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Trends in E-Waste Optimization: A Bibliometric Analysis

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ABSTRACT

Electronic waste (e-waste) optimisation has emerged as an important research area at the intersection of waste management, environmental sustainability, engineering, operations research, materials recovery and digital technology. The present study examines the development of research on e-waste management optimisation through bibliometric analysis and a focused literature review. The research methodology uses Scopus as the sole database and applies the Boolean search string "electronic AND waste AND optimisation" to article titles, abstracts and keywords. The initial search produced 2,562 records. After applying the defined screening criteria for the 2006–2027 period, document type, language and source type, the final dataset contained 1,755 journal articles and reviews. The selection process was designed to maintain a consistent and analysable corpus while preserving the interdisciplinary nature of the field. The data analysis reports 1,755 documents across 624 sources, contributed by 5,889 authors, with an average of 5.08 co-authors per document. Approximately 26.55% of the documents involve authors from more than one country. The acceleration became especially pronounced after 2023: publication output increased from 137 papers in 2023 to 178 in 2024, 300 in 2025 and 450 in 2026. Consequently, the two years 2025 and 2026 alone account for 750 documents, approximately 43% of the dataset. The bibliometric evidence shows rapid growth, expanding interdisciplinarity and increasing attention to battery recovery, sustainability assessment, reverse logistics and digital tools. The central issue for the field is consequently not simply whether an individual technology can recover a material efficiently, but whether the technology can be integrated into a practical system that is environmentally sound, economically viable, socially accessible and scalable.

Keywords: E-Waste Optimisation, Bibliometric Analysis, Materials Recovery, Circular Economy, Reverse Logistics, Digital Technology

1. INTRODUCTION

Electronic waste (e-waste) optimisation has emerged as an important research area at the intersection of waste management, environmental sustainability, engineering, operations research, materials recovery and digital technology. E-waste includes discarded electrical and electronic equipment, including components such as printed circuit boards and batteries, which can contain both hazardous substances and valuable materials. The literature increasingly treats e-waste not simply as a disposal problem, but as a secondary resource from which metals, energy and reusable components can be recovered. This change in perspective is closely connected with the development of circular-economy thinking, in which products and materials are kept in use for as long as possible and recovery is designed into the end-of-life stage. (Sukmasetya et al., 2026)

The present study examines the development of research on e-waste management optimisation through bibliometric analysis and a focused literature review. The research methodology uses Scopus as the sole database and applies the Boolean search string "electronic AND waste AND optimisation" to article titles, abstracts and keywords. The initial search produced 2,562 records. After applying the defined screening criteria for the 2006–2027 period, document type, language and source type, the final dataset

contained 1,755 journal articles and reviews. The selection process was designed to maintain a consistent and analysable corpus while preserving the interdisciplinary nature of the field. Subject area, country, affiliation and open-access filters were deliberately not imposed because e-waste optimisation spans several disciplines and geographical regions. The resulting dataset therefore provides a broad basis for identifying publication patterns, research themes, sources and geographical trends.

The scale of the dataset itself demonstrates the growing importance of the topic. The data analysis reports 1,755 documents across 624 sources, contributed by 5,889 authors, with an average of 5.08 co-authors per document. Only 37 authors published alone, indicating that e-waste optimisation is strongly collaborative and commonly requires expertise from different technical areas. Approximately 26.55% of the documents involve authors from more than one country. This level of collaboration is consistent with the complexity of e-waste systems, where material science, chemical processing, logistics, environmental assessment, economics and computational optimisation can need to be considered together.

The publication trend provides particularly strong evidence of expansion. Between 2006 and 2014, annual output remained below 25 papers, and early research was mainly concerned with metal recovery, disassembly and specific recovery-process problems. From 2015 to 2022, output increased more steadily, reaching 112 papers in 2022. The acceleration became especially pronounced after 2023: publication output increased from 137 papers in 2023 to 178 in 2024, 300 in 2025 and 450 in 2026. Consequently, the two years 2025 and 2026 alone account for 750 documents, approximately 43% of the dataset. The data analysis therefore indicates that the field is not growing linearly but is entering a much more rapid expansion phase. When 2026 is used as the endpoint rather than the small set of early-access 2027 records, output rises from six documents in 2006 to 450 in 2026, corresponding to an approximate compound growth rate of 24% per year.

