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Review

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Environmental footprint in specific industries: intellectual base and research status

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Abstract

Environmental footprint (EF) as a critical tool for assessing the environmental impacts of human activities has been widely applied in the sustainable development field. Building upon a review of the current research landscape, this study employs bibliometric analysis to identify the intellectual base of EF research through co-citation networks and to outline research status. Following the release of the European Commission EF framework, the research primarily focused on the development and standardization of the product and organization EF methods, and then expanded to global environmental governance frameworks, such as the circular economy and planetary boundaries, promoting multi-scale environmental impact assessment tools. The enhancement of databases and the increasing emphasis on uncertainty analysis in Life Cycle Assessment (LCA) and Multi-regional Input-output models have enhanced the comparability of assessments. EF research has expanded into sectors such as food systems, healthcare, information and communication technology, pharmaceuticals, batteries, and plastics, offering both theoretical and empirical support for green transitions and environmental performance optimization across sectors. Using metals, healthcare, and construction as cases, this study highlights the shared features and distinct characteristics of EF application across sectors. In the metals sector, research addresses both primary extraction and recycling, with inconsistent treatment of uncertainty. Healthcare studies focus mainly on devices and consumables, with limited attention to hospitals, departments, and treatment pathways. In construction, studies cover materials, structures, firms, and technologies, mostly using LCA, but often lack systematic uncertainty analysis. Future direction could further integrate EF with the planetary boundaries framework and circular economy strategies, improve dynamic modeling in methodological robustness, and broaden application to emerging fields such as hydrogen energy, cryptocurrency mining, cloud computing, and digital infrastructure.

Keywords: Environmental footprint, intellectual base, bibliometric, interdepartmental comparison

INTRODUCTION

How to systematically measure the environmental impacts of human activities has become one of the core issues in sustainability research. As a multidimensional and quantifiable environmental impact assessment tool, the Environmental Footprint (EF) has attracted growing attention from both academia and policymakers in recent years. EF refers to the quantitative description of the environmental impacts generated by human activities, typically measured across multiple environmental impact categories, such as greenhouse gas(GHG) emissions, water consumption, and land use[1-4]. The European Commission explicitly defines EF in its Product Environmental Footprint (PEF) and Organization Environmental Footprint (OEF) methodologies as a comprehensive indicator for measuring the multiple potential environmental impacts caused by a product or organization throughout its life cycle, which cover up to 16 environmental categories, including climate change, water use, land occupation, biodiversity loss, and resource depletion[5]. The European Union Environmental Footprint (EU-EF) framework emphasizes characteristics such as life cycle assessment (LCA), multi-indicator orientation, and high comparability, aiming to provide a unified and operational tool for environmental sustainability evaluation.

EF has been applied across diverse research fields, including healthcare, agriculture, business and economics, energy, and materials science. Using multi-regional input-output (MRIO) analysis, Lenzen found that healthcare services exert significant environmental pressures globally, including air pollution, particulate emissions, water consumption, and reactive nitrogen releases, accounting for 1% to 5% of global impacts, with some countries exceeding 5%[2]. The use of personal protective equipment (PPE) and disinfection procedures further intensified energy and resource consumption during the COVID-19 pandemic. A LCA study showed that reusable PPE could be an effective option for reducing energy consumption and EF[6]. The widespread use of disposable medical devices, such as gastrointestinal endoscopes, duodenoscopes, and coveralls, has also imposed significant environmental burdens; however, promoting the adoption of reusable devices and sustainable material design can mitigate these impacts[2,7]. Moreover, digital healthcare systems have demonstrated positive effects in reducing medical resource waste and environmental impacts[8], highlighting the necessity of promoting green healthcare practices and establishing environmental management systems.

Current research on the EF of agricultural systems primarily focuses on evaluating the comprehensive environmental impacts of agricultural production activities under multi-scale and multi-indicator frameworks. As a resource-intensive sector, agriculture exerts considerable pressure on land use, energy consumption, and water resources, while also triggering environmental problems such as soil degradation, water pollution, and biodiversity loss[9]. To assess these impacts, several indicators have been developed. The Agricultural Footprint Index (AFI) has been proposed as a general method to evaluate changes in the overall environmental impacts at the farm level[10,11].

Environmental Footprint Index (EFI), which integrates footprint indicators such as land footprint, water footprint, carbon footprint, nitrogen footprint, and phosphorus footprint with the Planetary Boundaries (PBs) framework, has been employed to systematically evaluate the environmental performance of agricultural systems[12]. In response to the over exploitation of ecosystems driven by food demand, a globally consistent and regionally adaptable method has been proposed for quantifying Agricultural Ecological

Boundaries (AEBs)[13], which further developed a region-specific Integrated Footprint-AEBs framework that combines six EFs with AEBs to capture the overall environmental impacts of agricultural ecosystems in China. These index-based approaches, often grounded in multi-criteria decision-making frameworks, emphasize local adaptability and stakeholder participation, enabling the identification of strengths and weaknesses in agricultural production and providing valuable support for optimizing agricultural environmental policies.

Research on the EF of food production systems has expanded considerably, focusing on achieving sustainable intensification of food production through management optimization and technological innovation[14,15]. Abundant empirical studies have demonstrated that adopting integrated agricultural practices, such as conservation tillage, crop rotation, intercropping, zero tillage, and precision input management, can significantly reduce water consumption, energy use, and GHG emissions while improving crop yields and economic benefits[16,17]. Employing methods such as LCA, the EFI, and AEBs, scholars have systematically evaluated the resource efficiency and environmental performance of food crops, including rice, wheat[14,18], maize[17], and soybeans[19,20] under various regional scenarios. Additionally, the production of beef, chicken, pork, milk, and eggs involves substantial land, water, and energy consumption, alongside emissions of GHGs and pollutants such as nitrogen and phosphorus, making livestock farming one of the primary sources of EF in agriculture[21,22]. In the United States, it has constructed multi-regional cattle production system models to systematically assess GHG emissions, water consumption, and energy use per unit of product, providing baseline data for the sustainability of livestock products[23]. In China, pig farming exhibits significant regional disparities, with intensive management and feed resource restructuring helping to substantially reduce carbon footprints, nitrogen footprints, and cropland occupation[24]. Regarding dairy farming, evidence from China indicates that adjusting feed rations and sourcing locations can reduce the EF and improve the net profitability of dairy farms[25]. Although chicken and aquaculture are often regarded as lower environmental-cost alternative proteins, their increasing feed demand and industrial expansion have also created new resource and policy pressures[24,26].

Dietary structure plays a decisive role in shaping the environmental impacts of the entire food system. A scenario study in the Netherlands showed that plant-based diets with reduced animal-based food intake can alleviate environmental burdens while lowering mortality risk[27]. Empirical studies in Spain[28], Lebanon[29], and Israel[30] demonstrated that adherence to the Mediterranean Diet Pattern (MDP), compared to Western diets, can significantly reduce environmental pressures, including GHG emissions, land use, and water consumption, thereby enhancing the sustainability of dietary systems. Related research in China indicated that dietary consumption varies substantially across different populations, geographic regions, and economic conditions, with excessive meat consumption and income disparities being major drivers of environmental burdens[31-33]. By simulating future healthy diet scenarios under varying demographic structures, the study found that policy-making should simultaneously consider nutritional needs, demographic changes, and resource carrying capacity to promote the transition of food systems toward green, healthy, and equitable development[31].

Under the framework of sustainable development, the multi-level and multi-domain driving factors of EF have become important topics in environmental economics and policy research. China's diverse cooperation paths in Africa exert differentiated environmental impacts: exports and construction activities increase local carbon emissions, whereas imports and foreign direct investment may have positive environmental effects[34]. At the enterprise level, empirical research from Denmark indicated that CEOs with higher education levels tend to improve corporate energy efficiency and exhibit greater environmental awareness, with their educational background playing a critical role in sustainable corporate decision making[35]. A case study from Israel revealed that although technological progress and behavioral changes help mitigate EF, relying solely on technology is insufficient to achieve national emission reduction targets under continuous population growth scenarios[36]. The evolution of EF is driven by multiple factors, including international cooperation, managerial literacy, and demographic structure, necessitating a coordinated approach to designing environmental policies and governance pathways across different levels.

Recently, EF research has also focused on plastics, new energy, metals, construction, and the integration of multidimensional methods, demonstrating thematic diversity and methodological fusion. The COVID-19 pandemic triggered a surge in protective plastic use, leading to the proposal of the concept of "plastic waste footprint" and calls for the establishment of flexible waste management mechanisms[37]. Upstream coal-based production in the plastic value chain has been identified as a major source of carbon footprints and health risks[38]. LCA of copper and aluminum has shown significant differences in energy and water consumption, with electrolytic aluminum imposing the greatest environmental burden. However, recycling can significantly reduce emissions in the field of metal resources[3,39]. Regarding energy materials research, the environmental performance of hydrogen production varies significantly across different production pathways, with water electrolysis and gaseous storage and transport being more favorable[40]; the environmental impacts of electric vehicles depend heavily on grid structure and battery parameters[41]; and increasing attention has been paid to the production pathways and database construction of rare earth functional materials[42]. Moreover, the integration of the EF approach with the PBs framework provides a theoretical basis in these fields[43].

Therefore, existing literature reviews on EF have primarily focused on conceptual evolution[44], methodologies[45], or specific application scenarios-such as food systems[46], healthcare[47], blockchain energy[48], and household activities[49]. While these offer valuable insights, they lack a systematic analysis of the intellectual structure and evolutionary dynamics of the EF research field. Given the expanding scale and increasing complexity of EF studies, there is a pressing need to adopt visual bibliometric tools to identify and clarify the knowledge clustering patterns of the field. In bibliometrics, the intellectual base typically refers to a set of foundational publications that are frequently co-cited and exert long-lasting influence within a research domain. These works form the theoretical and methodological foundation for subsequent research and paradigm development. As a key source of theory and methodology, the intellectual base supports the advancement of research frontiers, and its evolution directly shapes the field's trajectories and directions of innovation.

Building on the prior review of selected EF research themes, this study employs bibliometric analysis to conduct co-citation and timeline cluster analyses of core EF publications. The goal is to systematically identify the field's intellectual base, map its evolutionary pathways, and explore future research directions. By constructing a knowledge map, we reveal thematic trends and academic focal points, thereby offering a structured knowledge framework for future EF research. To address the current lack of industry-specific analysis and deepen the understanding of EF characteristics across application domains, we further select metals, healthcare, and construction sectors for in-depth investigation, which are resource-intensive, high in carbon emissions, and subject to strong policy attention. Spanning the service, heavy industry, and construction sectors, they enable comparative analysis across distinct accounting objects and methodological approaches, facilitating the development of cross-sector assessment frameworks. Each sector has established a growing body of EF research and demonstrates diverse practices in indicator development, data sourcing, methodological application, and uncertainty analysis. A systematic review of these cases helps uncover the adaptability and limitations of EF methods in various contexts, providing empirical support for theoretical integration and practical implementation.

Following the status of research themes, intellectual base, and evolution, and sectoral applications, this study offers a coherent roadmap for understanding the origins, evolution, and practical relevance of EF research and serves as a reference for future academic exploration and policy-making. The remainder of the paper is organized as follows: Section 2 outlines the methodology, Section 3 presents the intellectual base of the environmental footprint, Section 4 concludes the industry-specific analysis, and Section 5 provides the conclusion.

