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Evolution of toxicological research on e-waste: A bibliometric and text mining analysis (2006–2024)

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Abstract

Electronic waste (e-waste) has become one of the fastest-growing sources of environmental contamination, generating complex risks for human health. Although research on e-waste toxicity has expanded over the past two decades, the overall structure and evolution of this literature remain insufficiently synthesized. This study examines how toxicological research on e-waste has evolved between 2006 and 2024 using an integrated bibliometric and text-mining approach. A total of 525 peer-reviewed articles indexed in the Web of Science Core Collection were analyzed through a combined bibliometric and text-mining framework. Latent Dirichlet allocation was applied to identify dominant research themes, while the Louvain and Leiden algorithms were used to uncover conceptual groupings within the literature. The results reveal a clear progression from early studies focusing on heavy metals and persistent organic pollutants to increased attention to brominated flame retardants and polychlorinated biphenyls in the 2010s. Since 2020, research has shifted toward cadmium-related environmental and epidemiological studies, alongside growing interest in oxidative stress, indoor dust, and plasticizers. These trends reflect a broader emphasis on indirect exposure pathways and multisystem health effects. Overall, this study provides a broad overview of evolving toxicological research trends in e-waste studies and highlights recent thematic developments related to environmental health and exposure pathways.

Keywords: Electronic waste; Toxicology; Environmental pollution; Public health; Bibliometric analysis; Text mining

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1. Introduction

Electronic waste (e-waste) refers to any electrical and electronic equipment that has reached the end of its useful life and has become waste. Small or large household appliances, hospital medical equipment, government office machines (e.g., information technology [IT] and telecommunications equipment), private sector offices, and industrial equipment and machinery constitute the main sources of e-waste. Among other important sources of e-waste are consumer and lighting equipment, electrical and electronic appliances, entertainment devices, toys, electronic cigarettes, sports equipment, and monitoring and control equipment.[1]

In addition to the wide variety of electrical and electronic equipment, the fact that different items contain over 1,000 types of hazardous or non-hazardous substances is one of the major problems associated with e-waste.[2] The rapid advancement of IT, increasing consumer demand for electronic devices, and the frequent replacement of electronic goods due to their limited lifespan have made e-waste one of the fastest-growing solid waste streams. With an estimated growth rate of 5%, e-waste is one of the most rapidly expanding waste streams globally, posing a threat to the environment and human health worldwide.[3,4] Global e-waste generation reached a record 62 million tonnes in 2022 and, in the absence of adequate management interventions, is projected to reach 82 million metric tonnes by 2030.[4] Before the implementation of China's National Sword Policy in 2018, a substantial proportion of global e-waste was exported to Asian countries, particularly China. Although China significantly restricted waste imports after 2018, informal recycling activities and transboundary movements of e-waste continue to create environmental and public health concerns in several developing regions.[5,6]

Electronic waste has a complex structure that contains valuable metals and hazardous substances. Most electrical devices contain metals that are recyclable and suitable for reuse. Toxic metals such as lead (Pb), mercury, and cadmium (Cd) are frequently used in electronic devices due to their high electrical conductivity. Precious metals, on the other hand, have a wide range of applications in the manufacture of electronic devices as contact materials due to their high chemical stability and good conductivity properties.[7]

Most e-waste contains carbon, aluminum, iron, beryllium, silicon, plastic, copper, tin, lead, polyvinyl chloride (PVC), epoxy resin, polychlorinated biphenyls (PCBs), and glass fiber, while some e-waste contains tantalum, silver, yttrium, vanadium, titanium, thorium, terbium, selenium, ruthenium, palladium, rhodium, platinum, niobium, nickel, germanium, gallium, manganese, lithium, indium, gold, europium, cobalt, boron, antimony, americium, bismuth, barium, Cd, thallium, mercury, and arsenic.[8,9]

Electronic waste is often disposed of in regular storage areas, and although transboundary movements of hazardous e-waste are regulated under the Basel Convention, illegal and informal exports still occur in some regions. Unfortunately, in these countries, very few precautions are taken regarding human health and the environment, and this waste is disposed of by incineration and acid dissolution.[10] For all these reasons, the evaluation of e-waste in terms of public health and the implementation of preventive measures have attracted the attention of researchers as an important issue.

In this study, scientific literature focusing on the effects of e-waste on public health between 2006 and 2024 was comprehensively analyzed using data obtained from the Web of Science (WoS) database. The analysis, conducted on 525 articles covering a 19-year period, was not limited to traditional bibliometric methods but also utilized Python-based text mining and network analysis techniques. Co-authorship, keyword co-occurrence, source citation, and country collaboration networks were extracted using VOSviewer software, thus obtaining a bibliometric overview of the field. Using the Python programming language, preprocessing was performed on the texts consisting of the titles, abstracts, and keywords of the articles, and a co-occurrence network was created, revealing the conceptual skeleton of the field. Subsequently, community structures were identified using the Louvain and Leiden algorithms, thematic evolution was examined using latent Dirichlet allocation (LDA), and emerging research trends were revealed through emerging-topic analysis.

While bibliometric approaches to e-waste research have grown significantly in recent years, most existing studies remain anchored to descriptive outputs—publication counts, citation rankings, and co-authorship patterns—without probing the deeper conceptual architecture of the field or how it has shifted over time. More critically, the toxicological dimension of e-waste literature has not yet been subjected to an integrated analytical framework that combines network-based community detection with probabilistic topic modeling. The present study attempts to bridge this gap. By coupling VOSviewer's bibliometric mapping capabilities with Python-based LDA topic modeling, Louvain/Leiden community detection, and temporal trend analysis, we aimed to move beyond a snapshot of the field toward a longitudinal account of how research themes have emerged, converged, and evolved across nearly two decades. The use of two independent clustering algorithms—rather than one—was a deliberate methodological choice to cross-validate the resulting community structures and reduce the risk of algorithm-specific distortions. Taken together, this layered approach offers an analytical depth that purely descriptive bibliometric reviews of e-waste toxicology have not previously achieved.

2. Materials and methods

2.1. Data collection and study selection

Electronic waste-related publications were retrieved from the WoS Core Collection database in January 2025. WoS

was selected as the sole database for this study due to its comprehensive coverage of peer-reviewed journals in environmental science, toxicology, and public health, as well as its advanced field-tagging system, which enables precise Boolean searches across title, abstract, and keyword fields. Furthermore, WoS provides standardized bibliometric metadata—including citation counts, journal impact factors, and institutional affiliations—that are essential for the co-citation and bibliometric mapping analyses employed in this study.