The literature also shows that e-waste optimisation has become increasingly interdisciplinary. The most productive sources include Waste Management, Journal of Cleaner Production, Journal of Environmental Management and Resources, Conservation and Recycling, alongside energy and chemical-engineering journals. Waste Management is the dominant source, with 113 papers in the dataset, while the Journal of Cleaner Production has 54 and the Journal of Environmental Management has 40. Energy Conversion and Management, Energy, Applied Energy and Applied Thermal Engineering represent another important stream. This distribution indicates that optimisation is no longer confined to traditional waste-management questions. It now includes energy recovery, chemical separation, battery recycling, life-cycle assessment and decision-support systems.

A major theme in the literature is the optimisation of recovery processes. Recent studies increasingly investigate selective and less environmentally intensive methods for recovering critical materials from spent batteries and electronic components. Abdollahi Darestani et al., for example, optimised carbon-dioxide leaching of battery black mass and reported lithium leaching efficiencies of 91.59% under subcritical conditions and 98.35% under supercritical conditions. These results illustrate how optimisation can be applied to operating conditions to improve resource recovery. Similarly, Mojtahedi et al. investigated cobalt recovery from lithium cobalt oxide cathode scraps using green solvents. Although the recovered product had 99.12% purity, the reported laboratory recovery efficiency was only 57%, and the life-cycle assessment indicated that solvent production and electricity use were major environmental impact sources. This is important because it shows that a high-purity output alone cannot establish that a recovery process is sustainable. (Abdollahi Darestani et al., 2026)

The literature therefore increasingly connects process optimisation with life-cycle assessment. Life-cycle assessment evaluates environmental impacts across a product or process from raw-material inputs through processing and end of life. Within e-waste optimisation, it can identify whether a technically successful recovery route creates unacceptable energy, chemical or emissions burdens elsewhere in the system. The reviewed literature suggests that optimisation should consequently consider more than recovery efficiency. Economic cost, energy demand, carbon emissions, material yield, social outcomes and environmental impacts can all become decision criteria. Saeed et al., for instance, developed a multi-objective e-waste supply-chain model incorporating profit, carbon dioxide emissions, job creation and risk. This represents a broader understanding of optimisation in which competing objectives must be balanced rather than maximising a single technical measure.

Digital technology is another major direction in the literature. The literature review identifies the Internet of Things, artificial intelligence, blockchain, digital twins and big-data analytics as important enabling technologies for smart circular waste management. These tools can support monitoring, material tracking, route planning, process control and decision making. Luo et al. combined IoT sensors, a holographic twin model and automatic process control and reported a 95.2% recovery rate for cathode active materials. Lakshmaiya proposed an AI-integrated closed-loop battery recycling framework capable of classification and robotic disassembly; the reported classification accuracy was 98.5% and the simulated disassembly success rate was 97.6%. However, these results were based on benchmark datasets and simulations rather than an operating industrial plant. This distinction highlights a central research challenge: digital optimisation can show strong performance in controlled or simulated settings, but industrial validation is still necessary. (Luo et al., 2026)

E-waste optimisation also extends beyond recovery chemistry into reverse logistics. The efficient collection and movement of discarded electronics determine how much material actually reaches formal recovery systems. Ni et al. examined the “last mile” problem in e-waste reverse logistics and demonstrated the importance of community collection and treatment centres. Their model showed that eight community centres could achieve a collection rate of 61.6%. This finding reinforces the idea that optimisation is not limited to the recycling plant. Collection accessibility, transportation, network design and the movement of materials through certified channels are equally important parts of a circular e-waste system. (Ni et al., 2026)

The thematic evolution in the data analysis shows how this research focus has changed over time. In 2006–2022, optimisation, thermoelectric systems and heat formed a major motor theme, while e-waste and WEEE were central but less internally developed. Between 2023 and 2024, spent-battery recycling became a strong motor theme, while sustainability and assessment gained prominence. In 2025–2027, optimisation and sustainable recycling increasingly appear as a combined core theme, recovery of spent batteries remains a strong motor theme, and thermoelectric energy research becomes a more specialised stream. Recycling is increasingly represented through the broader concepts of recovery and optimisation. This evolution suggests a shift from general waste treatment toward targeted resource recovery supported by advanced analytical and computational methods.