METHODOLOGY

Bibliometric analysis

Bibliometric analysis provides an effective approach for systematically identifying its intellectual base, historical development, and emerging research fronts when a research field has accumulated a large volume of literature. There are two primary citation-based mapping techniques currently in use: bibliographic coupling and co-citation analysis. The fundamental concept of bibliographic coupling involves grouping citing articles based on the quantity of shared references they have. Conversely, the co-citation technique clusters cited documents based on their joint appearances in the reference lists of journal articles. From a bibliometric perspective, the citing articles form a research front, while the cited articles constitute an intellectual base. CiteSpace is one of the widely used visualization tools in bibliometric research, which integrates multiple bibliometric methods such as co-citation, co-occurrence, and coupling analysis to construct complex citation networks, uncover the relational features among scientific literature, and dynamically reveal the bidirectional relationship between the intellectual base and the research front in the process of temporal evolution[50]. In this study, co-citation analysis is employed to identify the intellectual base of the EF research field, and based on the co-citation relationships among references, a citation network is used to detect highly cited or frequently co-cited clusters of core literature within EF research by using CiteSpace software. This process facilitates the delineation of the intellectual base, which refers to the collection of publications that represent the theoretical origins, methodological tools, and key academic achievements of the research field.

Data collection and description

The primary source of input data for CiteSpace is from the the database of Web of Science Core Collection (WoSCC) in Web of Science (WoS), considering the rich achievements in the EF field, we directly set environmental footprint as a professional term, that was, set the retrieval parameter as Topic (TS) = "environmental footprint*" to carry out literature information retrieval to search for literature that record "environmental footprint*" in the Title, Abstract, Author Keywords and Keywords Plus fields. As a result, we obtained 5,751 records of literature information in preliminary retrieval. To ensure that information from high-core documents is incorporated into CiteSpace analysis, we first selected the literature types as Article, Review, and Proceedings paper in the database of WoSCC to refine the preliminary retrieval records. We then eliminated the invalid document types such as Book chapter and Retracted publications. As a result, we obtained a total of 5,593 records from 2006 to 2025, comprising 4,264 articles, 703 review articles, and 626 proceedings papers. Furthermore, we used CiteSpace to deduplicate these refined records of literature information, and 5,192 records were retained. All the literature information records were searched and downloaded on March 4, 2025, and processed in CiteSpace 6.2.R6 Advanced.

Figure 1 illustrates the annual publication output and citation frequency trends of EF research from 2006 to 2025. Overall, this field has experienced steady development since 2006, with the number of annual publications increasing from 10 in 2006 to 1,146 in 2024, showing a remarkable upward trajectory. After 2015, the number of publications entered a phase of rapid growth, reflecting the growing academic attention to EF-related issues. The citation frequency also shows a sharp increasing trend, particularly accelerating after 2012, and reaching 32,988 citations in 2024. This indicates the continuously expanding academic

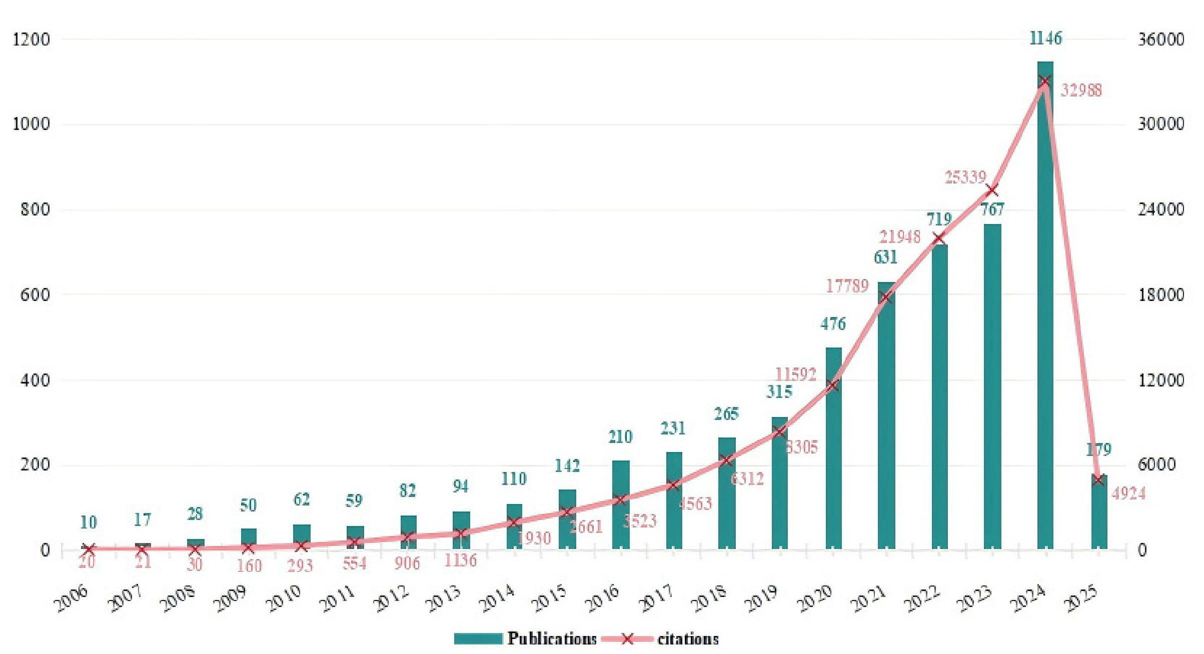

Figure 1. The number of articles published and cited in EF from 2006 to 2025. (Note: Publications represent the number of articles published annually, while citations indicate the total number of citations received each year). EF: Environmental footprint.

influence of EF research. In general, EF research has emerged as a prominent and rapidly evolving research hotspot in recent years.

For all three domains-metals, the healthcare sector, and the construction industry-the literature was retrieved from the WoSCC. For metals, the search was conducted using the following parameters: Topic (TS) = "environmental footprint*" and Title & Author Keywords = iron OR steel OR aluminum OR copper OR zinc OR lead OR magnesium OR titanium OR gold OR silver OR platinum OR tungsten OR molybdenum OR nickel OR tantalum OR vanadium OR lanthanum OR neodymium OR samarium OR cerium OR uranium OR thorium. For the healthcare sector, the search parameter was set as: Topic (TS) = "environmental footprint*" AND Topic (TS) = "healthcare sector". For the construction industry, the parameter was: Topic (TS) = "environmental footprint*" AND Topic (TS) = "construction industry". After manual screening, only studies directly related to environmental footprint accounting were retained. As a result, a total of 12 studies related to metals, 15 studies related to the healthcare sector, and 11 studies related to the construction industry were included in the final dataset.

The timeline visualization mapping

To explore the intellectual base, knowledge structure, and historical evolution of EF research, this study conducted a timeline visualization mapping of the co-citation network of cited references to organize and analyze the retrieved literature data and identify key foundational literature. First, the settings of CiteSpace were adjusted to ensure the rationality of the co-citation network and clustering results. The selection of parameters is primarily based on two key indicators: Modularity (Q) and Weighted Mean Silhouette (S). Modularity (Q), proposed by M. E. J. Newman in 2004, is an index for evaluating the quality of community detection. Generally, Q values lie in the interval [0,1], with higher values indicating denser intra-cluster connections and better clustering performance. Q values greater than 0.3 indicate significant clustering. Weighted Mean Silhouette (S), introduced by L. Kaufman and Peter J. Rousseeuw in 1990, measures the similarity between objects and their corresponding clusters, with higher values indicating better clustering results. Typically, S values above 0.7 reflect highly efficient and convincing clustering, while values above 0.5 are considered acceptable[51]. To assess the influence of parameter configurations on clustering quality, this study compares Q and S values across multiple parameter settings, as shown in Table 1. Based on this comparison, the parameters set with the largest Q and S values were selected for subsequent analysis. The specific parameter settings were as follows (the last row of Table 1): Time Span = 2006-2025 (Years Per Slice = 4), Node Types = Reference, Links Strength = Cosine, Links Scope = Within Slices, and Selection Criteria = Thresholds [c(2,2,20); cc(4,3,20); ccv(4,3,20)]. The Pathfinder algorithm was applied to prune the co-citation networks. After obtaining the co-citation network, the study further used the automatic clustering function of CiteSpace to extract cluster labels based on subject categories (Labels = S), with the clustering labels generated using the Log-Likelihood Ratio (LLR) algorithm. In total, 10 clusters were identified and visualized using the timeline mapping approach [Figure 2].

As shown in Figure 2, the clustering results indicate that cluster numbering is discontinuous, with clusters #5 and #10 missing. This is because the similarity between these clusters and their member documents was relatively weak, and their concentration did not reach a noteworthy level, leading to their complete omission by the software. As indicated by the parameters in the upper right corner of Figure 2, the clustering results based on cited references in this study yielded a Modularity (Q) of 0.8465 and a Weighted Mean Silhouette (S) of 0.9702, demonstrating that the clustering results are highly significant and convincing. These results were obtained after multiple rounds of threshold adjustment and time-slice optimization, representing the ideal clustering outcome.

While Figure 2 presents the visual trends, Table 2 offers a detailed numerical description of the corresponding data to facilitate interpretation and comparison. As shown in Table 2, cluster IDs are ranked based on cluster size, and "Size" represents the number of references contained in each cluster. It can be seen from Table 2 that the S values of all 10 clusters exceed 0.9, indicating highly satisfactory clustering performance. "Average Year" indicates the average publication year of the references within the cluster. "From" represents the publication year of the earliest reference in the cluster, while "To" denotes the publication year of the most recent reference in the cluster as of the retrieval time. "Activeness" is used to determine whether the cluster remains active in the current research stage. Through detailed reading and analysis, it was found that there is a certain degree of thematic overlap and intersection among the clusters. To avoid redundancy and repetition in the literature review, this study ultimately selected the five most representative clusters from the ten identified clusters as the focus for presenting the intellectual base of EF research. These five clusters cover all the core research themes within the field. The selected clusters are Cluster #11, Cluster #9, Cluster #3, Cluster #1, and Cluster #7, ordered according to their Average Year, and detailed analysis and discussion are conducted on this basis.

THE INTELLECTUAL BASE OF ENVIRONMENTAL FOOTPRINT

The intellectual base in cluster #11

Cluster #11 is the smallest and no longer active cluster, consisting of 18 members, with a silhouette value of 0.976. The cluster theme is identified as "Materials Science, Paper & Wood," covering the period from 2010 to 2017, with a median publication year of 2013 [Table 2]. As shown in Figure 2, the size of the nodes indicates that most of the key references within Cluster #11 were published after 2014. The intellectual base of this cluster mainly centers on the PEF and OEF methods released by the European Commission.

