 22.71%), despite some papers of this year are not yet Scopus indexed, it remains at a high level, confirming the continued relevance of the topic. The preliminary data for 2025 suggest that research activity is ongoing, although the current count is significantly lower than in previous years. This is likely because the Scopus search was conducted on January 20, 2025, meaning that many articles that will be published later in the year have not yet been indexed. This steady growth in publications highlights the increasing importance

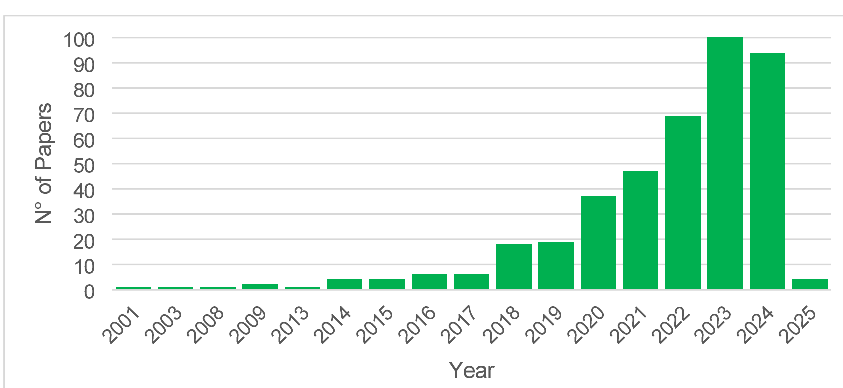

Fig. 3 Distribution of papers per year

of the intersection between I4.0 and LCA in the food industry. More researchers and institutions are dedicating efforts to exploring innovative approaches that integrate digital transformation with sustainability assessment. This trend aligns with the broader academic and industrial recognition of the need to develop advanced methodologies to enhance efficiency, reduce environmental impact, and address the evolving challenges of the food sector. A more detailed analysis of the correlation between research topics and publication years is presented in Sect. 4.3 (Fig. 9).

3.2 Country

Figure 4 illustrates the geographical distribution of publications on the intersection of I4.0 and LCA in the food industry. The data highlight that the most active research contributions come from China (12.94%) and India (12.77%), together accounting for over 25.71% of the global scientific output on this topic. This confirms the strong role of Asian countries in advancing research on sustainable digital transformation in the food sector. Following China and India, the United States (6.55%) emerges as the leading contributor from the American continent. In Europe, significant contributions come from the United Kingdom (6.39%), Italy (4.71%), Germany, and France (2.5%), making them the three most active European countries in this field. Other countries with notable research activity include Australia (2.86%), Canada (2.18%), and Brazil (1.51%). Interestingly, while a large portion of studies originates from leading global economies, emerging economies are also contributing to the field. Countries such as Iran (3.36%), Saudi Arabia (2.35%), Pakistan (3.85%), Indonesia (1.68%), and Egypt (1.34%) show engagement in the research landscape, reflecting a growing interest in integrating I4.0 technologies with sustainability assessment frameworks in food production.

3.2.1 *Chronological distribution of publications by first author's country*

The intersection between publication year and the first author's country of origin (Fig. 5) reveals several notable trends in the geographical evolution of scientific output over time. Starting from 2020, there is a marked acceleration in contributions from South and East Asian countries, particularly India and China, with 67 and 68 total publications, respectively. China shows a remarkable peak in 2024 alone, with 26 publications. These figures suggest an increasing leadership of these nations in the research field under

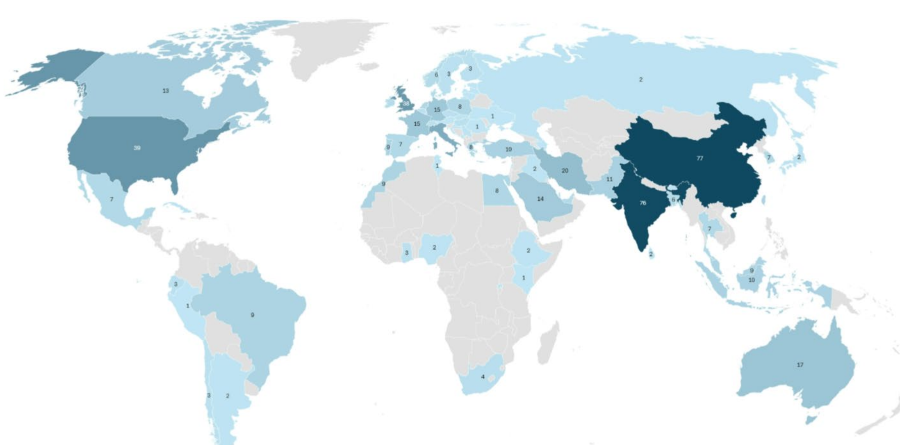

Fig. 4 Distribution of papers per geographical area, colour intensity indicates the paper amount