The search strategy was designed to identify studies focusing on the toxicological and public health dimensions of e-waste. The following search query was used: TS = (("e-waste" OR "e waste" OR "electronic waste" OR "electrical waste" OR "WEEE") AND ("public health" OR "exposure" OR "illness" OR "reproductive" OR "newborn" OR "child")).

The initial search yielded 11,685 records. Subsequently, the dataset was limited to English-language peer-reviewed articles published between 2006 and 2024, resulting in 8,113 records. A manual screening process based on titles, abstracts, and keywords was then conducted. Studies unrelated to toxicological effects, environmental exposure, or public health impacts of e-waste were excluded. Duplicate records, incomplete entries, conference abstracts, editorials, and non-research documents were also removed. After the screening process, a final dataset consisting of 525 articles was retained for bibliometric and text-mining analyses. The study selection process followed a structured screening protocol consistent with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 guidelines[11] and is summarized in Figure 1. The title, abstract, keywords, author, institution, country, and source journal information were extracted from each record.

Prior to analysis, standard preprocessing steps were applied to the texts consisting of the title, author, year, abstract, and keywords. This process involved converting the texts to lowercase, removing punctuation marks, numerical values, and meaningless characters, applying an English stop-word list, and merging synonyms. As a result, these steps yielded a corpus suitable for text mining.

2.2. VOSviewer analyses

VOSviewer is a Java-based open-source software developed by the Center for Science and Technology Studies at Leiden University in the Netherlands. It can be used to create maps based on network data and to visualize and examine these maps.[12]

The VOSviewer software can be used to create maps of authors or journals based on co-citation data, or to create keyword maps based on co-occurrence data. The program provides a viewer that allows scientific maps to be examined in full detail.[13] The VOSviewer program is recognized in the literature as an exceptionally effective program for visualizing and creating text maps based on bibliometric data.[14] Its ability to provide detailed analysis and its user-friendly interface are among the reasons it was chosen for this study.

The VOSviewer software (version 1.6.20) was used in this study for the bibliometric analysis of the data. The analyses performed using this software are as follows:

(a) Co-author analysis

Co-author analysis was performed using the VOSviewer program to determine the structure of scientific collaboration among researchers. This analysis visualizes the topics on which researchers collaborate in their publications, the number of publications, collaboration networks, and interactions between their publications. A high number of researchers connected to the target researcher means that the degree score within the network is also high.[15] When conducting the analysis, researchers with at least five articles in this field were filtered to obtain more meaningful results. Of the remaining 108 authors, those without connections were excluded from the mapping, and clustering was performed on 77 authors.

(b) Keyword analysis

Keyword analysis was performed to identify focal points in the field of e-waste's impact on public health and potential opportunities for future studies. Keywords used in fewer than five studies were eliminated, and a keyword co-occurrence map was generated for the remaining 67 studies using the VOSviewer program.

(c) Journal citation analysis

Journal citation analysis was performed to examine the citations made by scientific publications to each other, to determine which publications were influential on other publications and which publications received more citations. When performing the source citation analysis for the study, studies that were not closely related to the topic were excluded from the map, and the analysis was performed for 98 sources.

(d) Country-level citation analysis

Country-level citation analysis was conducted to reveal the scientific impact levels and international visibility of countries publishing on the effects of e-waste on public health. It was determined that articles in this field were prepared in 60 different countries, and countries were examined in terms of the number of citations they received

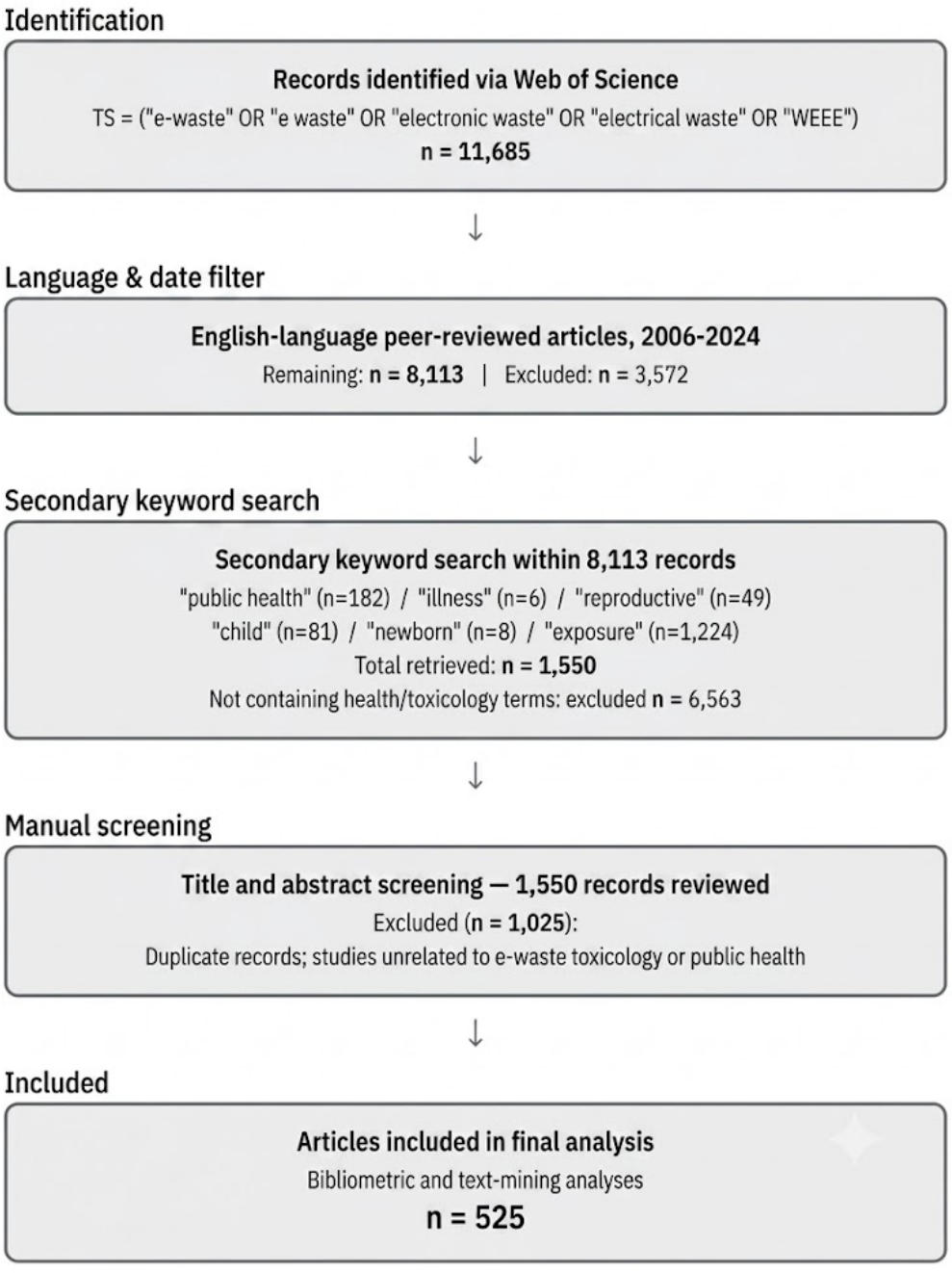


Figure 1. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses flowchart of the literature search and screening process for studies investigating the toxicological effects of e-waste on public health (2006–2024)

to identify the influential countries. Countries with at least five articles were included, and mapping was performed for the remaining 18 countries.