The European Commission officially published the PEF and OEF methodologies in 2013, integrating the LCA approach with the footprint concept. These methods cover up to 16 environmental impact categories, including climate change, water use, land use, biodiversity loss, and resource depletion[5]. The overarching

Table 1. Comparison of multiple parameter settings for the timeline map

Selection criteria	Time slicing	Pruning	Density	MQ	MS	M(Q,S)
Thresholding (2, 2, 20; 4, 3, 20; 4, 3, 20)	1	Pathfinder (pruning the merged network)	0.0073	0.836	0.9189	0.8755
Thresholding (2, 2, 20; 4, 3, 20; 4, 3, 20)	2	Pathfinder (pruning the merged network)	0.0063	0.8606	0.95	0.9031
Thresholding (2, 2, 20; 4, 3, 20; 4, 3, 20)	3	Pathfinder (pruning the merged network)	0.006	0.8364	0.9441	0.887
Thresholding (2, 2, 20; 5, 3, 20; 5, 3, 20)	4	Pathfinder (pruning the merged network)	0.0123	0.855	0.924	0.8882
Thresholding (3, 2, 20; 6, 3, 20; 7, 3, 20)	4	Pathfinder (pruning the merged network)	0.283	0.7714	0.9298	0.8432
Thresholding (2, 2, 20; 4, 3, 20; 4, 3, 20)	4	None	0.0105	0.8437	0.9449	0.8914
Thresholding (2, 2, 20; 4, 3, 20; 4, 3, 20)	4	Pathfinder (pruning the merged network)	0.0053	0.8465	0.9702	0.9041

Table 2. Summary of the largest 10 clusters

Cluster ID	Size	Silhouette	From	to	Duration	Average Year	Activeness
0	68	0.985	2015	2023	9	2018	Active
1	41	0.974	2017	2023	7	2020	Active
2	39	0.918	2018	2023	6	2020	Active
3	37	0.992	2015	2022	8	2018	Active
4	37	0.992	2016	2023	8	2019	Active
6	28	0.989	2009	2015	7	2012	Inactive
7	27	0.919	2015	2023	9	2019	Active
8	24	0.956	2016	2022	7	2018	Active
9	21	0.984	2014	2021	8	2018	Active
11	18	0.976	2010	2017	8	2013	Inactive

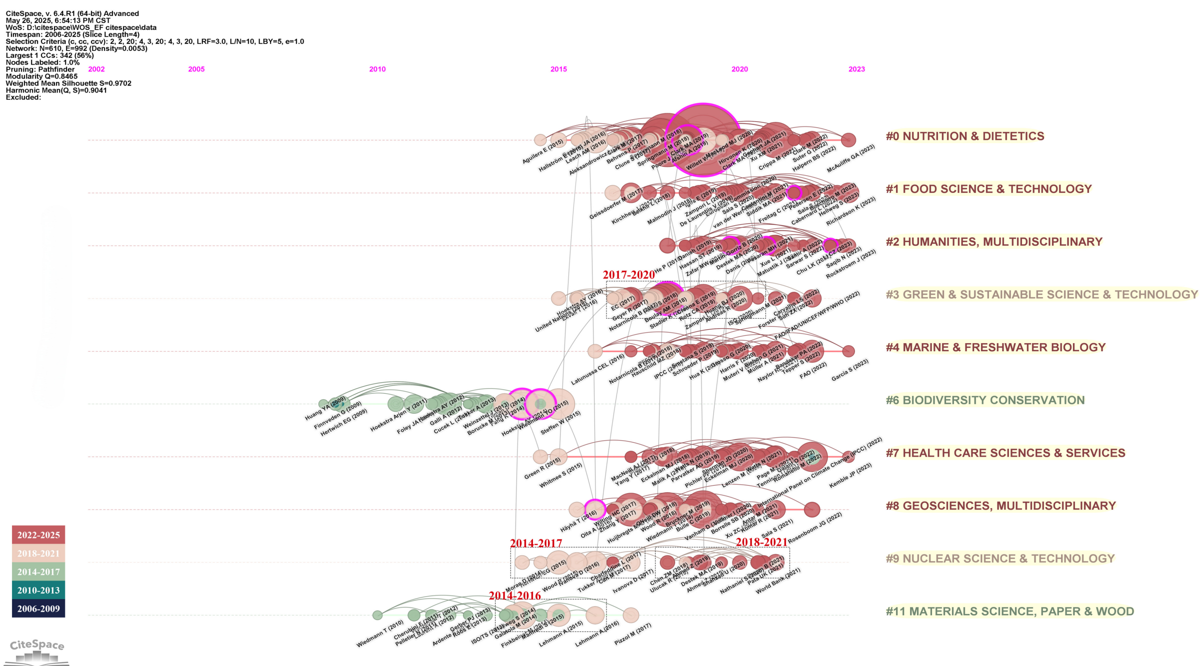

Figure 2. The timeline visualization mapping of the co-citation network of cited references. (Note: The ring structure reflects the citation history of the literature, where green rings represent earlier years, and red rings indicate more recent years, which can be identified based on the legend at the bottom left of Figure 2. The thickness of each ring is proportional to the number of citations in that year, and the overall radius of a node corresponds to its total citation frequency. Moreover, some nodes are highlighted with purple rings, indicating that these nodes have high betweenness centrality (≥ 0.1), reflecting their importance in bridging different clusters[51]. The same annotation applies to the image below).

goal of the PEF methodology is to reduce the environmental impacts of products and services by considering supply chain activities throughout their life cycle - from raw material extraction, production, and use to final waste management[52]. However, in 2014, Finkbeiner raised concerns regarding whether the PEF published by the European Commission truly represented a breakthrough in the policy implementation of LCA[53]. He argued that instead of providing a compromise solution to harmonize existing standards, the PEF introduced an entirely new standard that could potentially conflict with the existing ISO 14044 standard. Therefore, he suggested that the PEF might hinder harmonization efforts, causing confusion, fragmentation, and distrust. The debate initiated by Finkbeiner triggered discussions that contributed to the improvement of the EF methodologies by the European Commission. In response, Galatola and Pant acknowledged in 2014 that the proliferation of methods and approaches for measuring environmental performance could indeed complicate and increase the costs of making environmental claims on products or organizations in the EU single market[54]. They argued that the adoption of the EF method, as mandated by the European Council, could provide a common basis for measuring and communicating environmental performance and gain recognition among stakeholders across the European market.

In 2014, Pelletier *et al.* reviewed existing OEF methods based on four core criteria derived from the EU-developed OEF guidelines[55]. They found that there was almost no consistency among these methods and that very few met the four standards of the EU OEF methodology. After clarifying the methodological specifications of the OEF, they concluded that it represented a significant advancement in standardizing OEF assessment based on life cycle principles, surpassing other methods in several key aspects. Subsequently, a 2015 study by Manfredi *et al.* conducted a structured comparison between the EU PEF methodology and some existing European environmental accounting methods and standards[56]. Their findings showed that the EU PEF method offered higher methodological consistency and clearer requirements, thereby facilitating improved result consistency, comparability, and reproducibility. Nonetheless, several limitations of the EF methodology remained. Lehmann *et al.* in 2015 first compared the key differences between the PEF method and the ISO approach, highlighting the challenges regarding the applicability of the PEF, particularly in impact assessment[57]. Later, in 2016, Lehmann *et al.* conducted a comprehensive analysis of the PEF pilot phase [primarily based on the evaluation of all Product Environmental Footprint Category Rules (PEFCRs) drafts], concluding that the PEF still faced some methodological and practical challenges, such as the inapplicability of certain PEF rules and the immaturity of some predefined impact assessment methods[58]. They suggested that both the PEF methodology and PEFCRs required further refinement and improvement to ensure the successful implementation of the PEF policy.

Although Cluster #11 is no longer active, it reflects the early-stage academic discussions surrounding the development of the EU-EF methodologies. These discussions primarily focused on the comparison with existing environmental performance assessment methods and proposed constructive suggestions for improving the EU-EF methods. Overall, these debates were positive and played a crucial role in promoting the advancement and refinement of the EU-EF methodologies.

The intellectual base in cluster #9

Cluster #9 contains 21 members with a silhouette value of 0.984. The cluster theme is identified as "Nuclear Science & Technology," covering the period from 2014 to 2021, with a median publication year of 2018 [Table 2]. As shown in Figures 2 and 3, the development of Cluster #9 can be divided into two stages. From 2014 to 2017, the intellectual base primarily focused on studies utilizing MRIO databases. From 2018 to 2021, the knowledge base expanded to include two main research streams: testing the Environmental Kuznets Curve (EKC) hypothesis and exploring the influencing factors of Ecological Footprints.

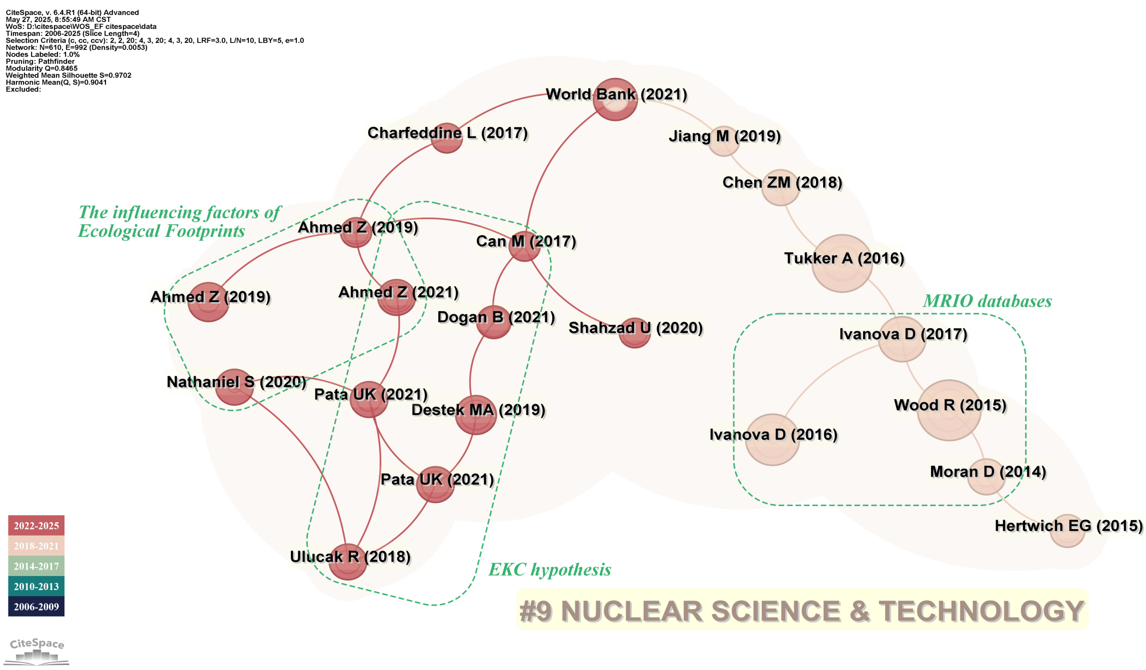

Figure 3. The cluster visualization mapping of the co-citation network of cited references of Cluster #9.

The Environmentally Extended Multi-Regional Input-Output (EEMRIO) framework has become a key approach for comprehensively describing the global economy and analyzing its environmental impacts. The MRIO model enables the tracing of environmental impacts from the consumption side to their sources, allowing for the allocation and tracing of environmental responsibilities across regions, sectors, and supply chains. As illustrated by the "MRIO database" section in Figure 3, Moran and Wood in 2014 provided an overview and comparison of the four largest independently constructed global MRIO databases: Eora, WIOD, EXIOBASE, and the GTAP-based OpenEU database[59]. They found that, for most major economies, the differences in carbon footprint estimates across these MRIO databases were less than 10%. They also emphasized that confidence estimation is essential when applying MRIO methods and consumption-based accounting in national-level environmental decision making. Among the existing EEMRIO databases, EXIOBASE is compatible with the System of Environmental-Economic Accounting (SEEA) and provides highly detailed sectoral data matched with various social and environmental satellite accounts. Wood *et al.* discussed the construction methods of the EXIOBASE database in 2015[60]. According to a 2016 research by Ivanova *et al.*, they used the EXIOBASE 2.2 database to assess the environmental impacts of household consumption, revealing that in 2007, household consumption accounted for over 60% of global GHG emissions and between 50% and 80% of total land, material, and water use[61]. In the following year, Ivanova *et al.* developed a carbon footprint inventory related to household consumption for 27 EU countries and 177 regions based on the EXIOBASE 2.3 database, making a significant contribution to integrating consumption-based accounting into local decision making[62].