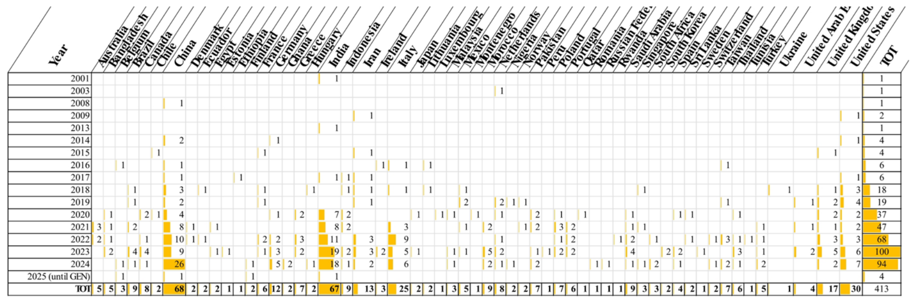

Fig. 5 Correlation between publication year and first author's country of origin

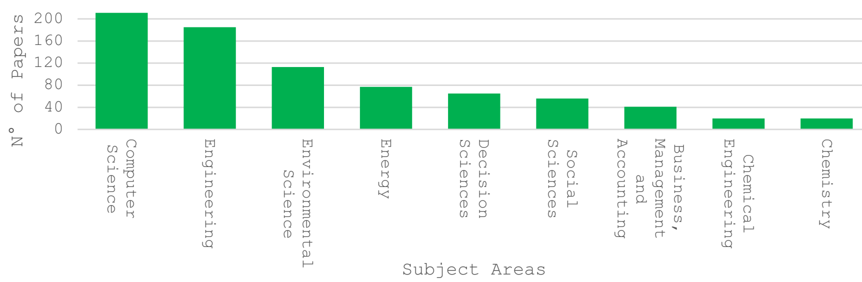

Fig. 6 Distribution of papers per subject area chosen in the filtering process

study. By contrast, the United States shows a more evenly distributed contribution over time, maintaining continuity but without the sharp growth observed in Asia. European countries, such as Italy, the United Kingdom, and Germany, demonstrate consistent but comparatively lower output. Of particular note is Iran, which shows a steady and substantial increase in publications from 2020 to 2023, peaking at 8 contributions in 2021. This positions Iran as one of the most active emerging contributors in the field. Other countries such as Turkey, Brazil, and Ethiopia have more sporadic but visible presences. The data overall indicate a progressive internationalisation of the research domain, though still concentrated in a relatively limited group of countries.

3.3 Subject areas

Figure 6 illustrates the distribution of subject areas covered in the selected publications on the intersection of I4.0 and LCA in the food industry. The analysis highlights that the majority of research contributions fall under Computer Science (51%) and Engineering (44.7%), reflecting the strong technological and industrial focus of the topic.

The Environmental Science category (27.3%) also accounts for a significant portion of the research, confirming the relevance of sustainability concerns in the digitalization of the food industry. Other important areas include Energy (18.6%), which aligns with the growing need to optimize resource consumption, and Decision Sciences (15.7%), indicating a methodological approach to supporting data-driven decision-making. Additionally, Social Sciences (13.5%) and Business, Management and Accounting (9.9%) are also represented, albeit to a lesser extent. These contributions suggest that the economic and managerial aspects of I4.0 and LCA integration are gaining increasing attention, particularly in terms of SC optimization. Finally, more specialized fields such as Chemical Engineering (4.8%) and Chemistry (4.8%) play a minor role in the current research landscape, likely due to their more specific application within food production processes.

Overall, the data suggest that research in this domain is primarily technological and sustainability-oriented, with growing attention toward decision-making, management strategies, and energy optimization. This confirms the interdisciplinary nature of the subject, requiring expertise from multiple academic fields to fully explore the integration of I4.0 and LCA in the food sector.

3.4 Source title

Of the 414 analysed papers, 243 (59%) were published in journals, while 171 (41%) appeared in conference proceedings. Given the greater academic relevance of journal publications, a detailed analysis of their distribution was conducted. Figure 7 presents a Pareto chart illustrating the distribution of articles across different journals. The data reveal a strong concentration of publications in a limited number of journals. The Journal of Cleaner Production stands out as the leading journal, with 20 articles (8.2%), followed by Sustainability (4.5%), Computers and Electronics in Agriculture (3.7%), and Science of the Total Environment (3.7%). The top five journals alone account for approximately 23% of all journal publications, underscoring their central role in disseminating research on I4.0 and LCA in the food industry. Beyond this core group of high-impact journals, a strong fragmentation is observed. More than 30 journals publish only two articles each (representing 13.2% of total journal publications), while an even larger group of 102 journals publish only a single article each (41.9%). This means that to reach 50% of all journal publications, 89% of journals must be considered, highlighting the high dispersion of research across multiple sources.

Table 2 further supports this finding:

- The top ten journals account for 36% of all journal publications.
- Journals publishing only one or two articles together constitute 55% of the total.
- The remaining 9% of publications are spread across a large number of journals with minimal contributions.

This distribution suggests that while some leading journals are emerging as key publication venues, the field remains highly fragmented, with no single dominant journal attracting the majority of research output. This dispersion may indicate two key trends:

- A diversity of research approaches and specializations within I4.0 and LCA in the food sector.
- A lack of a single, authoritative journal consolidating research efforts, possibly due to the interdisciplinary nature of the topic.

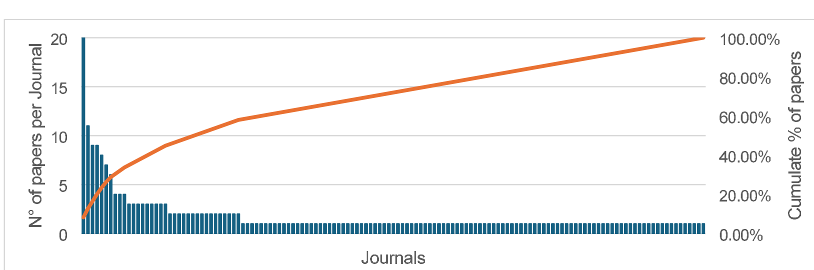

Fig. 7 Pareto analysis of the distribution of papers among journals

Table 2 Percentage and cumulate of papers and journals

Source title	N° art.	% on tot	C. Art.	% Journal
Journal Of Cleaner Production	20	8,23%	8,23%	0,73%
Sustainability Switzerland	11	4,53%	12,76%	1,46%
Computers And Electronics In Agriculture	9	3,70%	16,46%	2,19%
Science Of The Total Environment	9	3,70%	20,16%	2,92%
Plos One	8	3,29%	23,46%	3,65%
Sensors	7	2,88%	26,34%	4,38%
Journal Of Environmental Management	6	2,47%	28,81%	5,11%
Applied Sciences Switzerland	4	1,65%	30,45%	5,84%
Foods	4	1,65%	32,10%	6,57%
IEEE Access	4	1,65%	33,74%	7,30%
Agricultural Water Management	3	1,23%	34,98%	8,03%
Applied Energy	3	1,23%	36,21%	8,76%
Energies	3	1,23%	37,45%	9,49%
International Journal Of Advanced Computer Science And Applications	3	1,23%	38,68%	10,22%
Journal Of Ambient Intelligence And Humanized Computing	3	1,23%	39,92%	10,95%
Journal Of Industrial Ecology	3	1,23%	41,15%	11,68%
Scientific Reports	3	1,23%	42,39%	12,41%
Sensors Switzerland	3	1,23%	43,62%	13,14%
Smart Agricultural Technology	3	1,23%	44,86%	13,87%
Journal with only 2 articles	32	13,17%	58,02%	25,55%
Journal with only 1 article	102	41,98%	100,00%	100,00%