2.3. Python-based advanced analyses

Beyond classical analyses, Python-based advanced text mining and network analyses were applied in this study.

(a) Topic modeling

The evolution of topics over the years was examined using the LDA method.[16] The scikit-learn library in Python was used for this purpose. Texts created from titles and abstracts were digitized using CountVectorizer (max_df = 0.95, min_df = 5, stop_words = "English"). The LDA model was run with the parameters n_components = 5, random_state=42, and the model's other hyperparameters were left at Scikit-learn's default values (e.g., max_iter = 10, learning_method = "batch"). Here, max_df = 0.95 excludes terms appearing in more than 95% of documents (effectively removing corpus-wide stop words), while min_df = 5 retains only terms appearing in at least five documents to reduce noise. The number of topics was set to n_components = 5, based on preliminary model runs evaluated for interpretability. The random_state = 42 parameter was fixed to ensure reproducibility of results across runs. The 10 keywords with the highest weight for each topic were extracted. Additionally, the evolution of themes over the years was visualized by calculating the annual averages of topic probabilities.

(b) Co-occurrence network analysis

Co-occurrence network analysis was created from the keywords of the articles. Keywords were converted to lowercase, and duplicates were removed. The 100 most frequently co-occurring keyword pairs were selected, and a network structure was created using the "networkx" library. Edge weights were assigned according to co-occurrence frequency.

(c) Community detection analysis

Both the Louvain and Leiden algorithms were applied to increase the reliability of community structures, determining the modular structure of the scientific network and revealing thematic clusters. This was performed using the Louvain algorithm in Python (community_louvain. best_partition).[17] The resolution parameter was left at the default value of 1.0, and spring_layout (k = 0.3, seed = 42) was applied for visualization. Communities were visualized with different colors, revealing the conceptual infrastructure of the network. The Leiden algorithm[18] was implemented using the "leidenalg" package in Python. The network structure was converted to "igraph" format, and community detection was performed using the ModularityVertexPartition option. The resolution parameter was left at its default value of 1.0. Although the reproducibility of the results is limited due to randomness, the clusters were found to be largely consistent with the structures obtained using the Louvain algorithm.

(d) Emerging-topic analysis

Twenty key concepts, prominent in the literature, were identified and searched for in the abstracts and keywords of the articles. A co-occurrence network was created using networkx, using concept pairs that appeared together at least twice, with edge weights assigned according to co-occurrence frequency. The community structure was extracted using the Louvain algorithm (resolution = 1.0), with node sizes visualized according to degree and colors according to communities. This network structure reveals the thematic proximity and clustering tendencies of emerging topics. Thus, emerging topics were identified based on annual keyword frequencies, and research areas that have gained momentum, especially in the last five years, were identified.

(e) Trend analysis

Topics expected to rise in the 2025–2030 period were predicted using time series analysis. A prediction model was created using the Prophet library[19] based on annual publication counts. Seasonal fluctuations were not taken into account in the model. Common libraries such as Prophet, pandas, Scikit-learn, gensim, and networkx were used for Python analyses.

3. Results and discussion

3.1. Analyses performed with VOSviewer

3.1.1. Co-author (network) analysis

The co-author network map generated using VOSviewer is presented in Figure 2. As shown in Figure 2, the author "Huo, Xia" exhibits the largest node size and is considered the most influential researcher. The blue cluster collaborates with almost all other clusters, indicating its central position in the network.

3.1.2. Keyword analysis

The map related to the keyword analysis obtained using the VOSviewer program is shown in Figure 3. As shown in the map, the most frequently used keyword in the field of research is "e-waste," which has the largest node and is located at the focal point of the map. This is followed by keywords such as "electronic waste," "heavy metals," "lead," and "polybrominated diphenyl ethers." The lines between the keywords on the map represent the co-occurrence of each keyword with other keywords.

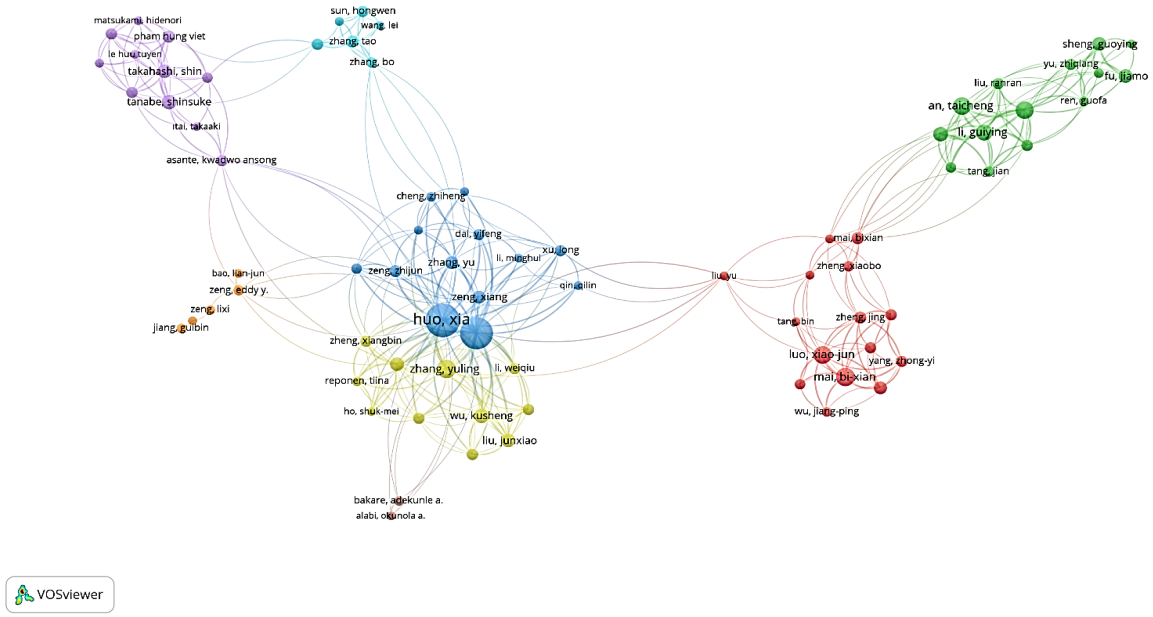


Figure 2. Co-author network visualization created with VOSviewer. Each node represents a researcher, and clusters of nodes of the same color indicate groups of closely collaborating researchers. Node size reflects the level of author activity in the field, while links between nodes represent co-authorship relations. Link thickness indicates the strength of collaboration between authors. Spatial proximity between nodes reflects the closeness of collaboration. The blue cluster contains a central node and multiple connected nodes, indicating a densely interconnected collaboration group.