The geographical results reinforce the global character of the field. China has the largest publication output, followed by India and the United States, with Italy and other countries contributing important specialist research. China's cumulative output is reported at roughly 1,600 papers by 2026, while India reaches approximately 495 and appears to overtake the USA around 2023. India's rapid recent growth is particularly relevant because the country has an expanding research interest in bioleaching, reverse logistics and AI-based e-waste management. At the same time, international collaboration remains limited compared with domestic collaboration, with about one-quarter of documents involving authors from more than one country.

Overall, the introduction to e-waste optimisation is therefore defined by a transition from isolated recovery and process-efficiency studies toward integrated, multi-objective and digitally enabled circular systems. The bibliometric evidence shows rapid growth, expanding interdisciplinarity and increasing attention to battery recovery, sustainability assessment, reverse logistics and digital tools. The literature review, meanwhile, shows that promising technologies already exist, but many remain at laboratory, simulation or benchmark stages. The central issue for the field is consequently not simply whether an individual technology can recover a material efficiently, but whether the technology can be integrated into a practical system that is environmentally sound, economically viable, socially accessible and scalable. The studies also show that optimisation is closely connected with recovery, assessment, digital systems and supply-chain decisions.

2. LITERATURE REVIEW

2.1 Digital, Recovery and Optimisation Technologies in E-Waste and Circular Waste Management: A Literature Review

Waste management is about how discarded materials are collected, treated, recovered or disposed of so that harm to people and the environment is kept low, and it has become a central part of the sustainable development agenda. A large and growing body of literature has investigated how electronic waste (e-waste), spent lithium-ion batteries and other end-of-life products can be treated as resources instead of as a disposal problem, and the 2026 records retrieved from Scopus, organised in Mendeley and mapped in VOSviewer (van Eck & Waltman, 2010) reflect this trend clearly.

The keyword map shows four clusters. The red one is about batteries and metal recovery, with terms such as lithium-ion batteries, cathodes, leaching and hydrometallurgy. The green one is built around electronic waste, life cycle assessment, optimisation and decision making. The blue one covers process optimisation, efficiency, carbon and economic and social effects, and the small yellow one brings together energy efficiency, waste heat and thermoelectricity. Much of the current literature is quite technical and focused on one process at a time. However, there is a relatively small body of literature that is concerned with how digital tools, recovery methods and decision support fit together across the whole waste lifecycle (Sukmasetya et al., 2026). This review looks at seventeen 2026 papers taken from these clusters to see which direction the field is heading.

Digital technology is one of the clearest themes. In recent years, there has been an increasing amount of literature on how it can be used in waste management. Sukmasetya et al. (2026) carried out a systematic review following PRISMA 2020 together with a bibliometric analysis. They found that the Internet of Things (IoT), artificial intelligence (AI), blockchain, digital twins and big-data analytics were the main enabling technologies. The outcomes reported most often were fewer overflowing bins, better collection routes and clearer tracking of material flows, but the authors point out that smart circular waste management needs a connected digital system and cannot rely on any one technology. Zhou et al. (2026) take a similar data-driven view in plastic manufacturing. Their circular economy design framework uses a convolutional neural network with sandpiper optimisation, and on a public plastic waste dataset it improved recyclability and cut carbon emissions.