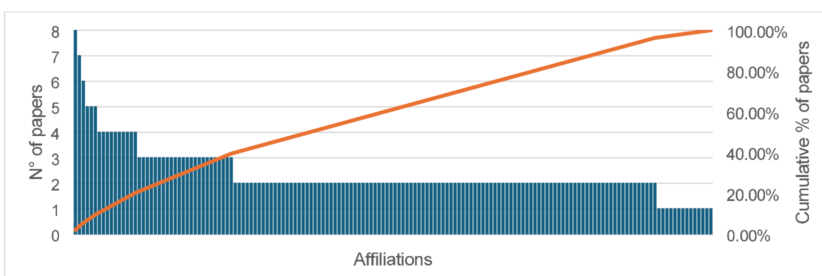

Fig. 8 Pareto analysis of the distribution of papers among authors' affiliations

Overall, this fragmentation reflects the broad scope of the research domain, which spans multiple disciplines and requires contributions from various academic perspectives.

3.5 Affiliation

The final parameter analysed was the affiliation of the authors. Figure 8 presents a Pareto chart illustrating the leading universities and research institutions contributing to the topic.

As emerges from the analysis of the data reported in Table 3, he University of Tehran leads with 8 publications (2.1%), followed by Zhejiang University (1.9%) and King Saud University (1.6%). Other institutions, such as the Ministry of Education of the People's Republic of China and China Agricultural University, contribute with 5 publications each (1.3%). Notably, no single institution dominates the research landscape, reinforcing the fragmentation of contributions across multiple universities worldwide (Table 3).

Table 3 Percentage and cumulate of papers and affiliation

Affiliation	Country	N° art.	% on tot	C. Art.	% Affiliation
University of Teheran	Iran	8	2.16%	2.16%	0.63%
Zhejiang University	China	7	1.89%	4.04%	1.25%
King Saud University	Saudi Arabia	6	1.62%	5.66%	1.88%
Ministry of Education of the People's Republic of China	China	5	1.35%	7.01%	2.50%
China Agricultural University	China	5	1.35%	8.36%	3.13%
Beijing Technology and Business University	China	5	1.35%	9.70%	3.75%
Wageningen University & Research	Netherlands	4	1.08%	10.78%	4.38%
Cranfield University	UK	4	1.08%	11.86%	5.00%
CNRS Centre National de la Recherche Scientifique	France	4	1.08%	12.94%	5.63%
Chinese Academy of Sciences	China	4	1.08%	14.02%	6.25%
Menoufia University	Egypt	4	1.08%	15.09%	6.88%
King Faisal University	Saudi Arabia	4	1.08%	16.17%	7.50%
Northwest A&F University	China	4	1.08%	17.25%	8.13%
IPB University	Indonesia	4	1.08%	18.33%	8.75%
College of Environmental and Resource Sciences	China	4	1.08%	19.41%	9.38%
Institutions with only 3 articles		72	19.41%	38.81%	24.38%
Institutions with only 2 articles		212	57.14%	95.96%	90.62%
Institutions with only 1 article		15	4.04%	100.00%	100.00%

The cumulative curve in Fig. 8 indicates a slow increase in publications as the number of institutions grows. This suggests that research output is widely dispersed, with most institutions contributing only a few articles. In fact:

- 56.68% of the total publications come from institutions that have only 2 published articles.
- 3.74% of the total publications come from institutions with only 1 article.
- Only 19.25% of the articles originate from institutions with at least 3 publications.

4 Keywords analysis

VOSviewer is a bibliometric mapping software designed to analyse bibliographic data and create interactive maps that represent relationships between scientific documents, journals, and keywords. It is particularly valued because it enables researchers to understand research trends in the literature of a specific field (in this case, I4.0 and LCA analysis in food sector). Additionally, it allows the identification of clusters of documents, authors, or terms (the latter being used in this context) that are interconnected, thereby highlighting the subfields of research within a specific discipline.

Figure 9 shows the Vosviewer Clustering map. Several steps were taken to refine the keyword analysis:

- A co-occurrence analysis was conducted to identify how frequently two or more keywords appear together in different articles.
- The minimum number of occurrences of a keyword was set to determine which keywords would form the bubbles in the visualization. For this study, a threshold of 9 was selected because, out of 4690 keywords, 121 met this criterion, closely aligning with the optimal target of approximately 100 keywords.

Subsequently, keywords that were of little interest to the topic were removed, specifically:

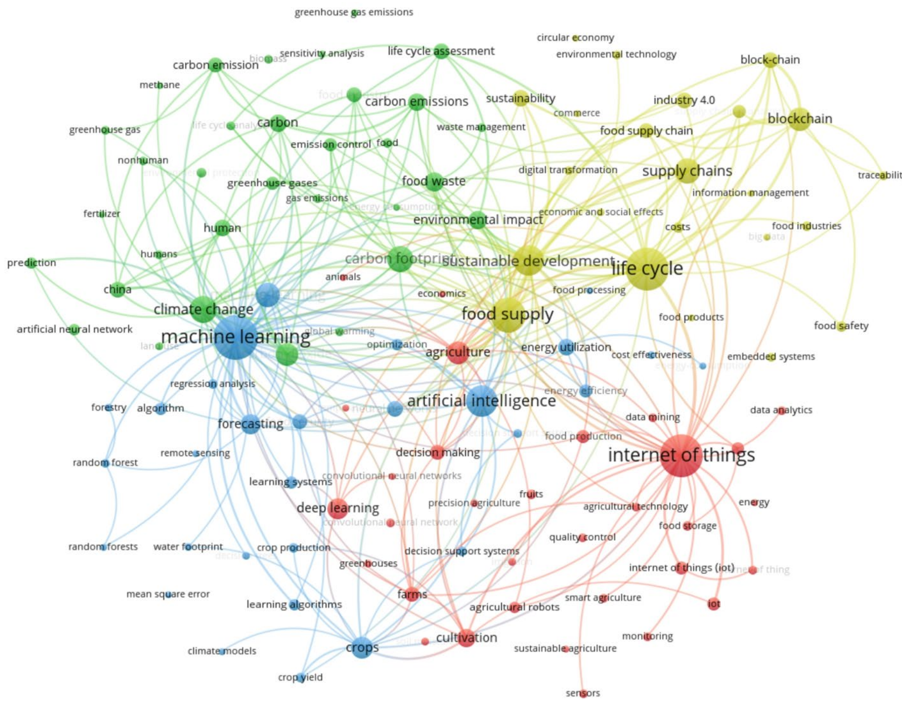

Fig. 9 VOSviewer clustering

Table 4 Followed steps for keywords' clusters definition

Step	Minimum cluster size	Number of clusters	Comment
1	1	15	Clusters composed of 2 keywords generating a meaningless result.
2	3	13	Clusters composed of 3 keywords, generating a meaningless result.
3	7	8	Too similar clusters, not well enough divided.
4	10	6	Too similar clusters, not well enough divided.
5	13	5	The smallest cluster in previous step was included in the biggest one. Further test performed.
6	17	4	Clusters are well divided.

- "article", "case-study", "controlled study" as they refer to types of articles, which are not relevant for this research.
- "population statistics", "procedures" because they are too general and do not express a meaning useful for this kind of research.
- The "Lines" parameter was adjusted by setting a 'Min. strength' value, which determines the minimum number of connections required for a line to appear between two keywords. A value of 7 was chosen, enhancing the readability of Fig. 9.
- Finally, an analysis of the clusters was conducted, setting the "Min. cluster size" to 17, meaning that each cluster could only be defined if it contained at least 17 keywords. However, in order to reach this conclusion, several tests were conducted, as shown in Table 4.

4.1 Clusters

Once the parameters of interest were set, 4 clusters emerged, as shown in Fig. 9. Below a thorough description is thus given:

- "IoT for Smart Agriculture" referring to the red area on the bottom right of the graph;
- "Environmental Impact of Food Industry" shown in the top left corner of the green area;
- "AI Driven Food Processes" on the bottom left of the figure with blue colour;
- "Food Supply Chain 4.0" in relation to top right of the chart depicted in the yellow area.

In the next subsections, a brief yet comprehensive description of each cluster follows. The number in parentheses (x) indicates the occurrence of a specific term. When different keywords indicate the same concepts, in parentheses are reported all the values (x + y + z).

4.1.1 Cluster 1 (red): IoT for smart agriculture

Analysing this cluster, it is evident that the most important words with the highest number of occurrences are "Internet of Things/Internet of Thing/ Internet of Thing (iot)/iot" (99 + 12 + 22 + 22) and "agriculture" (44); after it follows the word "deep learning" (39) and "cultivation" (33). This clearly indicates the importance of I4.0 technology in the agriculture sector. Secondly, there is a series of terms connected to agriculture, like "food production" (22), "agriculture robot" (18), "smart agriculture" (13), "quality control" (12), "sustainable agriculture" (9), all these terms clearly show that IoT and AI can be applied at various stages of food production, contributing to greater sustainability and quality, driving the transition towards smart agriculture. Data collection through I4.0 tools, such as "data mining" (12) and "data analytics" (12), is essential for improving the "decision-making" process (24), making it more reliable.

4.1.2 Cluster 2 (green): environmental impact of food industry

In this second cluster, there is more distributed number occurrence as the treated concept is a lot wider, as it regards the food's "environmental impact" (32). The general topic is "climate change" (54) especially caused by "GHG" (13 + 21 + 9). It was not unexpected that the most considered Green House Gas (GHG) is "carbon dioxide" (43 + 25 + 30). Among the various analysis methods, the one that stands out is the "carbon footprint" (53). On the other hand, "LCA" analysis (27 + 13), impacts related to "energy consumption" (10) and "waste" (34 + 13) are also quite recurrent. From the technological point of view, it's notable that the presence of "ANN" (17), which are particular suitable for "prediction" (17).

4.1.3 Cluster 3 (blue): AI driven food processes

Analysis of this cluster reveals the most frequent keywords related to "Artificial Intelligence" (67), specifically "machine learning" (106 + 47) and "neural network" (26). Key terms include "learning systems" (19), "algorithms" (20 + 18), such as "random forest" (13 + 9) and "regression analysis" (14). These terms are predominantly associated with "forecasting" (36) and "optimization" (17). Themes related to "decision support systems" (14 + 13), "crop yield" (42 + 15 + 14), "energy utilization" (29), and "energy efficiency" (22) also appear frequently. The topic of "energy consumption" (10) recurs in this cluster and in the previous cluster, indicating a consistent focus in the research.

4.1.4 Cluster 4 (yellow): food supply chain 4.0

Examining this cluster, it can be noted that it addresses the "food supply chain" (50 + 25), in relation to "I 4.0" (26). The technologies that are more suitable for this kind of "digital transformation" (13) are blockchain (46 + 27) and "big data" (10). The first technology is particularly valuable due to its "traceability" (12) capacity, which empower the reliability of the data used to evaluate the "life cycle" (100) and enable the realization of more transparent "circular economy" (9). "Big data" improve the knowledge about the SC, enabling a better "management" (22), which can ensure a better "food supply" (77), resulting in enhanced "economic and social effect" (11) and granting "food safety" (16). It is clear, therefore, that I4.0 is an extremely valuable instrument for the "sustainable development" (63).

4.2 Clusters links

In this section, the links between the main keywords across different clusters are analysed. Specifically, the analysis targets terms that have at least 10 connections; words with fewer connections are discarded to prevent the creation of excessively dense networks. After identifying the most important keywords for each cluster, we examined their connections with terms in other clusters, only reporting the ones where the connection strength is at least 10 (as defined above). The number in parentheses (x) represents the "link strength".