The EKC hypothesis posits that there may be an inverted U-shaped relationship between environmental pollution and economic growth, reflecting the dynamic evolution of environmental pressure during the process of economic development. Numerous studies have tested the EKC hypothesis using different research methods and environmental degradation variables to observe the situations of individual countries or cross-country groups. A summary literature review of "EKC hypothesis" studies within Cluster #9 of Figure 3 is presented in Table 3[63-69]. There is no unified indicator for measuring environmental degradation,

Table 3. Summary literature review of EKC in cluster #9

Reference	Research area	Period	Environmental degradation variables	Methods	EKC hypothesis
Can and Gozgor (2017)[63]	French	1964-2014	CO_2 emissions	The unit root test with two structural breaks and a dynamic ordinary least squares estimation	Yes
Charfeddine (2017)[64]	Qatari	1970-2015	CO_2 emissions, the total ecological footprint, and ecological carbon footprint	The Markov switching equilibrium correction model	Yes: CO_2 emissions and ecological carbon footprint No: the total ecological footprint holds for a U-shaped behavior
Ulucak and Bilgili (2018)[65]	45 countries are divided into three groups: low, middle, and high income	1961-2013	Ecological footprint	The best fitted model among the models of continuously updated fully modified (CUP-FM) and continuously updated bias corrected (CUP-BC) models	Yes
Destek and Sarkodie (2019)[66]	11 newly industrialized countries	1977-2013	Ecological Footprint	Augmented mean group (AMG) estimator and heterogeneous panel causality method	Yes
Pata (2021)[67]	the USA	1980-2016	CO_2 emissions and ecological footprint	The combined co-integration test and three different estimators	Yes
Ahmed *et al.* (2021)[68]	Japan	1971-2016	Ecological footprint	The asymmetric and symmetric ARDL	Yes
Pata and Caglar(2021)[69]	China	1980-2016	CO_2 emissions and ecological footprint	Augmented ARDL approach in the presence of one structural break	No: a U-shaped quadratic relationship

EKC: Environmental Kuznets curve; ARDL: Autoregressive Distributed Lag approach.

with both CO_2 emissions and Ecological Footprint commonly used as alternative indicators. Depending on the research methods, study regions, and variable selections, the results of relevant literature vary. Some studies found evidence of an inverted U-shaped relationship between economic growth and environmental degradation indicators, while others identified U-shaped or U-shaped quadratic relationships.

The final major knowledge base within Cluster #9 focuses on the influencing factors of Ecological Footprints. In addition to economic growth - which has been frequently examined in the context of testing the EKC hypothesis - previous studies have extensively explored various factors affecting ecological footprints, including globalization, human capital, energy consumption, trade openness, urbanization, and financial development[68,70-72].

The intellectual base in cluster #3

Cluster #3 contains 37 members with the highest silhouette value of 0.992. The cluster theme is identified as "Green & Sustainable Science & Technology," covering the period from 2015 to 2022, with a median publication year of 2018 [Table 2]. As shown in Figure 2, a significant number of studies within this cluster emerged between 2017 and 2020, including a high betweenness centrality reference with a centrality score of 0.11[73]. Although the number of references decreased after 2020, these studies still provide valuable perspectives for the further development of this research field. After reviewing the 37 articles in this cluster, the intellectual base of Cluster #3 can be categorized into four main research themes: methodological guidelines, normalization and weighting methods in LCA, environmental impacts of final consumption, and food systems.

Cluster #3 includes numerous standards and policy documents published by internationally recognized organizations, providing essential theoretical support and reference frameworks for methodological development and empirical research on EF. These key documents include ISO 14040 and ISO 14044 standards, "Suggestions for updating the PEF method"[74], "Supporting information to the characterisation factors of recommended EF Life Cycle Impact Assessment methods: New methods and differences with ILCD"[75], and "Product Environmental Footprint Category Rules Guidance"[76].

As a critical indicator system for quantifying the environmental pressures of human activities on ecosystems, the EF is typically measured using the LCA approach. LCA provides a systematic framework for data collection and impact assessment, ensuring methodological consistency and comparability in evaluating EF at the product, organizational, or national levels. Cluster #3 particularly focuses on the normalization and weighting methods during the Life Cycle Impact Assessment (LCIA) phase, addressing key methodological challenges in the integration of LCA results. Although ISO standards do not support the use of normalization and weighting methods when publishing LCA comparative conclusions, the increasing need to identify the most relevant impact categories has driven further research in this area. The 72nd LCA Forum discussed the current status, major challenges, and future development of normalization and weighting in LCA[77]. Conducting a global-scale environmental impact assessment is crucial for establishing comparative benchmarks of environmental performance for products and systems. To this end, in 2019, Crenna *et al.* collected data on global emissions and resource use and calculated global normalization factors (NFs) for 12 impact categories using midpoint indicators from the International Reference Life Cycle Data System (ILCD) and the EF dataset (including recently released models)[78]. Weighting helps identify the most relevant impact categories, life cycle stages, processes, and resource consumption or emissions, ensuring that communication efforts focus on the most important aspects. To improve the assessment of EF, the Joint Research Centre (JRC) of the European Commission published a technical report in 2017 titled "Development of a weighting approach for the Environmental Footprint"[79]. In addition to the LCA methodology, the EEMRIO model also serves as a key framework for environmental impact assessment. While Cluster #9 has provided a systematic literature review of MRIO databases, particularly EXIOBASE 2, Cluster #3 highlights the latest developments of EXIOBASE 3[73].

Sustainable Development Goal 12 (SDG 12) explicitly states that sustainable and responsible production and consumption are central to sustainable development, with sustainable consumption and production being one of the main principles for reducing global environmental impacts. In 2019, Sala and Castellani[80] and Beylot *et al.*[81] respectively applied the LCA method and the Environmentally Extended Input-Output (EEIO) model (using EXIOBASE 3) to study the environmental impacts of final consumption in Europe. In the same year, Sala and Castellani investigated five consumption domains and assessed environmental impacts across 16 categories based on the EF LCIA method. Their results showed that food consumption was the largest contributor to environmental impacts[80]. Also in that year, Beylot *et al.* analyzed 14 out of 16 environmental impact categories described in the EEIO model and found that environmental impacts were mainly driven by supply chains of products and services, with food - especially meat and dairy products - being the primary contributors to acidification, eutrophication, land use, and water use[81].

Food is not only fundamental to human health and food security but also a key driver of global environmental change. The complexity of food systems poses significant challenges to LCA. In 2017, Notarnicola *et al.* proposed research priorities to guide the scientific development and practical improvement of food systems[82]. Adopting healthy and sustainable diets is essential for preserving natural resources and reducing diet-related mortality. Springmann *et al.* estimated the global costs of healthy and sustainable diets in 2021 and found that, compared to current dietary costs, these diets would be 22%-34% cheaper on average in upper-middle- to high-income countries (based on statistical means), while in lower-middle- to low-income countries, the costs would be at least 18%-29% higher, depending on the specific dietary patterns[83]. A 2022 study by Sun *et al.* simulated the adoption of the EAT-Lancet planetary health diet across 54 high-income countries, representing 68% of global GDP and 17% of the global population[84]. Their findings suggested that such dietary shifts could reduce annual agricultural production emissions from food consumption in these countries by 61% and sequester up to 98.3 (55.6-143.7) Gt CO_2 equivalent, which is approximately equivalent to 14 years of current global agricultural emissions, until natural vegetation fully matures.

Driven by rising average personal incomes and global population growth, both per capita meat consumption and total meat consumption have been increasing worldwide. The consumption of different types of meat and meat products has significant health implications for people, while livestock production exerts considerable negative environmental impacts[85]. In 2019, Rotz *et al.* developed approximately 150 representative beef production systems across the United States and simulated their performance and environmental impacts using the Integrated Farm System Model (IFSM) with localized soil and climate data[86]. Their simulations quantified the environmental impacts of regional beef production systems, providing benchmark measurements for the sustainability of beef production in the United States. In the same year, Asem-Hiablie *et al.* also applied the IFSM to assess cradle-to-farm-gate beef production in the U.S. beef industry. Their results indicated that the feed production and cattle raising stages were the primary contributors to most environmental impact categories[87].

Cellular agriculture is an emerging branch of biotechnology aimed at addressing environmental impacts, animal welfare concerns, and sustainability challenges associated with conventional livestock production. This approach seeks to produce meat (i.e., cultured meat) without the drawbacks of traditional animal farming, thereby promoting future food and nutrition security. However, the study of Lynch and Pierrehumbert in 2019 found that cultured meat does not necessarily outperform conventional beef production in terms of climate impacts[88]. Instead, its relative environmental performance depends heavily on the availability of decarbonized energy sources and the specific production systems employed. Moreover, cultured meat still faces challenges related to consumer acceptance, technological development, and broader societal factors[89-91].

The intellectual base in cluster #1

The second largest cluster, Cluster #1, consists of 41 members with a silhouette value of 0.974. The cluster theme is identified as “Food Science & Technology,” covering the period from 2017 to 2023, with a median publication year of 2020 [Table 2]. The overall timeline of this cluster is relatively recent, allowing it to be regarded both as part of the research foundation and as a representation of emerging research fronts. The development of this cluster has been relatively stable [Figure 2], without highly cited burst references, and containing only one high betweenness centrality reference with a score of 0.12[92]. After reviewing the 41 articles in this cluster, as shown in Figure 4, its intellectual base can be summarized into four main categories: circular economy and PEF, PBs, uncertainty in LCA methods, and other research domains.

In “Circular economy” within Cluster #1 of Figure 4, two articles related to the circular economy focused primarily on the conceptual definition of the term. In 2017, Geissdoerfer *et al.* conducted a comprehensive

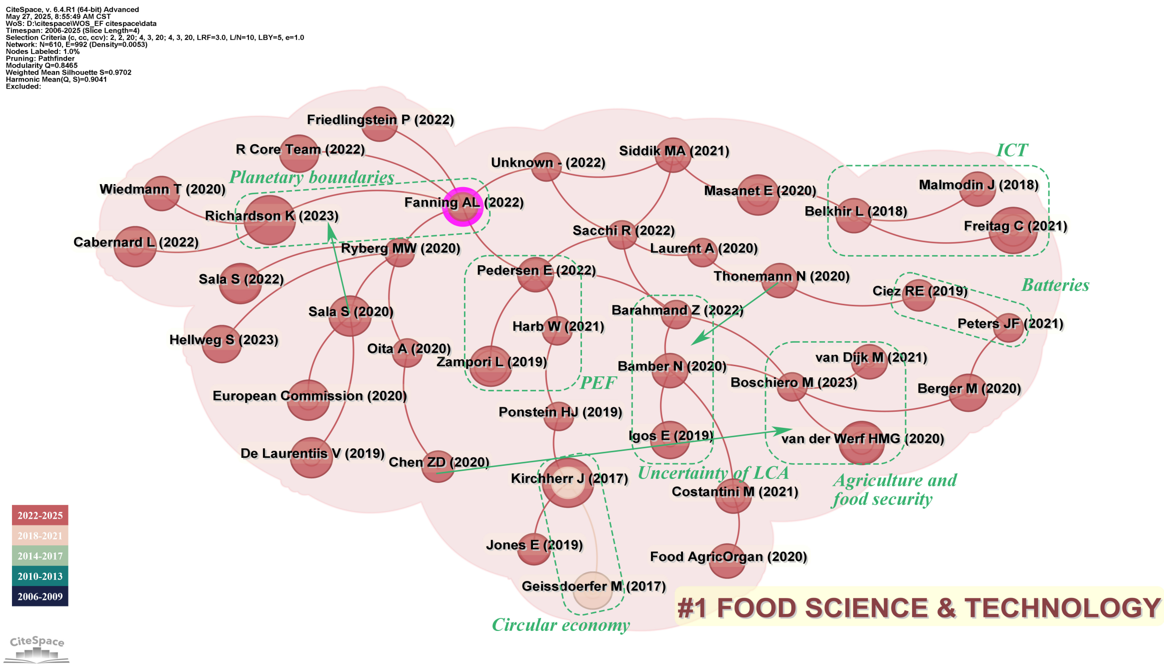

Figure 4. The cluster visualization mapping of the co-citation network of the cited reference of Cluster #1.

literature review and identified eight different relationship types between the circular economy and sustainable development, as well as their most notable similarities and differences[93]. Meanwhile, Kirchherr *et al.* collected 114 definitions of the circular economy and coded them across 17 dimensions, critically discussing various conceptualizations[94]. They defined the circular economy within their iteratively developed coding framework as an economic system that replaces the "end-of-life" concept with reducing, alternatively reusing, recycling, and recovering materials in production, distribution and consumption processes.