Spent lithium-ion batteries make up the biggest part of the 2026 literature. It has been established that hydrometallurgical recovery can be made more selective by using greener reagents. Abdollahi Darestani et al. (2026) optimised carbon dioxide leaching of battery black mass with the Taguchi method and reached a lithium leaching efficiency of 91.59% under subcritical conditions, which went up to 98.35% when conditions became supercritical. Mirsalami et al. (2026) compared thermal and non-thermal ways of treating printed circuit boards and concluded that supercritical fluids, especially supercritical carbon dioxide, look promising within hydrometallurgy, although the processes still need more optimisation. Mojtahedi et al. (2026) recovered cobalt from cathode scraps using green solvents and obtained a cobalt oxide/hydroxide product with 99.12% purity. Their life cycle assessment showed that solvent production and electricity use caused most of the environmental impact, and the laboratory recovery efficiency was only 57%, which shows that these methods are still at an early stage. Because critical raw materials are in limited supply, this work also has a strategic side for regions such as the European Union (Abdollahi Darestani et al., 2026).

Digital tools are also being combined with these chemical processes. Luo et al. (2026) built a system that links IoT sensors, a holographic twin model and automatic process control, and they reported a 95.2% recovery rate for cathode active materials. Lakshmaiya (2026) designed a closed-loop recycling pipeline that identifies batteries, predicts their degradation and uses robots for disassembly. The classification accuracy was 98.5% and the simulated disassembly success rate was 97.6%, but these figures come from benchmark datasets and simulations rather than from a working plant. In the same way, Xue et al. (2026) argue that machine learning could help recover rare metals from phosphogypsum, but they admit that direct quantitative evidence for this material is extremely scarce. Feng et al. (2026), meanwhile, review green silicon sources from minerals, industrial waste and biomass for battery anodes, which shows that waste is also becoming an input for making new batteries.

Heat-based treatment has been studied for e-waste that is hard to recycle mechanically. Alreshidi et al. (2026) reviewed five pyrolysis techniques for electronic plastics (vacuum, catalytic, co-pyrolysis, microwave-assisted and plasma pyrolysis) and said that material degradation, catalyst performance and energy optimisation still stop commercial use. Khan and Janajreh (2026) simulated the co-gasification of printed circuit boards with sewage sludge. A mix of 40% circuit boards and 60% sludge gave the highest hydrogen mole fraction (0.430) and a cold gasification efficiency of 49.86%. These studies suggest that e-waste can be turned into energy carriers as well as metals, although both routes are still being scaled up. This matters because plastics and circuit boards are among the hardest parts of e-waste to deal with, and conventional disposal methods such as landfilling and incineration still leave many of them unrecovered.

Another group of studies deals with logistics and decision making. Saeed et al. (2026) built a multi-objective mixed-integer linear programming model for e-waste supply chains that looks at profit, carbon dioxide emissions, job creation and risk together. Their neutrosophic optimisation approach performed about 6.82 and 11.82 times better than the epsilon-constraint and goal programming methods. Ni et al. (2026) pointed out that although China's official e-waste recycling rate is above the global average, the certified reverse logistics network still loses material to uncertified channels. They built a model for this 'last mile' problem and showed that eight community collection and treatment centres could reach a collection rate of 61.6%. Rajadurai and Kaliyaperumal (2026) used neutrosophic numbers in a superiority and inferiority ranking method to compare e-waste management strategies under uncertainty, and tested the results with sensitivity and Monte Carlo analyses. Solgi et al. (2026) reviewed 261 closed-loop supply chain studies, of which 73 were about the tire industry, and pointed out several areas that have not been explored enough.

The small energy cluster connects waste with the electronics it comes from. Gómez-Gijón et al. (2026) explain that energy harvesting can power devices without batteries, which could reduce the e-waste created by IoT devices, but power efficiency, energy storage and unstable energy supply remain open problems. Hosseinzadeh-Bandbafha et al. (2026) estimated that battery electric vehicles could lower cumulative global warming potential by around 40% compared with gasoline by 2050. They also warned that battery supply chains and end-of-life handling could raise toxicity risks, which is one reason why the recovery of lithium, cobalt and nickel appears so often in the studies above.