3.1.3. Journal citation analysis

The map related to the source citation analysis obtained with the VOSviewer program is shown in Figure 4. As shown in Figure 4, the connections between source journals indicate the frequency with which one journal cites others and the intensity of this relationship. The thickness of the lines indicates the strength of the relationships with the cited journals.

The journal *Science of the Total Environment*, written in large, bold letters in the center, indicates that this journal has more citations than other journals in the field. This shows that the journal plays an important and influential role in the development of the field investigated in this study. Other leading journals in the field include *Environmental Science and Pollution*, *Chemosphere*, *Environmental Pollution*, and *Environment International*, which are shown as larger nodes than the others.

3.1.4. Country-level citation analysis

The map related to the country-level citation analysis obtained with the VOSviewer program is shown in Figure 5. As shown in Figure 5, China, which has the largest number of nodes and is located in the center of the map, produced 320 studies during the study period and received a total of 14,708 citations, making it the most influential country in this field. Other countries with significant influence in this field alongside China are the United States with 90 studies, Ghana with 46 studies, Canada with 32 studies, and Japan with 30 studies.

3.2. Python-based analyses

3.2.1. Topic modeling

Using the LDA method, five main themes (topics) were identified in articles published between 2006 and 2024. These themes and related keywords are summarized in Table 1. Topic 0 reflects human exposure and risk associated with persistent organic pollutants such as PCBs and polybrominated diphenyl ethers, often identified at higher concentrations, primarily within China. Topic 1 focuses on specific emerging contaminants and associated health risks, including brominated flame retardants and polycyclic aromatic hydrocarbons related to dismantling activities and dust exposure. Topic 2 highlights localized environmental contamination and public health issues, specifically addressing lead exposure and resulting health impacts on children within the Guiyu recycling region.

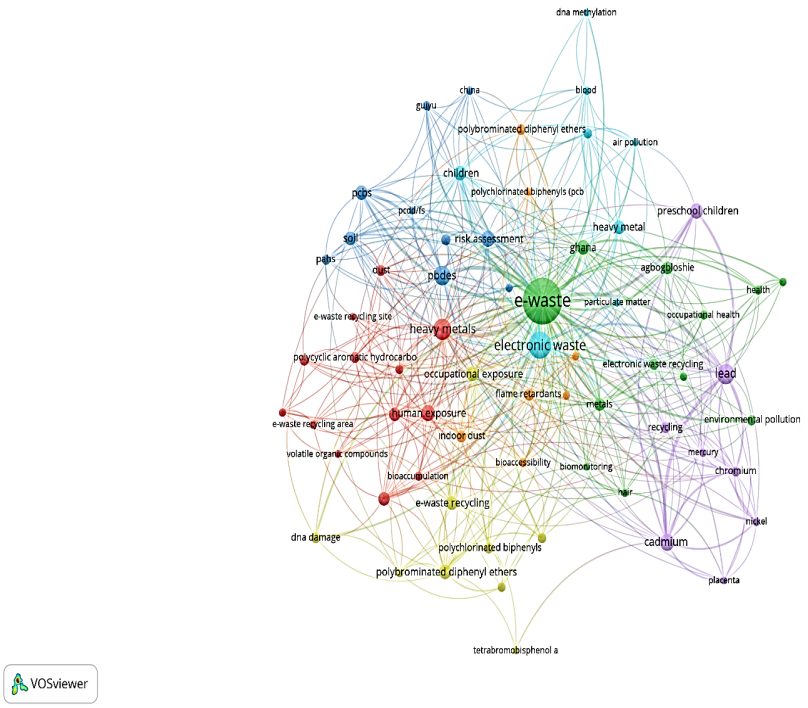


Figure 3. Keyword co-occurrence network generated using VOSviewer

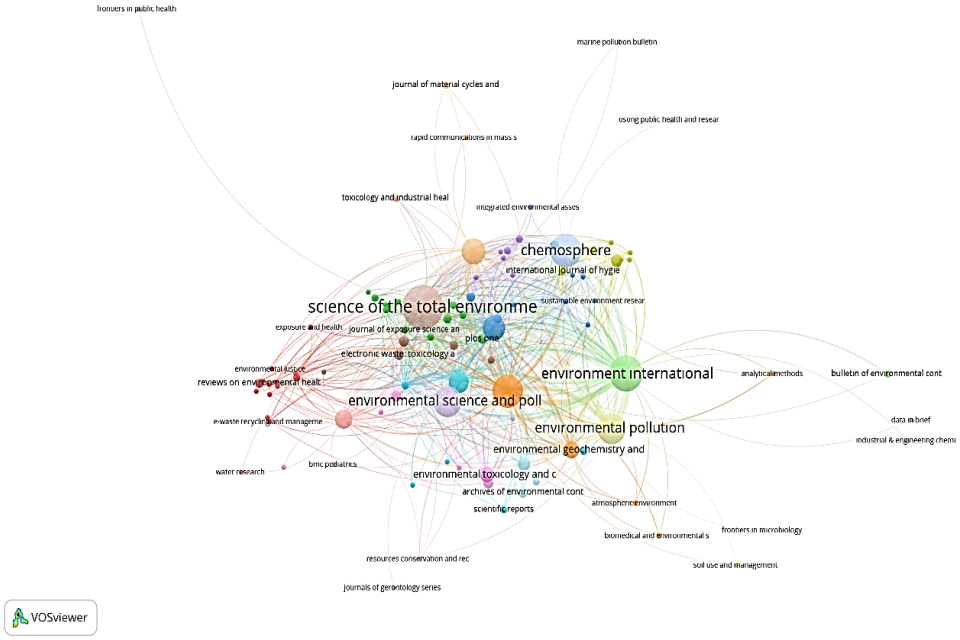


Figure 4. Source citation network showing inter-journal citation relationships. Image generated using VOSviewer.