In the Circular Economy Action Plan of the European Green Deal, the European Commission explicitly mentioned the PEF as part of its agenda for promoting sustainable growth. As shown in Figure 4, Cluster #1 includes two types of studies on "PEF": methodological refinement and empirical research. During the transitional stage of refining the PEF methodology, a report titled "Suggestions for updating the PEF method" was published in 2019[74], proposing modifications to the implemented PEF method. In 2022, Pedersen and Remmen conducted a review of PEF-related literature and found that although some issues had been addressed in the updated PEF guidelines, several challenges remained[52]. For instance, the functional units defined in the PEFCRs were insufficient to ensure fair product comparisons; the impact categories of biodiversity and indirect land use change were still under development; and both existing and new PEFCRs needed to adopt a benchmarking approach. Harb *et al.* conducted a PEF study[95] in 2021 on a Lebanese red wine "Coteaux Les Cedres" produced by HF S.A.L (Couvent Rouge winery) in the Bekaa Valley and consumed in the UK, based on the PEFCRs ON WINE version 5.2 draft. The results showed that for a 0.75-liter package of red wine, the most relevant life cycle stages were grape production, primary packaging, and distribution, contributing on average 39%, 34%, and 13% to the overall environmental impacts, respectively.

As shown in the "PBs" section of Figure 4, Fanning *et al.* in 2022 applied the doughnut-shaped "safe and just space" framework to analyze the historical dynamics of 11 social indicators and 6 biophysical indicators across more than 140 countries from 1992 to 2015[92]. Their study found that countries often exceeded biophysical boundaries faster than they reached social thresholds, and no country achieved the minimum social thresholds within the biophysical boundaries during this period. Moreover, in his 2023 study, Richardson updated the PBs framework, revealing that six out of nine boundaries have already been transgressed, indicating that the Earth has far exceeded the safe operating space for humanity. Ocean acidification is approaching the boundary limit, and aerosol loading has exceeded the boundary at the regional scale, with the transgression levels of all previously breached boundaries increasing[96]. The PBs framework also helps assess whether production and consumption systems are environmentally sustainable concerning the Earth's ecological limits and carrying capacity. In 2020, Sala *et al.* assessed the environmental impacts of EU production and consumption in 2010 using one production-based perspective and four consumption-based perspectives, including both top-down (IO LCA) and bottom-up (process-based LCA) approaches. Their comparison with PBs revealed that EU consumption had already approached or exceeded the global boundaries in terms of climate change, particulate matter, land use, and mineral resource use[97].

The EU-EF is an LCA-based method designed to assess the environmental impacts of products and organizations across 16 midpoint impact categories[98]. However, the application of LCA as a decision-support tool may be affected by many uncertainties in its calculations[99]. As indicated by the "Uncertainty of LCA" part of Figure 4, according to Barahmand and Eikeland's study in 2022, the main sources of uncertainty in LCA include model and process parameters, data variability, and the use of different methods and databases[100]. In 2019, Igos *et al.* provided recommendations for handling uncertainties at three levels based on a literature review and an analysis of LCA tool functionalities[99]. Their basic recommendation was to include at least a qualitative discussion of uncertainties in a dedicated paragraph; at the intermediate level, Monte Carlo simulation could be used for uncertainty analysis; and for advanced practitioners, it was recommended to comprehensively screen uncertainty sources and perform Latin hypercube sampling and global sensitivity analysis. In addition, LCA can be divided into attributional and consequential approaches. Bamber *et al.* in 2020 described common sources and methods of uncertainty analysis in both attributional and consequential LCA and assessed their frequency of application[101]. In the same year, Thonemann *et al.* found through a literature review that uncertainty was the primary challenge in applying prospective LCA and summarized methods for addressing these challenges[102].

Cluster #1 also encompasses the intellectual base of several other research domains, as shown in Figure 4, including "Agriculture and food security"[103-105], "information and communication technology (ICT)"[106-108], and "batteries"[109,110]. In the area of agriculture and food security, van Dijk *et al.* in 2021 conducted a systematic literature review and meta-analysis of 57 global food security projections and quantitative scenario studies published over the past two decades[105]. They estimated that between 2010 and 2050, global food demand would increase by 35% to 56%, while the population at risk of hunger would change by -91% to +8%. In the ICT industry, research findings have presented a paradox. Studies by Belkhir and Elmeligi[106] in 2018 and Freitag *et al.*[107] in 2021 indicated that without any control measures, the global carbon footprint or GHG emissions of ICT would not decrease. In contrast, the findings of Malmodin and Lundén[108] in 2018 suggested that despite the continuous growth of users and data traffic, the carbon footprint of ICT and the electro-mechanical industry had shifted from previous growth to a decreasing trend.

The intellectual base in cluster #7

The Cluster #7 consists of 27 members with a silhouette value of 0.919. The cluster theme is identified as "Health Care Sciences & Services," covering the period from 2015 to 2023, with a median publication year of 2019 [Table 2]. The references within this cluster are mainly concentrated after 2017 [Figure 2], and the intellectual base focuses on multidimensional research in the healthcare sector, reflecting the growing academic interest in the intersection of environmental impacts, climate change, and sustainable development within this field [Figure 5].

This cluster includes several highly authoritative and policy-relevant framework documents, as marked by the asterisks in Figure 5, such as the IPCC report "Climate Change 2022: Impacts, Adaptation and Vulnerability"[111], two editions of the "Lancet Commission Report"[112,113], and three editions of the "Lancet Countdown Report"[114,115]. As a key outcome of Working Group II of the IPCC Sixth Assessment Report, "Climate Change 2022: Impacts, Adaptation and Vulnerability"[111] systematically assessed the multidimensional impacts of climate change on natural and social systems, highlighting that health systems are highly vulnerable to extreme climate events and play a crucial role in climate adaptation and resilience building. The "Lancet Commission Report" is one of the seminal works in climate change and health research, which first systematically proposed that "climate change is the greatest threat to human health in the 21st century, but also the greatest opportunity"[113], generating widespread global influence. Building on this, since 2016, the annually published "Lancet Countdown Report" has become a flagship report series under the Lancet's climate and health research agenda, systematically tracking global and national progress in health responses to climate change, and has become a key intellectual base in this field. Collectively, these documents constitute an important knowledge base at the intersection of climate change and public health, providing systematic evidence for global climate risk responses and offering policy frameworks and academic support for the environmental transformation of the healthcare sector and the adaptation pathways of health systems.

As illustrated in the "Carbon emission of the healthcare sector" module in Figure 5, the study of Lenzen *et al.* in 2020 indicated that with the intensification of global climate change, the healthcare sector, as a highly resource-intensive industry, has attracted increasing attention for its own carbon emissions and sustainable transformation potential. Depending on the environmental indicators considered, the healthcare sector is estimated to contribute between 1% and 5% of the global environmental impact, with this proportion exceeding 5% in certain countries and regions[2]. In recent years, more countries have begun to pay attention to the environmental responsibility and emission reduction potential of their healthcare systems. Tennison *et al.* in 2021 applied a hybrid model to quantify the emissions within Scopes 1, 2, and 3 of the GHG Protocol for the UK National Health Service (NHS) from 1990 to 2019, including emissions from patient and visitor travel[116]. The study found that in 2019, the total emissions of healthcare services reached 25 Mt CO_2e, representing a 26% reduction since 1990, with emissions per completed inpatient admission decreasing by 64%. In 2018, Malik *et al.* conducted an observational economic input-output LCA of the Australian healthcare system, revealing that the carbon footprint of healthcare accounted for 7% of Australia's total carbon footprint, with hospitals and pharmaceuticals being the main contributors[117]. A 2018 study by Eckelman *et al.* applied an economic-environmental-epidemiological linkage modeling framework to quantify pollutant emissions and their public health impacts based on nationwide healthcare expenditures in Canada from 2009 to 2015[118]. On a life-cycle basis, the Canadian healthcare system emitted 33 Mt CO_2e, accounting for 4.6% of the national total. Moreover, two years later, Eckelman *et al.* updated the national healthcare sector emissions in the United States, showing that from 2010 to 2018, GHG emissions from the U.S. healthcare sector increased by 6%, reaching 1,692 kg CO_2e per capita in 2018, the highest among industrialized countries[119]. Overall, existing studies have conducted quantitative analyses of the carbon footprint and environmental impacts of healthcare systems in different countries using various methods, demonstrating the significant carbon responsibility and emission reduction potential of the healthcare sector at the national level.

In recent years, alongside the rising prominence of healthcare sustainability issues, an increasing number of studies have focused on the carbon emissions and environmental impacts of specific departments,

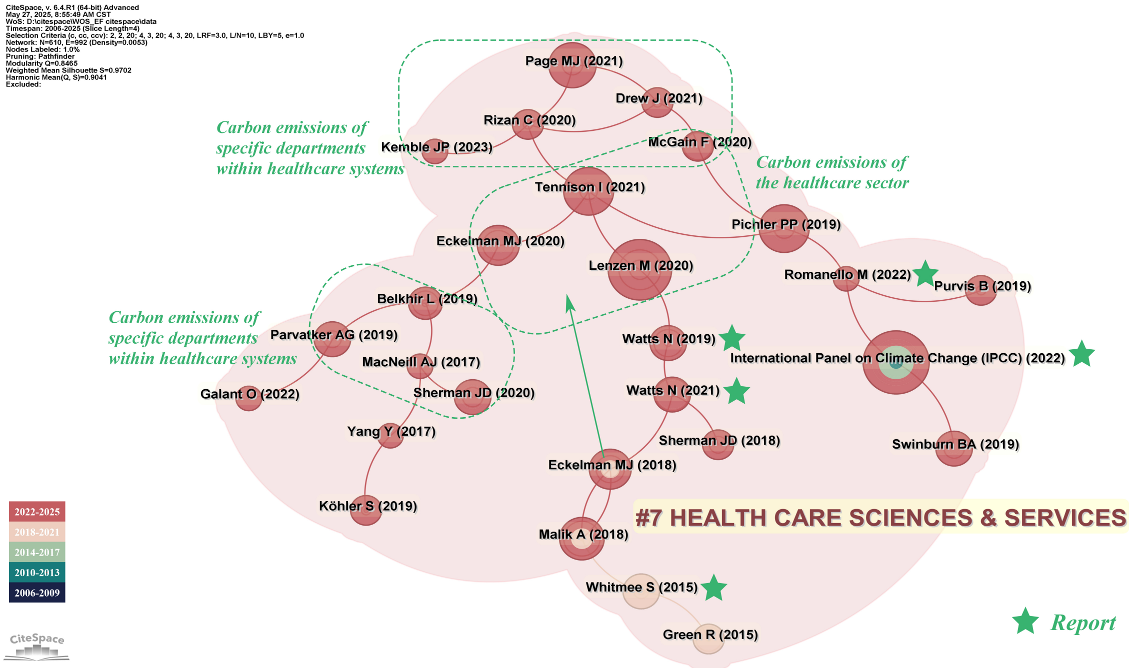

Figure 5. The cluster visualization mapping of the co-citation network of cited references of Cluster #7.