In terms of methods, the 2026 papers are a mix of experiments, models and reviews. Systematic and bibliometric reviews are common (Hosseinzadeh-Bandbafha et al., 2026; Solgi et al., 2026; Sukmasetya et al., 2026), and the first of these also adds scenario modelling of future emissions. Experiments are mostly found in battery recycling (Abdollahi Darestani et al., 2026; Luo et al., 2026; Mojtahedi et al., 2026), while optimisation models dominate supply chain research (Ni et al., 2026; Saeed et al., 2026). Only a few authors test their models on real cases (Ni et al., 2026; Saeed et al., 2026), and much of what is known about AI-enabled recycling is based on simulated or benchmark data. This suggests that proper validation is the biggest methodological gap.

Across these papers, a shared vocabulary has emerged, and some of the terms are both critical to the field and fairly new in the 2026 literature. Table 1 defines the keywords from the VOSviewer clusters that keep coming up in the reviewed studies.

Table -1: Critical and emerging terms and their relevance

Critical term	Definition and relevance to the study	Key reference
Electronic waste (e-waste), green	Discarded electrical and electronic equipment such as circuit boards and batteries; it holds both hazardous substances and valuable metals, so it is now treated as a secondary resource.	(Mirsalami et al., 2026; Saeed et al., 2026)
Lithium-ion batteries, red	Rechargeable cells with cathodes containing lithium, cobalt, nickel and manganese; recycling spent cells reduces dependence on critical raw materials.	(Abdollahi Darestani et al., 2026; Lakshmaiya, 2026)
Leaching, red	Dissolving target metals from solid waste such as black mass into a liquid; being redesigned with carbon dioxide, deep eutectic solvents and controlled acids.	(Abdollahi Darestani et al., 2026; Mojtahedi et al., 2026)
Hydrometallurgy, red	Non-thermal metal recovery using aqueous leaching, separation and precipitation, as opposed to high-temperature pyrometallurgy; emerging with supercritical fluids and green solvents.	(Mirsalami et al., 2026; Mojtahedi et al., 2026)
Metal recovery, red	Reclaiming valuable metals such as lithium, cobalt and rare earth elements from waste; increasingly supported by machine learning and digital monitoring.	(Luo et al., 2026; Xue et al., 2026)
Life cycle assessment, green	Method that measures the environmental impact of a product or process from raw materials to end of life; used to find hotspots in recovery routes.	(Hosseinzadeh-Bandbafha et al., 2026; Mojtahedi et al., 2026)
Sustainable development, green	Development that balances economic, environmental and social needs; in these studies it is put into practice through circular economy and SDG-aligned models.	(Saeed et al., 2026; Sukmasetya et al., 2026)
Process optimisation, blue	Tuning operating conditions such as temperature, time and liquid-to-solid ratio to maximise recovery; uses Taguchi design and response surface methodology.	(Abdollahi Darestani et al., 2026; Luo et al., 2026; Zhou et al., 2026)
Decision making, green	Choosing between alternatives under several criteria and uncertainty; neutrosophic and multi-criteria methods are a newer way of handling indeterminacy.	(Rajadurai & Kaliyaperumal, 2026; Saeed et al., 2026)
Economic and social effects, blue	Profit, cost, job creation and community access outcomes that sit alongside environmental measures when judging waste systems.	(Ni et al., 2026; Saeed et al., 2026)
Energy efficiency and waste heat, yellow	Cutting energy demand and turning ambient or waste heat into electricity (thermoelectricity); supports self-powered electronics and lower-energy recycling.	(Alreshidi et al., 2026; Gómez-Gijón et al., 2026)

Taking these studies together, it is seen that the field is moving in one clear direction. Recovery chemistry is shifting towards greener and more selective processes, such as subcritical and supercritical carbon dioxide and deep eutectic solvents. Optimisation, machine learning, digital twins and neutrosophic decision tools are being added on top of both recovery processes and supply chain design. Life cycle assessment is also used more and more to check whether a recovery route is really sustainable and not just technically possible. The clusters are closely linked too, because a single study often combines recovery chemistry, optimisation and life cycle thinking.