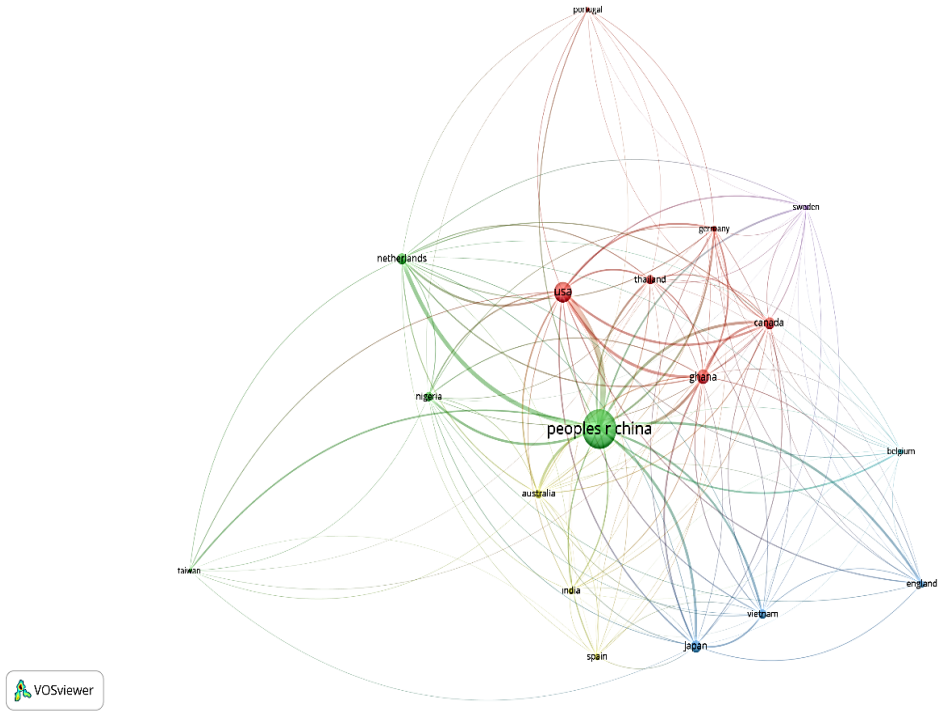


Figure 5. Country-level publication and citation network (countries with ≥5 publications). Image generated using VOSviewer.

Table 1. Main topics and representative keywords identified through latent Dirichlet allocation topic modeling (2006–2024)

Topic	Top keywords	Thematic label
Topic 0	Exposure, higher, China, levels, samples, PCBs, recycling, concentrations, Hg, and polybrominated diphenyl ethers	Persistent organic pollutants and exposure in China
Topic 1	Risk, retardants, concentrations, flame, recycling, dismantling, exposure, PAHs, Hg, and dust	Emerging contaminants (e.g., BFRs, PAHs) and associated risk
Topic 2	Higher, exposed, Guiyu, lead, group, recycling, blood, exposure, children, and levels	Lead exposure and child health in Guiyu
Topic 3	Study, electronic, heavy, risk, exposure, soil, Pb, metals, recycling, and health	Heavy metals, environmental risk, and health outcomes
Topic 4	Levels, study, Cd, people, ill, environmental, China, university, and exposure	Cadmium, general environmental exposure, and epidemiological studies (China)

Abbreviations: BFRs: Brominated flame retardants; Cd: Cadmium; Hg: Mercury; PAHs: Polycyclic aromatic hydrocarbons; PCBs: Polychlorinated biphenyls.

Topic 3 captures broader research on heavy metals (e.g., Pb), soil contamination, general health effects, and the overall environmental risk framework related to e-waste recycling. Finally, Topic 4 encompasses general environmental and epidemiological studies, often related to Cd levels and carried out by Chinese universities.

The thematic evolution graph (Figure 6) reveals the shifting weight of the five themes listed in Table 1 over the years. Research conducted during the early study period (2006–2010) primarily focused on persistent organic pollutant exposure (Topic 0) and Pb exposure in Guiyu (Topic 2), alongside general heavy metals

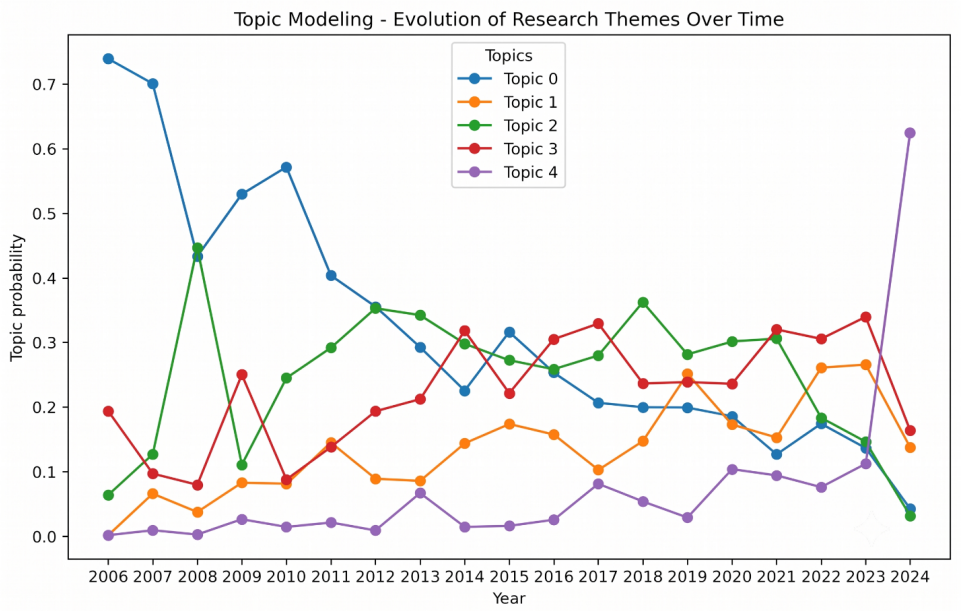


Figure 6. Thematic evolution of e-waste research based on latent Dirichlet allocation topic modeling (2006–2024)

research (Topic 3). After 2010, the field diversified, with research on emerging contaminants (Topic 1) and broader environmental health (Topic 3) maintaining a strong presence. A significant paradigm shift was observed after 2020: narrow, site-specific studies (Topic 2) significantly decreased, while Topic 4 (Cd, general environmental exposure, and epidemiological studies) showed a sharp increase in 2024. This indicates a transition in e-waste research from a localized, immediate toxicological focus toward more systemic, broader environmental, and regulatory approaches.