operational processes, and medical devices within healthcare systems, based on national-level carbon accounting. Among them, operating rooms are considered the most resource-intensive departments within hospitals. As shown in the "Carbon emissions of specific departments within healthcare systems" modules in Figure 5, MacNeill *et al.* in 2017 estimated the carbon footprint of operating rooms in three healthcare systems and found that anesthetic gases and energy consumption were the largest sources of GHG emissions[120]. Moreover, the energy consumption of operating rooms was three to six times that of the overall hospital energy consumption, primarily due to heating, ventilation, and air conditioning demands. In 2020, Rizan *et al.* reviewed studies and found that the carbon emissions from a single surgery ranged from 6 to 1,000 kg CO_2e, with electricity consumption and procurement of consumables being the main carbon hotspots[121]. Additionally, the fields of intensive care and anesthesia have also received extensive attention. The studies of Drew *et al.* in 2021 and McGain *et al.* in 2020 have explored the GHG impacts of anesthetic agents, the reusability of anesthesia equipment, and the effects of energy-saving management measures on the overall carbon footprint[122,123]. In the pharmaceutical and pharmaceutical manufacturing sector, Parvatker *et al.* in 2019 constructed a pharmaceutical life-cycle inventory using process scaling and process design methods, revealing a positive correlation between the complexity of drug synthesis and its carbon emission intensity[124]. In the same year, Belkhir and Elmeligi found that the emission intensity of the entire pharmaceutical industry exceeded that of the automotive manufacturing industry, indicating significant emission reduction potential[125]. Regarding medical devices, comparative studies of single-use and reusable equipment have also increased. Studies by Kemble *et al.* in 2023 and Sherman *et al.* in 2018 on laryngoscopes and flexible cystoscopes have shown that reusable devices generally have lower carbon footprints in most use scenarios. Although their per-unit manufacturing emissions are higher, the environmental cost per use is significantly lower due to the higher number of reuses compared to single-use products[126,127]. Overall, the above-mentioned studies reveal the improvement potential of healthcare subsystems in carbon reduction from multiple dimensions, including equipment selection, operational processes, and institutional optimization, providing empirical foundations and policy implications for building green healthcare systems.

Future research directions

Building upon the current knowledge base, several promising directions can further advance EF research. One direction involves integrating the EF framework with PBs to enhance global sustainability assessments. By linking footprint indicators with Earth system thresholds, future studies can evaluate whether specific countries, industries, or consumption patterns exceed safe ecological limits, especially at the macro-regional or global scale. In addition, deeper alignment with circular economy principles presents strong potential. Rather than merely quantifying the environmental burden of linear production systems, EF models can be applied to assess the benefits of circular strategies such as material reuse, recycling, eco-design, and service-oriented business models. Embedding EF indicators into circular economy performance metrics could provide a more robust environmental basis for evaluating circular initiatives.

Enhancing spatial and temporal resolution remains a critical methodological priority. The incorporation of geospatial data, Geographic Information Systems (GIS), dynamic LCA, and scenario-based forecasting will enable more fine-grained and policy-responsive analyses across sectors and regions. Strengthening methodological robustness is essential, particularly for complex and data-intensive systems such as healthcare and construction. Future studies should focus on refining system boundary definitions, enhancing sensitivity and uncertainty analysis, and promoting transparent and standardized accounting frameworks to ensure comparability and reproducibility across studies.

The potential use of EF indicators as composite environmental proxies also deserves further attention. Existing literature shows that ecological footprint, carbon emissions, and related metrics have been employed to empirically test the EKC hypothesis. With proper weighting and normalization, EF indicators could be developed into multidimensional indices, serving as a more comprehensive alternative environmental indicator.

Lastly, based on the diverse research themes captured in the clusters and the previous review of current developments, it is evident that EF research is increasingly shifting toward interdisciplinary integration and multi-contextual applications. Topics such as agricultural and food systems, healthcare, plastics, battery supply chains, and artificial intelligence infrastructure have emerged as prominent research frontiers. To keep pace with this trend, EF accounting should be further extended into newly emerging domains. In addition to the areas mentioned above, other emerging fields warranting attention include hydrogen energy, cryptocurrency mining, cloud computing, digital infrastructure, and synthetic biology. These complex and rapidly evolving sectors present significant challenges for system boundary definition and data acquisition, yet offer high-impact opportunities for the early integration of environmental assessment tools.

INDUSTRY-SPECIFIC ANALYSIS

Following the systematic review of the research status, intellectual base, and emerging fronts of EF studies, it remains necessary to further investigate accounting practices within specific industries. On the one hand, bibliometric and knowledge mapping approaches primarily reveal the structural and evolutionary patterns of research but offer limited insight into the accounting characteristics under real-world application contexts. On the other hand, substantial differences exist across industries in terms of accounting objects, system boundaries, methodological applicability, and data availability. These differences present significant challenges to the practical implementation of EF accounting. A comparative analysis of EF practices across sectors thus serves as both a practical extension of the previously identified knowledge structure and a foundation for more context-specific theoretical guidance and methodological adaptation.

The introduction has reviewed the current state of EF research across sectors such as agriculture, plastics, renewable energy, and healthcare. To avoid redundancy, this study focuses in the later sections on two industries-metals and construction-that were relatively underexplored in the introduction but are nonetheless of critical importance. Meanwhile, although the healthcare sector was previously discussed, it emerges in the CiteSpace co-citation analysis as a distinct and thematically cohesive cluster (Cluster #7), indicating its unique intellectual position within EF research. Therefore, this study also includes healthcare in the subsequent industry-specific analysis to reflect both its theoretical relevance and practical significance.

These three sectors-healthcare, metals, and construction-are representative in several ways. First, they span across the service, heavy industrial, and construction sectors and are all characterized by high levels of resource consumption and environmental impact, including intensive carbon emissions, energy use, and material inputs. Second, they share common technical challenges in EF accounting, such as complex system boundary definitions and heterogeneous data sources, which have driven the development and integration of multiple methodological approaches. Moreover, a growing body of literature has emerged in recent years, providing a solid foundation for cross-sectoral comparison and method adaptation. By synthesizing research across these three industries, this study aims to enhance the overall analytical framework while offering deeper insights into the current state of EF accounting in sector-specific contexts.

Metals

In the field of EF related to metals, as shown in Table 4, existing studies exhibit significant heterogeneity in terms of research scope, geographic coverage, data sources, methodological choices, selected environmental indicators, and uncertainty analysis. This reflects the diversity and evolving nature of research in this area. In terms of research scope, the literature covers a wide range of key metals, including traditional bulk metals such as aluminum[39] and copper[3,128,129], as well as strategically important metals such as gold[130,131], rare earth elements[132], and uranium[133]. The focus is not limited to primary resource extraction and processing but has increasingly expanded to include secondary resource recovery and recycling pathways-for example, copper slag recycling[134] and gold recovery from electronic waste[131]. Geographically, the studies span China, global regions, Europe, and several developing mining countries. A substantial portion of the literature focuses on China's metal supply chains and their environmental impacts[39,128,129], reflecting the country's growing research activity and policy demand in the area of metal resource management. Other studies adopt a global or cross-national perspective[3,135], emphasizing the heterogeneity of metal production systems across different regions.

Regarding data sources, most studies rely on internationally recognized life cycle databases such as Ecoinvent (versions 2.2 to 3.8) and GaBi, supplemented by industry statistics and national yearbooks[128]. Some studies draw on corporate annual reports or author-estimated data[3,136], which tend to offer lower transparency and consistency. Methodologically, the majority employ LCA and adopt various impact assessment models such as ReCiPe, IMPACTWorld+, and TRACI. The applications further vary across attributional LCA, Life Cycle Sustainability Assessment (LCSA), and PEF frameworks. A few studies also incorporate statistical analysis or emission factor-based estimation approaches[3,136]. In terms of environmental impact indicators, the number and dimensions of indicators vary significantly, from as few as three (e.g., water use, energy consumption, and GHG emissions) to comprehensive assessments involving up to 18 categories. Core indicators across most studies include global warming potential, energy use, acidification, eutrophication, toxicity impacts, and resource depletion. Some studies have extended the scope to include additional categories such as ionizing radiation, nuclear energy use, and short- and long-term climate change[131,133], reflecting the growing emphasis on comprehensiveness and system thinking in next-generation LCA. Regarding uncertainty analysis, various methods such as sensitivity analysis, Monte

Table 4. Summary of literature review studies on the environmental footprint of metals

Reference	Accounting objects	Research area	Data source	Methods	Environmental factors	Uncertainty analysis
Zhang *et al.* (2016)[39]	Aluminum oxide, primary aluminum, secondary aluminum	China	The Chinese process-based life cycle inventory database, the yearbook of Nonferrous Metals Industry of China (2013), and the Chinese Industrial Information Network, *etc.*	LCA analysis with the ReCiPe model and IMPACTWorld+model	Twelve categories: respiratory inorganics, respiratory organics, carcinogens, non-carcinogens, global warming, ozone layer depletion, freshwater ecotoxicity, land occupation, terrestrial acidification, aquatic eutrophication, metal depletion, and fossil depletion	Yes, Monte Carlo simulation
Northey *et al.*, (2013)[3]	Copper mine	The mines are from Australia, Chile, Peru, Argentina, Laos, Papua New Guinea, South Africa, Turkey, Finland, the USA, and Canada	The sustainability and financial reports are published by copper-producing mines, operations, and companies	Statistical analysis	Three categories: energy, greenhouse gas (GHG) emissions, and water intensity	No
Norgate and Haque (2012)[130]	Gold ores	Global	Published papers and reports, as well as company websites	LCA analysis using the SimaPro (version 7.3) software program	Four categories: Embodied energy, greenhouse gas emissions, embodied water, and solid waste burden	Yes, sensitivity analysis
Kuipers *et al.* (2018)[135]	Copper demand and supply	Global	Ecoinvent v2.2 database	Life cycle sustainability analysis (LCSA) methodology and scenario forecasting analysis	Five categories: Global warming, acidification, energy requirements, terrestrial ecotoxicity, and freshwater ecotoxicity	Yes, scenario analysis
Dong *et al.* (2020)[128]	Copper production and consumption	China	Ecoinvent v3.4 database CNREC (2017) China Nonferrous Industry Statistical Yearbook, and the United States Geological Survey (USGS), *etc.*	Life cycle sustainability analysis (LCSA) methodology and scenario forecasting analysis	Eight categories: Acidification potential, climate change, freshwater aquatic ecotoxicity, human toxicity, photochemical oxidation, abiotic depletion of resources-fossil fuels, abiotic depletion of resources-elements, and cumulative energy demand	Yes, scenario analysis
Lagos *et al.* (2018)[136]	Copper mining	Chilean	Published papers and authors' estimates	Emission factor method, *etc.*	Three categories: water and energy, and the GHG emissions	No
Chowdhury *et al.* (2021)[132]	Rare-earth elements (REEs) recycling from NdFeB Magnet Swarf	America and China	Ecoinvent 3.7 database	Attributional LCA with TRACI V2.1 and cumulative energy demand V1.11	Eleven categories: global warming, ecotoxicity, cumulative energy demand (CED), *etc.*	Yes, Monte Carlo Simulation
He *et al.* (2023)[131]	Gold recycling from electronic waste	N/A	Ecoinvent v3 database	Attributional LCA using SimaPro software (v.9) and IMPACT world + method and allocation	Eighteen categories: climate change in the short term, climate change in the long term, fossil and nuclear energy use, mineral resources use, *etc.*	No
Zhou *et al.* (2024)[134]	Recycling copper slags as cement replacement material in mine backfill	N/A	Ecoinvent v3.8 database	LCA using OpenLCA software and ReCiPe 2016 Midpoint (H)	Eighteen categories: agricultural land occupation, climate change, fossil depletion, freshwater ecotoxicity, *etc.*	Yes, sensitivity analysis
Altay *et al.* (2022)[133]	Uranium recovery from brine	N/A	Published papers and the Ecoinvent 3 database	LCA using SimaPro software (v.9) and IRE & IRHH midpoint	Sixteen categories: climate change, ozone depletion, human toxicity(non-cancer effects), human toxicity (cancer effects), particulate matter, ionizing radiation HH, *etc.*	Yes, sensitivity analysis
Monteleone *et*	Foundry production	Ten cast iron foundries in	Ecoinvent v.3.7.1 database	PEF using SimaPro software	Sixteen categories: climate change, ozone	No

al. (2024)[150]		Italy		(v.9) and normalization and weighting of the results	depletion, human toxicity (non-cancer effects), human toxicity (cancer effects), particulate matter, ionizing radiation HH, *etc.*	
Wang *et al.* (2024)[129]	Copper wire rod manufacturing	China	Previous assessment studies by the author and the GaBi database	LCA using GaBi software and the CML 2001 method	AP, EP, GWP, ODP, POCP, and PED	Yes, Monte Carlo Simulation and sensitivity analysis

LCA: Life cycle assessment; AP: acidification potential; EP: eutrophication potential; GWP: global warming potential; ODP: ozone depletion potential; GHG: greenhouse gas; POCP: photochemical ozone creation potential; PED: primary energy demand.