4.2.1 Cluster 1 (Red) - "IoT for smart agriculture"

This first cluster focuses on the application of IoT and DL in agriculture. The main keywords are evaluated in their links in the following Table 5.

Regarding the main keyword "IoT," it is well connected with all four identified clusters. Within Cluster 1, it is linked to "cultivation" (14), "monitoring" (10), and "digital storage" (10). "Decision-making" is connected only to "artificial intelligence" (10) in Cluster 3. Observing Cluster 2, "IoT" is linked to "food waste" (10) and "carbon footprint" (10). In Cluster 3, "IoT" relates to "crops" (12), reinforcing its connection to "cultivation" in Cluster 1. Cluster 4 shows links between "IoT" and "sustainable development" (12), "blockchain" (11), "supply chain" (12), "food supply" (19), and "life cycle" (31). The value

Table 5 Links with cluster 1: "IoT for smart agriculture"

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Internet Of Things/Internet of Thing/ Internet of Thing (Iot)/Iot	Cultivation (14/-/-/-); Digital Storage (10/-/-/-); Monitoring (10/-/-/-)	Food Waste (10/-/-/-); Carbon Footprint (10/-/-/-)	Crops (12/-/-/-)	Life Cycle (31/-/-/-); Food Supply (19/-/-/-); Sustainable Development (12/-/-/-); Supply Chains (12/-/-/-); Blockchain (11/-/-/-)
Agriculture/cultivation/smart agriculture/sustainable agriculture	Internet Of Things (-/14/-/-)		Crops (-/16/-/-); Machine Learning (13/-/-/-); Artificial Intelligence (-/11/-/-)	Food Supply (18/-/-/-); Sustainable Development (15/-/-/-); Life Cycle (12/-/-/-); Supply Chains (10/-/-/-)
Decision making process			Artificial Intelligence (10)	

of "agriculture" is evident in ensuring "food supply" (18) within the "supply chain" (12). Connections in Cluster 3 confirm the role of "AI" (11), especially "machine learning" (13), in supporting "cultivation" and predicting the "life cycle" (12) of "crops" (16). The keyword "deep learning" does not have connections stronger than 10.

4.2.2 Cluster 2 (Green) - "environmental impact of food Industry"

This cluster includes three main concepts: climate change, GHG emission and the models to evaluate the environmental impact. Details are shown in Table 6.

The keyword 'Climate Change' is linked within its own cluster to related causes such as 'carbon dioxide' (12), and to entities with high pollution levels, such as 'China' (13). The keyword "carbon footprint" (10) is associated as a method to evaluate impact. Links were found with Cluster 3, showing how "artificial intelligence" (12), especially "machine learning" (26/11), supports fighting climate change. Connections to "food security" (10), "food supply" (15), and "sustainable development" (15) were also observed in Cluster 4. No links were found between 'Climate Change' and Cluster 1 ("agriculture"), nor between 'Decision Making' and climate change. Additionally, 'IoT' and 'Deep Learning' lack links in this area. The keyword 'carbon dioxide' also links to Cluster 3 via "machine learning" (19/10) and "forecasting" (12), but not to Cluster 1's 'Deep Learning' or to 'AI' in general. 'IoT' is connected with Cluster 1 for "emission control" (13) and "real-time measuring" and with Cluster 3 for analysis of "carbon footprint" (10), "supply chains" (12), and "food supply" (17). 'LCA' (Life Cycle Assessment) relates to "environmental impact" (14), "life cycle" (18), and "food supply" (10), with weak links to agriculture and decision-making. 'Food waste' links to 'IoT' (10) and 'machine learning' (11) but has limited connections to broader topics such as climate change or sustainable development. 'ANN' is absent, indicating limited research focus compared to 'ML'.

4.2.3 Cluster 3 (Blue) - "AI driven food processes"

This cluster focuses mainly on AI and machine learning for forecasting of crop yield and energy. Keywords' connections are reported in Table 7.

Table 6 Links with cluster 2: "Environmental impact of food Industry"

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Climate change		China (13); carbon dioxide (12); carbon footprint (10)	machine learning (26); artificial intelligence (12); machine-learning (11); food security (10)	Food supply (15); sustainable development (15)
Carbon dioxide/carbon emissions/carbon emission		Carbon (-/17/12); Climate change (12/-/-); China (-/-/10)	Machine learning (19/10/13); forecasting (12/-/-); machine-learning (10/-/-)	
Carbon footprint	Internet of things (10)	Emission control (13); climate change (10)	machine learning (15); artificial intelligence (10)	Food supply (17); Supply chains (12)
Life cycle assessment/life cycle analysis		Environmental impact (14/10)	machine learning (10/-)	Life cycle (18/-)
Food waste	Internet of things (10)		machine learning (11)	
Environmental impact		Life cycle assessment (14); life cycle analysis (10)		Sustainable development (18); Life cycle (15); food supply (10)

Table 7 Links with cluster 3: "AI driven food processes"

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Artificial intelligence	Cultivation (11); decision making (10)	Climate change (12); carbon footprint (10)	Machine learning (15); crops (11); decision support systems (10)	Life cycle (13); sustainable development (12); food supply (10)
Machine learning/machine-learning	agriculture (13/-)	Climate change (26/11); Carbon dioxide (19/10); China (17/-); human (15/0); carbon footprint (15/-); Prediction (14/-); Carbon (14/-); carbon emission (13/-); environmental protection (12/-); food industry (11/-); food waste (11/-); life cycle assessment (10/-); carbon emissions (10/-)	Forecasting (20/-); Learning algorithms (15/-); Artificial Intelligence (15/-); Food security (14/-); crops (12/-); algorithm (11/-); learning systems (10/-)	Sustainable development (18/-); Food supply (18/-); Life cycle (14/-)
Forecasting		carbon dioxide (12)	Machine learning (20)	
Crops/crop yield/crop production	Cultivation (16/-/-); internet of things (12/-/-)		Machine learning (12/-/-); artificial intelligence (11/-/-)	Food supply (12/-/-)

"Artificial intelligence" is linked across all clusters. Within Cluster 1, it is connected to "decision-making" (10) and "cultivation" (11). Links also exist with "crops" (11) in Cluster 3 and "food supply" (10) in Cluster 4. AI supports measures addressing "climate change" (12) and evaluation of "carbon footprint" (10) in Cluster 2, and contributes to "decision support systems" (10), foundational for "sustainable development" (12).