Despite these advances, the literature does not suggest that one technology can solve the e-waste problem. Several studies only report simulation, benchmark or laboratory results (Khan & Janajreh, 2026; Lakshmaiya, 2026; Mojtahedi et al., 2026), and the reviews on pyrolysis and phosphogypsum both point to a gap between experimental success and industrial use (Alreshidi et al., 2026; Xue et al., 2026). Few studies also link technical performance to social outcomes such as community access to collection (Ni et al., 2026). A further prospect for future research would be pilot-scale testing of AI-enabled recovery systems together with life cycle and cost assessment, so that technologies are judged by their real circular outcomes and not by laboratory efficiency alone.

3. RESEARCH METHODOLOGY

3.1 Research Design

This study is a bibliometric review of the literature on e-waste optimization. A bibliometric review is a quantitative approach in which large volumes of published research are analysed across factors such as publication year, document type, subject area, source, and keywords to identify trends, thematic clusters, and gaps in a research area, rather than reading each paper individually.

A bibliometric approach was selected because a preliminary search on Scopus indicated that the topic spans several thousand documents across engineering, environmental science, energy, computer science, and materials science. Reviewing this volume of literature manually would not be feasible, and a bibliometric method allows patterns across the full body of research to be identified systematically. The study followed a PRISMA-style screening process, adapted from clinical systematic review methodology for bibliometric use, to move from an initial database search to a final, analysable dataset.

3.2 Database Selection

Scopus was selected as the sole data source for this study. Scopus is one of the largest curated databases of peer-reviewed literature, with strong coverage across the engineering, environmental science, and energy disciplines that are central to e-waste research. It also provides standardised metadata, including author keywords, affiliations, and complete reference lists, which is required for citation-based and keyword co-occurrence analysis at later stages of the study.

Two alternative databases were considered and rejected. Web of Science was considered but not used, since its more selective indexing criteria would have excluded a portion of applied engineering and environmental journals that are relevant to this topic, narrowing the dataset unnecessarily. Google Scholar was also considered but rejected, as it indexes theses, working papers, and content from low-quality or non-peer-reviewed sources, which would compromise the consistency and reliability required for a bibliometric dataset. A single, well-curated database was preferred over combining multiple sources, since merging databases with different metadata standards introduces inconsistency into the dataset.

3.3 Search Strategy

The search was conducted using the Boolean query *electronic AND waste AND optimisation*, applied to Article Title, Abstract, and Keywords. This query was designed to capture the intersection of electronic waste and optimization-related research, covering areas such as collection logistics, recycling process optimization, and materials recovery, while remaining specific enough to stay within scope.

A narrower query substituting the industry-specific term "WEEE" (Waste Electrical and Electronic Equipment) in place of "electronic waste" was considered. This was not used, as it would have restricted the dataset to literature using formal regulatory terminology and excluded a substantial body of work that refers to the subject using more general language, biasing the dataset toward a specific subset of the field. A broader query removing the term "optimisation" was also considered and rejected, as it would have returned a much larger and less focused dataset covering general e-waste management topics unrelated to optimization methods, with little common thematic ground for analysis.

The initial, unfiltered search returned 2,562 records, forming the Identification stage of the review.

3.4 Screening and Eligibility Criteria

Four filters were applied in sequence to narrow the initial dataset to a consistent, analysable set of documents. Each filter, the number of records excluded, and the rationale behind the decision are detailed below.

3.4.1 Time Span (2006-2027)

The dataset was restricted to documents published between 2006 and 2027. This filter excluded 57 records, reducing the dataset from 2,562 to 2,505.

The year 2006 was selected as the lower bound because e-waste began to be formally recognised as a distinct policy and research area around this period, following the implementation of early e-waste regulatory frameworks such as the EU WEEE Directive. Records published before this period were found to treat electronic waste as a subset of general industrial waste management rather than as its own research domain, and were therefore not representative of the field as it is studied today. The upper bound of 2027 was retained, rather than capped at 2026, to include in-press and early-access articles already indexed by Scopus ahead of their formal publication date.