The sharp increase observed in Topic 4 after 2020 can be attributed to several converging factors. First, the COVID-19 pandemic (2020–2021) accelerated global digitalization, driving increased reliance on electronic devices for remote work, online education, and telemedicine. This rapid expansion in electronic device use heightened public and scientific awareness of e-waste as an emerging public health concern, contributing to increased research attention toward broader environmental and epidemiological dimensions of the problem, consistent with the thematic content of Topic 4.[20] Second, this period coincided with significant regulatory developments in global e-waste governance. The Basel Convention's e-waste amendments, adopted at the United Nations Biodiversity Conference (COP15) in 2022, extended prior informed consent requirements to all categories of electronic waste, marking a pivotal shift toward more comprehensive transboundary control.[21] Alongside these international developments, evolving national e-waste management frameworks in major producing countries further redirected research attention from site-specific contamination studies toward systemic environmental governance and population-level health assessments. Third, the growing integration of Cd into emerging contaminant monitoring frameworks—particularly in relation to soil and food chain contamination—may have contributed to the increased visibility of Cd-related studies during this period.

3.2.2. Louvain/Leiden clusters

Network analysis based on keywords revealed the fundamental conceptual clusters in the literature using the Louvain and Leiden algorithms. The fact that both algorithms yielded similar results demonstrates that the thematic structures obtained are methodologically sound.

In the network map shown in Figure 7, the concept of "e-waste" remains at the undisputed center and acts as a primary bridge linking chemical pollutants and human health effects. Concepts such as "risk," "health," and the highly prominent "association" are clearly observed as nodes that facilitate essential transitions and strengthen the connections between the thematic clusters. This structure demonstrates that the core relationship between environmental pollution and health effects is a dominant research axis in the literature, with the explicit testing of statistical associations and focus on oxidative stress gaining crucial momentum in recent years.

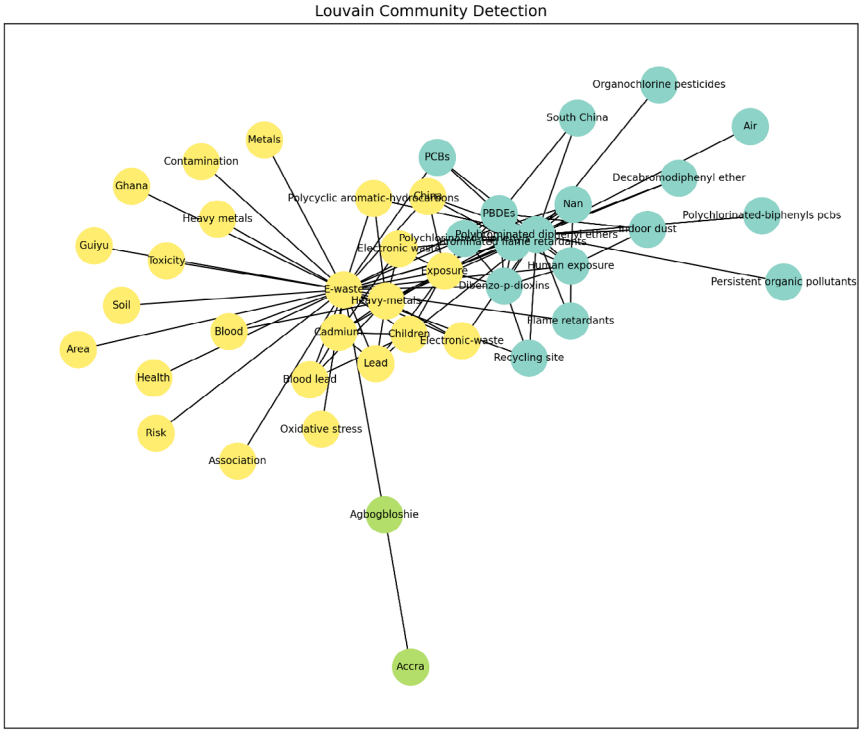


Figure 7. Main conceptual clusters in e-waste and public health research identified using the Louvain and Leiden algorithms

The analysis revealed three main areas of focus in the e-waste literature, as detailed in Table 2:

(i) Cluster 1 (chemical pollutants and environmental dispersion): This cluster includes compounds such as polybrominated diphenyl ethers, PCBs, brominated flame retardants, and persistent organic pollutants. Research in this area focuses on the accumulation, distribution, and key exposure pathways (e.g., indoor dust and air) of organic pollutants originating from e-waste.

(ii) Cluster 2 (e-waste sites and environmental/social impacts): This cluster represents field research at e-waste recycling centers, particularly in Guiyu, China, and Agbogbloshie/Accra, Ghana. The focus is on the risks these activities pose in terms of soil contamination, human health, and socio-environmental impacts.

(iii) Cluster 3 (health effects and child exposure/toxicology): This cluster examines the effects of e-waste pollution, particularly on children. Studies focus on assessing exposure to heavy metals such as Pb and Cd through biological indicators (e.g., blood lead levels), with a newly intensified focus on the biological effects and mechanisms, such as oxidative stress.

3.2.3. Emerging topics

An analysis of "emerging topics" was conducted to identify research trends that have gained momentum over the past five years. This analysis reveals topics that are becoming a growing focus of interest in the literature and the relationships between these topics.

Figure 8 shows that the most central and dominant concepts in the network are risk, health, pollution, human health, soil, heavy metals, and indoor dust. This structure clearly indicates that environmental pollutants and health effects remain at the core of the emerging themes. Concepts related to primary exposure pathways, such as indoor dust and soil, are positioned centrally and are strongly linked to health and risk. Furthermore, while PM2.5 and related particulate matter concepts maintain a link, the analysis highlights a continued significant upward trend in risk analysis, specifically focusing on the connection between oxidative stress and health-risk assessment concepts.

Figure 9 presents the most frequently used and rising topics over the last five years:

(i) Oxidative stress and indoor dust: These two concepts are currently the most frequently used topics, indicating a rapid shift in focus toward understanding the

Table 2. Keyword clusters identified using the Leiden algorithm

Cluster no.	Representative topics	Sample keywords
1	Chemical pollutants and environmental dispersion	Polybrominated diphenyl ethers, PCBs, brominated flame retardants, indoor dust, organochlorine pesticides, and persistent organic pollutants
2	E-waste sites and environmental/social impacts	E-waste, soil, contamination, Guiyu, Agbogbloshie, Ghana, risk, and health
3	Health effects and child exposure/toxicology	Children, cadmium, lead, blood lead, oxidative stress, and exposure

Abbreviations: E-waste: Electronic waste; PCBs: Polychlorinated biphenyls.