"Machine learning" connects with "agriculture" (13), Cluster 1; "food industry" (11), Cluster 2; "food security" (14) and "crops" (12), Cluster 3; and "food supply" (18). It is linked to "prediction" (14) and "life cycle" (14), enabling the assessment of carbon emissions through "life cycle assessment" (10) and "carbon footprint" (15).

Connections exist to "food waste" (11), "algorithm" (11/15/10), and "forecasting" (20) related to "climate change" (26) and "environmental protection" (12). "IoT" provides data crucial for ML training, impacting accuracy. Notably, links to "decision-making process," "big data," and "forecasting" remain weak. "Crops" link with "machine learning" (12), "artificial intelligence" (11), and "IoT" (12). No connections of strength ≥ 10 were found for "energy utilization" or "energy efficiency," indicating low current research attention in the food sector.

4.2.4 Cluster 4 (Yellow) - "food supply chain 4.0"

This final cluster (Table 8) emphasizes the value of I4.0 for the SC of food improving the food supply and the life cycle towards a sustainable development. The most impactful technology appears to be blockchain thanks to its traceability capability.

Table 8 Links with cluster 4: "food supply chain 4.0"

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Life cycle	Internet of Things (31); agriculture (12); digital storage (10)	Life cycle assessment (18); Environmental impact (15)	Machine learning (14); artificial intelligence (13)	Supply chains (25); Blockchain (25); Food supply (22); Sustainable development (20); Block-chain (15); Supply chain management (12); food industries (10)
Food supply	Internet of Things (19); Agriculture (18); farms (11)	Carbon Footprint (17); Climate change (15); environmental impact (10)	Machine learning (18); Food security (16); crops (12); artificial intelligence (10)	Supply chains (33); Life Cycle (22); Sustainable development (22); Food supply chain (18); Blockchain (17); Block-chain (12); supply chain management (10)
Sustainable development/sustainability	Agriculture (15/-); Internet of things (12/-)	Environmental impact (18/-); climate change (15/-)	Machine learning (18/-); artificial intelligence (12/-)	Life cycle (20/-); Food supply (22/-); Supply chains (15/-); Industry 4.0 (10/-)
Supply chain/food supply chain	Internet of things (12/-); agriculture (10/-)	Carbon Footprint (12/-)		Food supply (33/18); Life cycle (25/-); blockchain (19/-); sustainable development (15/-); block-chain (15/-)
Industry 4.0				sustainable development (10)
Blockchain/Block-chain	Internet of things (11/-)			Life cycle (25/15); Food supply (17/12); Supply chains (-/15); sustainable management (10/-); traceability (10/-); food safety (10/-); supply chain management (10/-)

The analysis reported in Table 8 shows a high density of links within the clusters, highlighting the central role of I4.0 technologies for the sustainable development of the food sector supply chain.

The keyword "Life cycle" links strongly with "Internet of Things" (31) and "agriculture" (12) in Cluster 1, and to "supply chains" (25) and "food industries" (10) in Cluster 4. Cluster 3 connects "artificial intelligence" (13) and "machine learning" (14) with "life cycle." Expected links exist with "life cycle assessment" (18) and "environmental impact" (15) in Cluster 2. "Digital storage" (10) also shows relevant connections within Cluster 1.

"Food supply" shows widespread connectivity, linking all clusters: with "Internet of Things" (19), "Agriculture" (18) and "farms" (11) in Cluster 1; "Carbon Footprint" (17), "Climate change" (15), and "environmental impact" (10) in Cluster 2; "Machine learning" (18), "artificial intelligence" (10), "Food security" (16) and "crops" (12) in Cluster 3; and "Food supply chain" (18), "Supply chains" (33), "Sustainable development" (22), "Blockchain" (17), and "Block-chain" (12) in Cluster 4.

"Sustainable development" is linked with "agriculture" (15) and "IoT" (12) in Cluster 1, "machine learning" (18) and "artificial intelligence" (12) in Cluster 3, and "environmental impact" (18) and "climate change" (15) in Cluster 2.

The "supply chain" keyword connects mostly with "agriculture" (10), "IoT" (12) in Cluster 1, and "carbon footprint" (12) in Cluster 2, having limited links with AI-related keywords.

"Industry 4.0" connects minimally within Cluster 4, while "blockchain" links with "traceability" (10), "supply chain" (15), "supply chain management" (10), "life cycle" (25/15), and "food supply" (17/12).

"Big data" lacks significant links with any keywords.

4.3 Time analysis

From Fig. 10, it is clear that all keywords considered are associated with recent works published between 2020 and 2024, highlighting the relevance and timeliness of this research.

Clusters 1 and 4 contain the earliest keywords by Average Publication Year (APY). For example, "Life cycle" in Cluster 1 has an APY of 2020.81, and "IoT" in Cluster 4 has an APY of 2021.27. While "AI" in Cluster 3 has an APY of 2020.79, the cluster's overall keywords are more recent due to the prominence of "ML," which has an APY of 2023.26. Established technologies such as "IoT" appeared earlier, followed by emerging ones like "ML" and "DL" (2022.59), and "Blockchain" (2022.74).

Regarding sustainability-related concepts, "Life cycle" is the oldest, while more recent keywords include "sustainable development" (2022), "carbon footprint" (2021.89), and "climate change" (2022.22). The newest research topics include "carbon emissions" (2023.08), "GHG emissions" (2023.22), and "GHG" (2023.62).