Carlo simulation, and scenario analysis have been widely adopted to enhance result robustness and interpretability. However, several studies did not explicitly address uncertainty[3,131], which may limit the verifiability of their results.

Healthcare sector

EF research in the healthcare sector has shown a trend toward increasing granularity. Based on the classification of research objects in the existing literature [Table 5], and as illustrated in Figure 6, the complexity of healthcare service systems can be categorized into five hierarchical levels: Level 1 refers to the overall healthcare sector level, Level 2 to the hospital or institutional level, Level 3 to the department level, Level 4 to the treatment pathway level, and Level 5 to the medical devices and consumables level. Among the reviewed studies, the vast majority focus on Level 5, primarily evaluating the life cycle environmental impacts of reusable versus disposable products such as personal protective equipment, scrub suits, duodenoscopes, and dental retainers[137,138]. These studies typically employ standardized LCA methods, commonly utilizing SimaPro or OpenLCA software in conjunction with the Ecoinvent database, and often incorporate sensitivity analysis or Monte Carlo simulations to enhance the robustness of the results. By contrast, studies at Level 2 and Level 3 are relatively scarce. These tend to analyze entire hospitals or specific departments (e.g., intensive care units), often applying hybrid LCA or material flow analysis (MFA) approaches to capture more complex system interactions[139,140].

In terms of geographic distribution, existing studies are primarily concentrated in North America and Europe, with Canada, the United States, Sweden, France, the Netherlands, and Spain forming the core of the current knowledge base. Research from developing countries is significantly underrepresented, highlighting a notable geographical imbalance. Methodologically, most studies adopt LCA approaches, including attributional or hybrid LCA models. Some also integrate life cycle cost assessment (LCCA) to evaluate the co-benefits of environmental and economic performance, particularly at the product and treatment levels. The scope of environmental impact categories considered has also expanded: while early studies mainly focused on GHG emissions, more recent research increasingly adopts the 16 impact categories recommended by the EU PEF methodology. These include climate change, ecotoxicity, eutrophication, ionizing radiation, water consumption, and resource depletion[137,141]. However, studies at higher hierarchical levels (Levels 2-4) often involve fewer impact categories and seldom conduct uncertainty analysis, which may limit the comprehensiveness and comparability of their results.

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Table 5. Summary of literature review studies on the environmental footprint of the healthcare sector

Reference	Hierarchical level	Accounting objects	Research area	Data source	Methods	Environmental factors	Uncertainty analysis
Kjaer *et al.* (2015)[151]	Level 2	Healthcare organizations and companies, and a tanker ship	Danish	FORWAST database	Hybrid EIO approach	Greenhouse gases, air pollution(SO_2, NMVOC, NH_3, particles (< 10 μm), and NOx), water use, *etc.*	Yes
Cimprich and Young (2023)[152]	Level 2	A Canadian hospital	Canada	The hospital's environmental sustainability team, "supply-chains" dataset, financial statements, facilities maintenance and operations team, food operations manager, and contracted service managers	O-LCA using OpenLCA (1.10.2)	Ten categories: global warming potential, acidification potential, ozone depletion potential, smog formation potential, respiratory effects, human toxicity (carcinogenics), human toxicity (non-carcinogenics), ecotoxicity, fossil fuel depletion	Yes
Prasad *et al.* (2022)[140]	Level 3	Regular and intensive inpatient care	NYU Langone Hospital-Brooklyn, USA	Site observations, hospital records, and manual waste audits	Augmented process-based hybrid LCA	Solid waste and GHGs	Yes, sensitivity analysis
Hunfeld *et al.* (2023)[139]	Level 3	Intensive care unit (ICU)	The Erasmus University Medical Center	Different management reports, including cleaning, disposables, medicines, and textiles purchased for the ICU	Material flow analysis (MFA)	Global warming potential, agricultural land occupation, and water usage	No
Kaas *et al.* (2025)[153]	Level 4	Radiotherapy and surgery in NSCLC treatment	Netherlands	Ecoinvent v3.9.1	LCA using SimaPro software v9.2 and ReCiPe method	Greenhouse gas emission	No
Unger and Landis (2016)[154]	Level 5	Reprocessed medical devices	Phoenix Baptist Hospital (PBH) in Phoenix, Arizona, USA	ELCD (European Reference Life Cycle Database) and ecoinvent v2.2	LCA + LCCA	Global warming, carcinogenic, non-carcinogenic, and respiratory effects	No
Petre and Malherbe (2020)[138]	Level 5	Scrub suits (reusable *vs.* disposable)	French	The reusable scrub suits were collected from Elis, its suppliers and clients. Information on disposable scrub suit	LCA	Ten categories: climate change, particulate matter, acidification, freshwater eutrophication, marine eutrophication, water depletion, photochemical ozone formation, terrestrial eutrophication, freshwater ecotoxicity, and land use	Yes, sensitivity analysis
Boberg *et al.* (2022)[155]	Level 5	Mixed trocar systems used for laparoscopic cholecystectomies (reusable *vs.* disposable)	Three hospitals in southern Sweden	Manufacturer and ecoinvent v3.6 database	LCA using SimaPro software v9.1.1.1 and IMPACT 2002+ method + LCCA	Fifteen categories: Mineral extraction, non-renewable energy, global warming, aquatic eutrophication, aquatic acidification, land occupation, terrestrial acidification and nutrification, terrestrial ecotoxicity, aquatic ecotoxicity, respiratory organics, ozone layer depletion, ionizing radiation, respiratory inorganics, non-carcinogens, and carcinogens	Yes, Monte Carlo Simulation
Snigdha *et al.* (2023)[7]	Level 5	Personal protective equipment (reusable *vs.* disposable)	India	The relevant literature, government reports, expert consultation, telephonic interviews with industry personnel, Ecoinvent database, and mathematical modeling	LCA using SimaPro software v9.2 and ReCiPe method	Six categories: global warming potential, terrestrial acidification, freshwater eutrophication, terrestrial ecotoxicity, human carcinogenic toxicity, water consumption	Yes, sensitivity analysis

Maloney *et al.* (2022)[156]	Level 5	Cloths for clinical surface decontamination (reusable *vs.* disposable)	Seven countries: Canada, the Republic of Ireland, New Zealand, Scotland, the UK, the USA, and Australia	Ecoinvent v3.7.1	LCA using OpenLCA v1.10.3	Sixteen European-recommended environmental impact categories from the product environmental footprint (PEF) recommended methodology, and eight human health categories	No
López-Muñoz *et al.* (2025)[157]	Level 5	Duodenoscopes (reusable *vs.* disposable)	Spain	EF Secondary Data sets V. EF 2.0	Attributional LCA using openLCA v.2.0.3	Acidification potential, water use, resource use (minerals and metals), and ionizing radiation	No
Chang *et al.* (2024)[158]	Level 5	Operating room bed covers and lift sheets (reusable *vs.* disposable)	A care hospital in Cleveland, Ohio, US	Ecoinvent v3 and US Life Cycle Inventory (LCI) database	LCA using SimaPro software v9.5.0.1	Ozone depletion, global warming, smog, acidification, eutrophication, carcinogenics, non carcinogenics, respiratory effects, ecotoxicity	No
Lichtnegger *et al.* (2023)[141]	Level 5	IPC Sleeves (reusable *vs.* disposable)	North and Central America	Ecoinvent v3.8	LCA EF 3.0 using Umberto software	Seventeen categories: carcinogenic effects, climate change, fossils, freshwater and terrestrial acidification, freshwater ecotoxicity, freshwater eutrophication, ionizing radiation, land use, marine eutrophication, minerals and metals, non-carcinogenic effects, ozone layer depletion, photochemical ozone creation, respiratory effects, inorganics, terrestrial eutrophication, and water scarcity.	Yes, sensitivity analysis
Bertolo *et al.* (2024)[159]	Level 5	Cystoscopes (reusable *vs.* disposable)	N/A	Registered data, observations, and expert opinions	Statistical analysis	Water consumption and waste generation	Yes, sensitivity analysis
Da Tan *et al.* (2024)[137]	Level 5	Hawley *vs.* Essix post-orthodontic dental retainers	Dublin Dental University Hospital (DDUH)	Ecoinvent v3.7.1	LCA using openLCA and ReCiPe H Endpoint	Seventeen categories: carcinogenic effects, climate change, fossils, freshwater and terrestrial acidification, freshwater ecotoxicity, freshwater eutrophication, ionizing radiation, land use, marine eutrophication, minerals and metals, non-carcinogenic effects, ozone layer depletion, photochemical ozone creation, respiratory effects, inorganics, terrestrial eutrophication, and water scarcity	No

LCA: Life cycle assessment; GHG: greenhouse gas; ICP: intermittent pneumatic compression.

Construction industry

As shown in Table 6, the studies cover a wide range of accounting objects-from material level to company level-demonstrating methodological diversity and contextual complexity. In terms of accounting objects, research has examined corporate-level entities (e.g., Bilfinger Construction Company[142]), specific building structures[143,144], construction materials[145,146], and emerging construction technologies such as 3D-printed permanent formwork[147]. Geographically, the studies are mainly concentrated in Europe, Asia, and the Middle East, including countries such as Sweden, Qatar, Sri Lanka, and Turkey. Most of the literature relies on internationally recognized databases such as Ecoinvent, GaBi, and EPD, which enhances comparability and applicability. In addition, data sources also include specific databases (e.g., ATHENA, US LCI), model-generated data (e.g., BIM), field-collected information (e.g., procurement orders and utility bills[146]), EPD documents, and published literature, reflecting the diversity in data acquisition approaches.