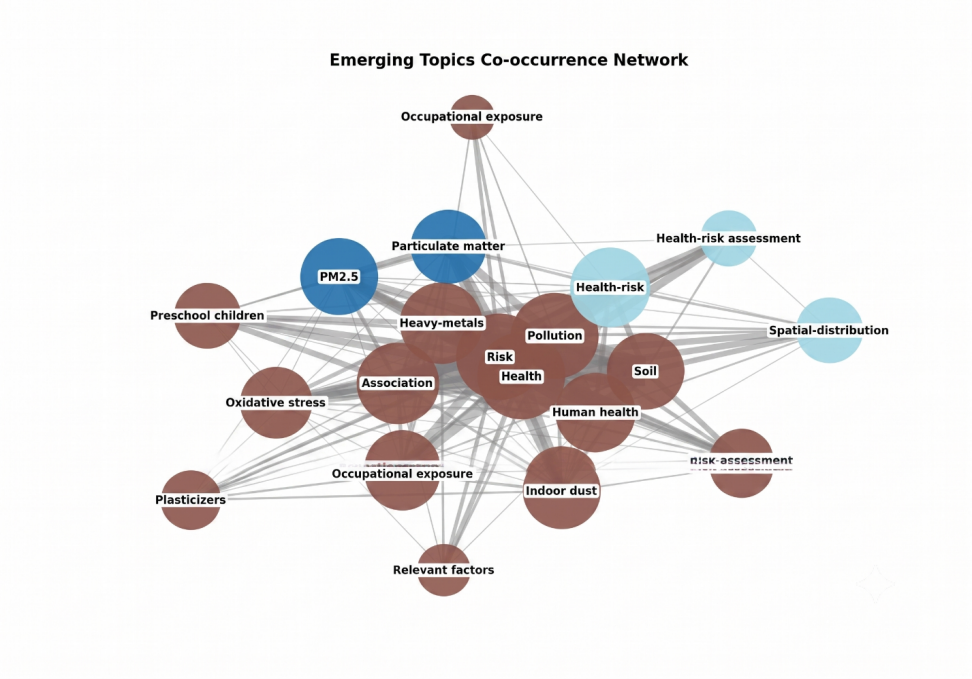


Figure 8. Keyword co-occurrence network of emerging topics (2020–2024)

biological mechanisms of toxicity and characterizing specific exposure pathways, particularly through indoor environments.

(ii) Association and risk: These topics maintain high rankings, reflecting the continuous effort to test statistical relationships between environmental pollution and health effects and to perform detailed risk assessments.

(iii) Plasticizers: Although this topic has dropped in rank compared to older analyses, plastic additives remain an important, rising area in e-waste research, reflecting the increasing concern over novel contaminants.

(iv) PM2.5, particulate matter, and health risk: The high frequency of these concepts indicates a significant focus on air pollution as an exposure vector and emphasizes quantitative health risk analysis.

Figure 10 presents the annual distribution of scientific publications on e-waste research between 2006 and 2024, together with a forecast generated using the Prophet time-series model. Publication output was relatively modest during the 2006–2010 period, typically ranging between 10 and 20 articles per year, before rising more steadily

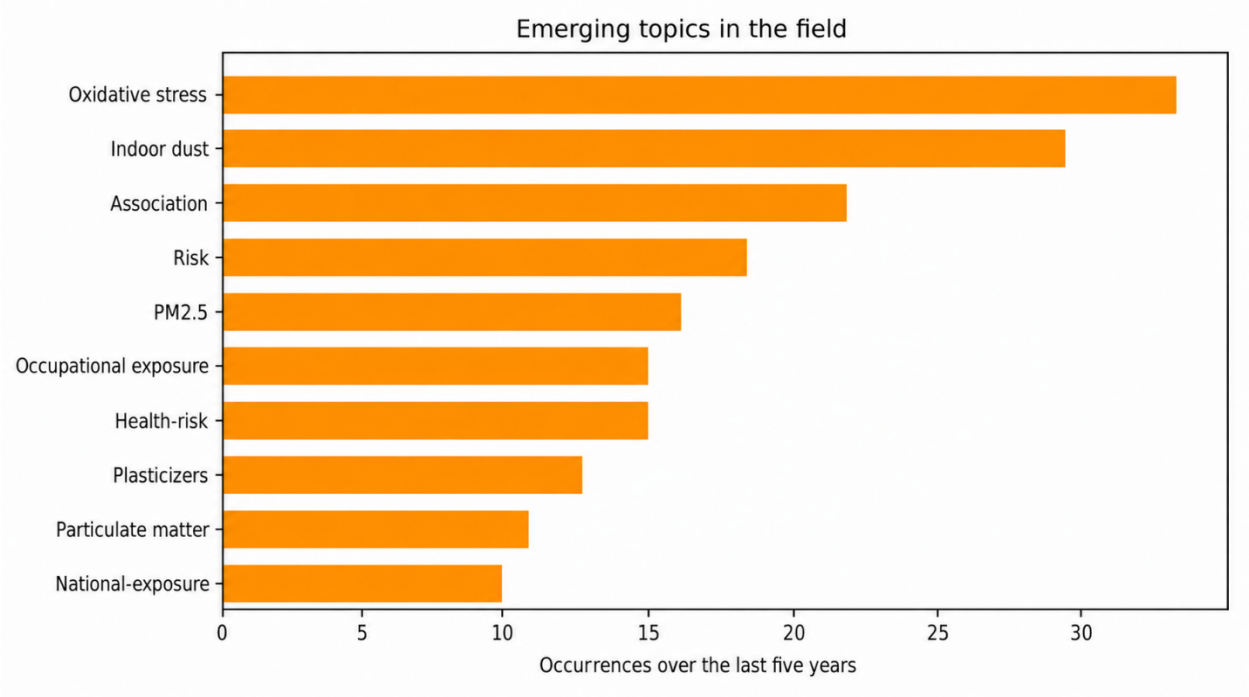


Figure 9. Emerging and rising topics over the last five years (2020–2024)