"LCA" (2022.19) is associated with "ML", one of the most recent terms. Additionally, the agriculture-related terms "agricultural technology" (2022.92), "farms" (2023.32), and

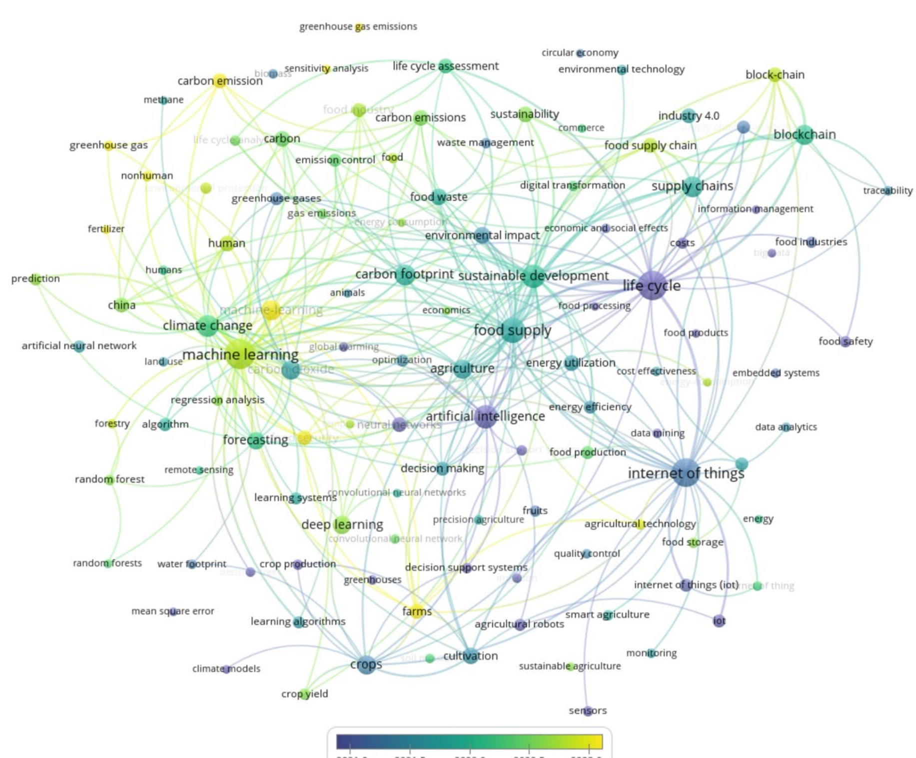

Fig. 10 VOSviewer time analysis

"food security" (2023.20) show that these subjects have gained relevance in the most recent years.

5 Discussion

5.1 Patterns and interpretations from bibliometric analysis

The geographical distribution of publications shows strong concentration in countries with advanced industrial and technological infrastructures, such as China, the USA, and major European nations. This trend is likely driven by policy incentives and industrial investments, which create fertile ground for research at the intersection of Industry 4.0 and sustainability in the food sector [11]. Simultaneously, the lack of a dominant institution and the high dispersion of outputs among many universities signal both the interdisciplinary nature and the early stage of consolidation in this field. This fragmentation suggests methodological immaturity and the presence of multiple research perspectives, consistent with findings in recent bibliometric studies [12, 13]. Further analysis of publication trends over time confirms a rising interest in the topic, especially in the last five years, indicating that research efforts are aligning with broader global priorities on food sustainability and digital transformation. However, compared to other industrial sectors, the food industry's approach remains less integrated and methodologically fragmented, as observed in thematic clusters.

5.2 Cluster insights and cross-cluster comparisons

The four identified clusters depict a heterogeneous landscape.

- IoT for Smart Agriculture

The integration of IoT and deep learning technologies in smart agriculture predominates in bibliometric networks, evidencing their maturity for practical implementation [1, 24]. The persistent gaps between IoT and decision-making, as well as weak links to sustainability, indicate that the interaction between digital instrumentation and actionable management is not yet fully developed [25]. Recent technological trends highlight widespread deployment of smart sensors, real-time farm monitoring, and AI-driven analytics platforms, yet their potential for direct sustainable decision support remains underexplored. This highlights an opportunity to strengthen data-driven decision support frameworks and to investigate the real-world impact of these technologies in fulfilling Sustainable Development Goals.

- Environmental Impact and Energy Forecasting:

Research focused on environmental assessment and energy management mainly leverages AI tools such as neural networks for forecasting and optimization. Studies have demonstrated the effectiveness of ANNs and ML in modelling carbon emission intensity and improving the accuracy of energy demand forecasts in the food sector [29–32]. This demonstrates the potential value of I4.0 in addressing climate change and food waste issues [33–36]. The dominance of Chinese contributions in this area reflects strategic national priorities towards green innovation, despite ongoing challenges due to reliance on carbon-intensive energy sources. This situation underscores the necessity for integrated approaches to transition towards sustainable food production systems. However, theoretical synergies between climate change, decision-making, and IoT technologies remain weakly represented in the literature, highlighting a critical integration deficit for leveraging I4.0 tools in holistic sustainability management [26–28].

- AI-Driven Food Processes:

The bibliometric mapping reveals a clear separation of AI research oriented toward process optimization, yield prediction, and digital management [37, 38]. Yet, the network shows gaps in connecting these technologies with energy efficiency and big data analytics, as well as insufficient linkage to vertical applications such as environmental monitoring. This fragmentation confirms that much AI research remains at the development stage, postponing questions about adoption and integration in operational food processes [39–41].

- Food Supply Chain 4.0:

The supply chain cluster concentrates on traceability and digitization, primarily through blockchain and big data. These technologies have significantly enhanced transparency and support circular economy initiatives within the food sector [4, 42–45]. However, the sparse connections observed between these tools and other key I4.0 technologies such as IoT, AI, and advanced big data analytics suggest a slow pace of digital integration beyond niche applications. This limited cross-domain synergy indicates that the transition toward fully data-driven and sustainable food supply chains remains a work in progress.

Across all clusters, a recurring theme is the underexploited potential for technological integration. For example, the linkages between LCA and decision-making, and between IoT and AI, are systematically weak, implying limited methodological interconnection and practical application.