Table 6. Summary of literature review studies on the environmental footprint of the construction industry

Reference	Accounting objects	Research area	Data source	Methods	Environmental factors	Uncertainty analysis
Neppach *et al.* (2017)[142]	The former Bilfinger Construction Company	A Construction Company	Finance and procurement departments, and an interview with the supervisors	LCA (OEF) and feasibility study	Fourteen categories, but it was not possible to implement an OEF due to the limited time of the research (four months in the company) and a lack of information	No
Sinha *et al.* (2016)[144]	A wooden frame and a concrete frame building	Stockholm	EcoInvent 2.2 GaBi 6. ETH-ESU 96 and US LCI 2013 database	ELP-s *vs.* LCA using GaBi and SimaPro	Four categories: eutrophication, acidification, photochemical ozone creation, and radioactive waste	No
Ajayi *et al.* (2019)[148]	Modeling of eight building types	N/A	Model-generated data based on BIM simulations combined with the ATHENA database	LCA	Energy and GWPs	Yes, sensitivity analysis
Al-Hamrani *et al.* (2021)[143]	Cyclopean concrete (CYC) vs conventional concrete (CC)	The construction of the Education City Stadium in Qatar	Ecoinvent v3.6	LCA	Raw materials consumption, fuel consumption, water consumption, CO2-eq emissions	No
Albrecht *et al.* (2025)[147]	Application of 3D printed permanent formwork in the construction of a winder staircase	N/A	Ecoinvent 3.9.1 and 3.10	LCA	Eleven categories: global warming potential (GWP); ozone depletion potential (ODP); acidification potential (AP); eutrophication potential-aquatic freshwater (EP-freshwater); eutrophication potential-aquatic marine (EP-marine); eutrophication potential-terrestrial (EP-terrestrial); abiotic depletion potential for non-fossil resources (ADPE); abiotic potential for fossil resources (ADPF); water use (WDP); total use of renewable primary energy resources (PERT); and total use of non-renewable primary energy resources (PENRT)	No
Turk *et al.* (2017)[149]	Three innovative calcium carbonate-based consolidants	N/A	Ecoinvent 3.1	LCA using GaBi and IMPACT 2002+	Seventeen categories: global warming potential, aquatic/terrestrial ecotoxicity potential, aquatic/terrestrial acidification potential, aquatic eutrophication potential, *etc.*	No
Danish *et al.* (2024)[160]	Reclaimed fly ash in geopolymer	N/A	Ecoinvent 3.9.1 and the environmental product declaration (EPD) document	LCA	Five categories: global warming potential (GWP), ozone depletion potential (ODP), eutrophication potential (EP), acidification potential (AP), and energy consumption (EC)	No
Baykara *et al.* (2024)[145]	Chitosan-Cement Composite Mortars	N/A	Published papers, experimental data, and Ecoinvent 3.7	LCA using OpenLCA and ReCiPe Midpoint H	Four categories: climate change, terrestrial acidification, ozone depletion, and terrestrial ecotoxicity	No
Yu *et al.* (2024)[161]	Construction materials based on EPD data	N/A	One Click LCA database	Descriptive statistics analysis	Five categories: global warming potential (GWP), acidification potential (AP), eutrophication potential (EP), Ozone Depletion Potential (ODP), and photochemical ozone creation potential (POCP)	No
Vijerathne *et al.* (2024)[146]	Crushed Natural Aggregate	Sri Lanka	Firsthand site-specific data, gathered from utility bills, production records, purchasing orders, and invoices	LCA using SimaPro 9.6 and ReCiPe	Seventeen categories: mineral resource scarcity, stratospheric ozone depletion, marine eutrophication, water consumption, ionizing radiation, fine particulate matter formation, terrestrial acidification, global warming potential (GWP), *etc.*	No

Yardimci and Kurucay (2024)[162]	Construction material	A residential building located in Turkey	Field research and GaBi 2018 database	LCA using GaBi 8.5 and the TOPSIS method	Nine categories: acidification potential, eutrophication potential, global warming potential, ozone depletion, smog formation potential, primary energy demand, non-renewable energy demand, renewable energy demand, and material waste	No

OEF: Organization environmental footprint; LCA: life cycle assessment.

With regard to methodological approaches, LCA is the most commonly used tool, implemented through various software platforms such as GaBi, SimaPro, and OpenLCA. Some studies integrate additional decision-making methods (e.g., TOPSIS) or comparative frameworks like ELP-s[144]. A few works incorporate modeling and sensitivity analysis to enhance methodological robustness[148], although most studies do not include systematic uncertainty analysis-an important gap that future research should address. In terms of environmental impact categories, most studies include at least global warming potential (GWP), acidification potential (AP), eutrophication potential (EP), and ozone depletion potential (ODP). Some extend to as many as 17 categories[146], reflecting a more comprehensive assessment of environmental impacts. Differences in database versions and study objectives lead to variations in the selection of impact indicators. For instance, Baykara *et al.*[145] focused on four midpoint categories, while Albrecht *et al.*[147] and Turk *et al.*[149] covered a broader range of impact categories.

CONCLUSION

Based on co-citation analysis, this study systematically identifies the intellectual base of EF research, and the field exhibits clear stage-based characteristics and a thematic expansion trajectory. Following the release of the EU-EF (PEF/OEF) framework, the studies mainly focused on its formulation and standardization, with particular attention to the relationship and conflicts between PEF and existing standards such as ISO 14044. Subsequently, EF research gradually expanded toward applications in the context of the circular economy and the integration of the PBs framework for assessing environmental sustainability, contributing multi-scalar assessment tools to global environmental governance. The continuous evolution of methodological approaches in LCA and MRIO models and the refinement of analytical tools have supported both knowledge accumulation and practical applications in EF research. Normalization factors, weighting methods, and uncertainty analysis associated with LCA frequently appear across clusters, underscoring their importance in shaping the development of EF methodologies.

Recent studies increasingly reflect a trend toward methodological integration and scenario simulation, combining both production- and consumption-side perspectives to explore the dynamic relationships between EF and economic, social, and technological dimensions. For instance, the widespread testing of the EKC hypothesis and the application of multivariate econometric models to analyze environmental drivers have enriched the theoretical framework of EF research. A significant portion of the intellectual base employs the ecological footprint as a key indicator for assessing environmental degradation and sustainability, particularly in examining the dynamic relationship between economic growth and environmental pressure. This highlights the potential of EF to evolve into a more comprehensive environmental indicator-capable not only of providing an integrated accounting framework, but also of identifying and analyzing the drivers of environmental impacts and incorporating interactions between ecological stress and socioeconomic systems.

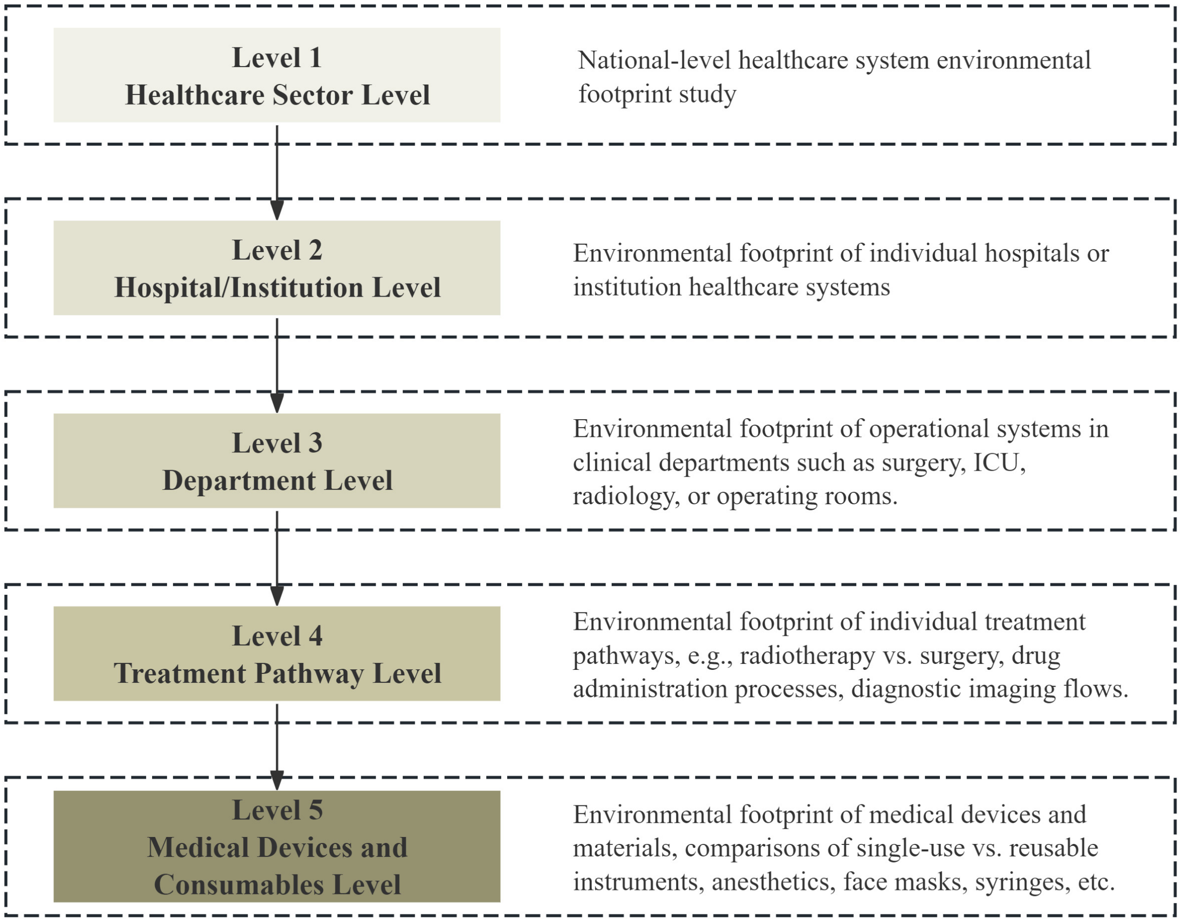

Figure 6. Five-Tier Hierarchical Framework for the Environmental Footprint of the Healthcare Sector.

Existing literature has explored how globalization, energy consumption, urbanization, trade openness, and human capital influence ecological footprints, reflecting a systematic approach to understanding the relationship between human activities and environmental pressures. These findings suggest the need for EF research to further expand its analytical perspective by integrating multidimensional drivers and compound effects. Instead of relying solely on static measurements of resource consumption and emissions, future research should incorporate economic, social, technological, and institutional variables into explanatory frameworks, thereby deepening the understanding of the origins of environmental stress, regional disparities, and governance pathways. Furthermore, the thematic development of EF research reveals a trend toward interdisciplinary integration and multi-contextual applications, with growing potential for adoption in emerging fields.

From the perspective of sectoral applications, EF studies reveal both similarities and differences across industries. In the metals sector, studies vary significantly in scope, covering both primary extraction and secondary recovery of metals such as aluminum, copper, gold, and rare earth elements. Geographic coverage ranges from China to Europe and developing mining regions. While most studies rely on LCA using databases such as Ecoinvent and GaBi, they differ in environmental indicators and treatment of uncertainty. In the healthcare sector, EF research is increasingly disaggregated into five hierarchical levels-from the entire healthcare system to specific devices and consumables. The majority of studies focus on Level 5, assessing reusable versus disposable products. Most apply standardized LCA approaches with sensitivity or Monte Carlo analysis. However, studies at higher system levels are limited and often lack comprehensive indicator coverage and uncertainty evaluation, particularly in low- and middle-income country settings. In the construction sector, research spans from materials and technologies (e.g., 3D printing) to building and corporate levels. LCA remains the dominant method, supported by BIM modeling, EPD data, and comparative analysis tools (e.g., TOPSIS). Despite the broadening scope of impact categories, systematic uncertainty analysis remains underdeveloped in many studies.

DECLARATIONS

Authors' contributions

Writing-original draft, methodology, software, data curation, visualization, formal analysis: Huang, X.
Conceptualization, writing - review and editing, visualization, resources, funding acquisition, supervision: Chen, R.
Resources, Grammar: Zhuang, E. H .H.
Visualization: Kong, S.
Supervision: Zhiquan, Y.; Kong, Y.

Availability of data and materials

The data presented in this study are available from the corresponding author upon reasonable request, due to privacy considerations.

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Conflicts of interest

All authors declared that there are no conflicts of interest.

Ethical approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

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