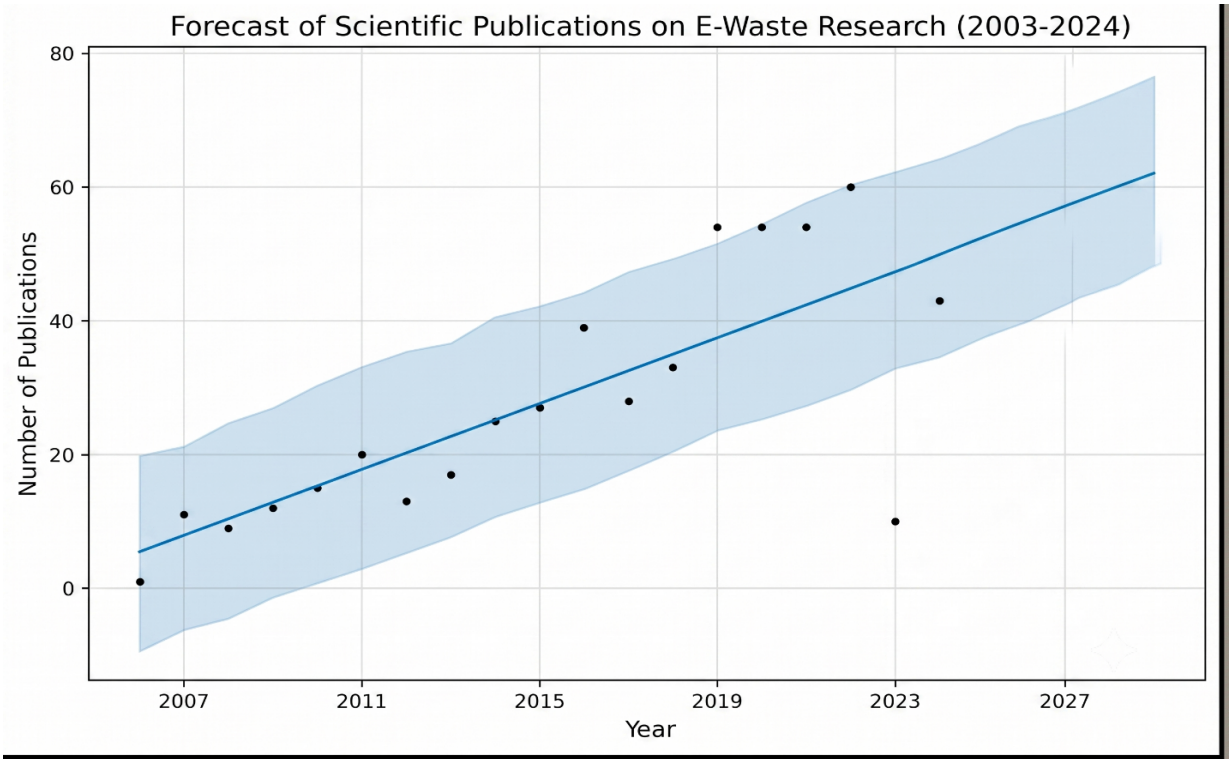


Figure 10. Annual publication counts and Prophet model-based forecast for e-waste research (2006–2030). Black dots represent observed publication counts; the blue line indicates the model's trend estimate; the shaded area denotes the 95% uncertainty interval.

through 2011–2018 and exceeding 50 publications in 2018. Some fluctuation is evident from 2019 onward, which may partly reflect broader disruptions to global research activity during the COVID-19 pandemic. Notwithstanding these short-term variations, the overall trajectory remains clearly upward.

The Prophet model's projections suggest that publication activity in this field will continue to grow through 2030, with annual output expected to approach or exceed 60 articles. This sustained increase likely reflects a combination of factors, including heightened global awareness of e-waste as a public health concern, expanding regulatory frameworks, and growing methodological diversity in the field. However, it should be noted that the forecast is based on 19 annual observations, and the widening confidence interval toward 2030 underscores the inherent uncertainty of longer-range projections. The trend should therefore be read as indicative of the field's general direction rather than a precise prediction.

4. Limitations of the study

Several limitations of this study should be acknowledged. A potential limitation is the exclusive use of the WoS database. Although WoS offers robust bibliometric metadata and broad coverage of high-impact journals in environmental science and toxicology, databases such as Scopus, PubMed, and Dimensions index additional journals—particularly regional and open-access publications—that may not be fully represented in WoS. Consequently, some relevant studies may have been overlooked, and the findings should be interpreted with this constraint in mind. Future studies are encouraged to adopt a multi-database approach to enhance comprehensiveness.

5. Conclusion

This study comprehensively mapped the scientific literature on the effects of chemicals in e-waste on public health by combining VOSviewer's traditional bibliometric analyses with Python-based advanced text mining methods. The findings provide key insights into the current conceptual structure of the field and its future development trends. The study demonstrates that the field is not limited to publication counts and citation relationships but also allows for in-depth tracking of thematic evolution and emerging topics.

VOSviewer analyses revealed that the most influential researcher is Huo, Xia, and the country with the most publications and citations is China. China is at the center of research in this field due to its large population, rapidly developing technology, and role as a major e-waste importer. Keyword maps show that the literature is concentrated on three main axes: chemical pollutants, e-waste sites, and child health exposures.

Python-based analyses provided more advanced conceptual insights. Topic modeling revealed that the literature from 2006 to 2024 was shaped around five main themes—heavy metals and persistent organic pollutants dominated in the early period, but the focus shifted sharply to general environmental and epidemiological studies (Topic 4) in 2024. Network clusters obtained using the Louvain and Leiden algorithms showed that the field is methodologically concentrated in three robust thematic cores: (i) chemical pollutants and environmental dispersion, (ii) e-waste sites and environmental/social impacts, and (iii) health effects and child exposure/toxicology. The emerging topics analysis showed that the concepts of "oxidative stress" and "indoor dust" have increased rapidly in the last five years, indicating a shift toward biological mechanistic analyses and specific exposure pathways.

While the bibliometric and trend analyses conducted in this study do not yet register microplastics, rare earth elements, and artificial-intelligence–supported risk assessment models as dominant themes within the 2006–2024 corpus, converging signals in the broader environmental health literature suggest that these topics are likely to gain increasing prominence in e-waste research in the coming years. The growing concern over plastic-associated contaminants in e-waste streams, the expanding use of rare earth elements in modern electronics, and the rapid adoption of machine learning tools in environmental risk assessment collectively point toward a gradual thematic expansion of the field beyond its current core. These trajectories, however, remain nascent within the present dataset and warrant dedicated investigation in future bibliometric studies.

(i) Studies focusing on new pollutants such as microplastics, nanoplastics, and rare earth elements should be expanded.
(ii) Multiple exposure models examining the simultaneous effects of heavy metals, organic pollutants, and particulate matter should be given more consideration.
(iii) Risk assessment models developed using Python and other data science tools should be used to identify public health risks from e-waste and focus on implementing appropriate mitigation measures.
(iv) The effectiveness of national and international policy regulations should be examined through comparative analyses.
(v) It is important to integrate sustainable and circular approaches in e-waste management with social, economic, and health dimensions.

(vi) Although the analyses in this study focus on the public health dimension of e-waste, the methodological approach used (e.g., bibliometric mapping, text mining, and network analysis) can also be adapted to other sub-areas such as the environmental impacts of e-waste, recycling technologies, sustainability policies, and the circular economy.

In summary, this study advances the existing literature by integrating VOSviewer-based bibliometric mapping with Python-based text mining techniques, offering a more granular and longitudinally grounded account of toxicological e-waste research than has previously been available.

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Conflict of ınterest

The author declares no conflict of interest.

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