5.3 Theoretical implications

The findings highlight the ongoing methodological fragmentation in integrating Industry 4.0 technologies and sustainability assessments within the food sector, reflecting a need for more unified theoretical frameworks. The lack of strong interconnections between clusters and between LCA, IoT, AI, and decision-making suggests that future research should focus on developing comprehensive models to support data-driven sustainability and digital transformation [12, 26]. This analysis confirms that the convergence of advanced technologies in food systems is still at an early stage, offering a broad foundation for further theoretical inquiry.

5.4 Managerial and policy implications

For practitioners and policymakers, these results indicate that gradual adoption of mature Industry 4.0 technologies, such as IoT and cloud systems, can help the food sector meet regulatory demands and improve environmental performance. Strategic investments in digital infrastructures can be leveraged to build capacity for more advanced tools, like AI and blockchain, enabling a stepwise transition to efficient and sustainable operations. This incremental approach is particularly relevant for small and medium-sized enterprises and emerging economies, supporting competitive advantage without disruption [2, 44]. Moreover, the alignment with SDGs is crucial, with I4.0 technologies playing a significant role in advancing social, environmental, and economic targets [46,

Table 9 Research gap and potential research questions

Research gap	Potential research questions in the food sector
IoT and Decision-making relation	How to integrate IoT into the decision-making process?
IoT and AI relation	How are IoT and AI related?
	How to integrate them?
DL evaluation	When and where should ML and DL be adopted?
	What is the different impact of them in different applications?
AI and sustainability relation	How can AI improve sustainability?
Decision-making and forecasting relation	How can I4.0 improve decision-making with enhanced forecasting?
Other I4.0 technologies	Which I4.0 technologies can improve sustainability?
	How to integrate them into a complete solution?
Primary sector and sustainability relation	How can I4.0 improve sustainability of the primary sector?
	How can I4.0 improve water and resource consumption?
LCA and I4.0 relation	How can I4.0 support the LCA?
	How does Digital Transformation affect LCA?
Energy and sustainability relation	How can energy production and consumption affect the sustainability?
	How can I4.0 improve energy management?
Taxonomy of Industry 4.0 technologies connection with LCA	What are the positive, negative, direct and indirect environmental impacts according to LCA criteria?

47, 49, 50]. Effective digitalization of energy systems and smart management practices provide opportunities to reduce carbon footprints and optimize resource consumption [48, 51, 52].The growing deployment of renewable energy technologies and advanced energy storage methods further supports sustainable operations in food production and supply chains [53, 54]. The integration of IoT for green building and facility management exemplifies how smart infrastructures can contribute to sustainability goals [55, 56]. However, to fully realize these benefits, clearer roadmaps and integrated frameworks are needed to guide consistent implementation, especially in diverse economic contexts and among technologically less mature sectors.

5.5 Directions for future research

Future research should focus on bridging the gaps between clusters and technologies identified in this study. Priority directions include: investigating effective methods to integrate IoT data flows with decision-support and forecasting systems; analysing the interface between AI methodologies and climate change mitigation efforts in the food sector; expanding studies on energy management and food waste, especially their connections to sustainability and digital transformation; developing cross-sectoral frameworks that connect LCA with practical decision-making, exploiting real-time data for enhanced sustainability assessment. Only by addressing these gaps will the field evolve from a fragmented landscape to a cohesive research agenda capable of supporting sustainable development across the entire food supply chain. From the analyses of thematic clusters and their interconnections, several research gaps were identified. These gaps, together with corresponding potential research questions in the food sector, are summarized in Table 9, providing a roadmap for future investigations in the field.

6 Conclusions

This study conducted a bibliometric review of 414 Scopus-indexed publications to examine the intersection between Industry 4.0 technologies and Life Cycle Assessment in the food sector. The results show a growing research interest in this interdisciplinary field, especially after 2020 (RQ1), with IoT and Machine Learning emerging as the most frequently studied technologies in relation to sustainability (RQ2). However, limited integration was found between LCA and advanced I4.0 tools like blockchain, digital twins, and big data analytics, highlighting gaps in real-time monitoring, energy optimization, and data-driven decision-making (RQ3). These findings point to a fragmented research landscape and call for more integrated, interdisciplinary approaches to fully leverage I4.0 for environmental sustainability. The implications extend to both academic, industrial and policy spheres: scholars can use this map to address underexplored intersections, while policymakers and practitioners may consider promoting digital tools that support measurable, lifecycle-based sustainability metrics. In fact, sustainability is a pivotal aspect that food sector must improve, due to its huge impact on environment and climate change. Policymakers should therefore provide benchmarks based on the adoption of instruments like LCA, supporting companies in evaluating their impact compared to competitors. Moreover, incentives for companies based on the reduction of the overall impact, calculated for instance comparing the previous value of LCA and the one after an investment, can encourage further investments to reduce the environmental impact of the sector. In this direction, the collaboration among universities and companies can help to develop both methodologies and solutions to conciliate the requirements of the sector with the sustainability goals, like SDGs and green agendas of governments. This reciprocal support is pivotal to drive innovation towards the realization of viable tools that can be widely adopted, also in developing countries, which have less resources to radically innovate. Therefore, research in richer and more industrialized countries can lead to an improvement also in poorer and rural ones, resulting in a globally higher reduction in environmental impact.

This study is limited by its reliance on bibliometric indicators without full-text content analysis or co-citation techniques. Future research could address these limitations to offer a more granular view of how I4.0 technologies support sustainable transitions in the food industry. The main contribution of this work is to provide a structured overview of an emerging and highly interdisciplinary field. Although the methodology used is well-established, the originality of this review stems from its focus on a topic that has not yet been systematically explored in the literature.

Abbreviations

ANN	Artificial neural network
APY	Average Publication Year
DL	Deep learning
GHG	Green House Gas
ERP	Enterprise Resource Planning
I4.0	Industry 4.0
IoT	Internet of Things
LCA	Life Cycle Assessment
ML	Machine learning
SC	Supply chain
SDGs	Sustainable development goals

Author contributions

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