A narrower window of the past five years was considered as an alternative but rejected, as it would not provide a sufficient time frame to assess longer-term publication trends and growth patterns. An unrestricted time span was also considered and rejected, as it would have included legacy literature that predates the formal recognition of e-waste as a research area, without adding representative value to current trend analysis.

3.4.2 Document Type (Articles and Reviews)

The dataset was restricted to documents classified as Articles and Reviews. This filter excluded 677 records, reducing the dataset from 2,505 to 1,828.

Articles and reviews were retained because they undergo a rigorous peer-review process and are associated with more complete and standardised metadata, including full reference lists and author keywords, which are required for citation and keyword co-occurrence analysis. Conference papers, book chapters, conference reviews, books, retracted articles, errata, short surveys, and letters were excluded. Conference papers in particular were excluded as they are frequently republished later as full journal articles, and including both versions would introduce duplication into the dataset. Books and book chapters were excluded due to inconsistent indexing and variable levels of peer review across publishers.

3.4.3 Language (English)

The dataset was restricted to English-language publications. This filter excluded 67 records, reducing the dataset from 1,828 to 1,761.

Of the languages present in the dataset at this stage, records were also identified in Chinese, Portuguese, Spanish, Turkish, Russian, Japanese, German, and French. English was retained as the sole language because accurate analysis of non-English records would require translation, which risks losing technical nuance, particularly around recycling process terminology and optimization method descriptions, potentially distorting keyword and thematic analysis. Restricting the dataset to a single language also ensures that equivalent concepts are not inadvertently coded as separate terms across different languages during keyword analysis. This filter removed a relatively small proportion of records, approximately 3.7% of the dataset at this stage, indicating limited impact on the representativeness of the overall corpus, though it is acknowledged as a limitation in Section 6.

3.4.4 Source Type (Journals)

The dataset was restricted to documents published in academic journals, excluding trade journals. This filter excluded 6 records, reducing the dataset from 1,761 to 1,755.

Journals were retained as the sole accepted source type because they are subject to formal peer review and consistent editorial standards, which supports reliable source-level and citation-based comparison. Trade journals were excluded because they typically lack the same degree of editorial oversight and peer review, and their inclusion could introduce inconsistency into source-level analysis. The small number of records removed at this stage, six in total, indicates that the dataset was already composed almost entirely of journal-sourced literature prior to this filter.

3.5 Filters Deliberately Not Applied

Certain Scopus filters were considered but deliberately not applied to the dataset.

Subject area was not restricted. E-waste optimization research spans engineering, environmental science, energy, computer science, materials science, and chemical engineering. Limiting the dataset to one or two subject categories would have excluded relevant methodological contributions from adjacent fields, particularly optimization techniques originating in computer science and engineering.

Open access status was not restricted. Limiting the dataset to open-access publications would have overrepresented certain publishers and funding bodies, introducing bias into the source and citation analysis.

Country and affiliation were not restricted. No geographic limitation was applied, since mapping the global distribution of research output and collaboration patterns is a planned component of the subsequent bibliometric analysis.

Keyword filters were not applied at the search stage. Pre-filtering by keyword would have effectively predetermined the thematic clusters expected in the keyword co-occurrence analysis. The dataset was left unrestricted in this respect so that dominant themes could emerge from the data itself during analysis.

3.6 Final Dataset

The four filters applied in sequence reduced the initial dataset of 2,562 records to a final dataset of 1,755 records. The reduction at each stage is summarised below.

Table -2: Final Dataset

Stage	Filter	Records Before	Excluded	Records After
Identification	Initial search string	—	—	2,562
Screening	Time span (2006–2027)	2,562	57	2,505
Eligibility	Document type (Articles + Reviews)	2,505	677	1,828
Eligibility	Language (English)	1,828	67	1,761
Eligibility	Source type (Journals)	1,761	6	1,755
Inclusion	Final dataset	—	—	1,755

The final dataset of 1,755 documents forms the basis for the subsequent bibliometric analysis, including keyword co-occurrence mapping, publication trend analysis, source and citation analysis, and geographic distribution mapping. The PRISMA flow diagram below summarises the identification, screening, and eligibility process described above.

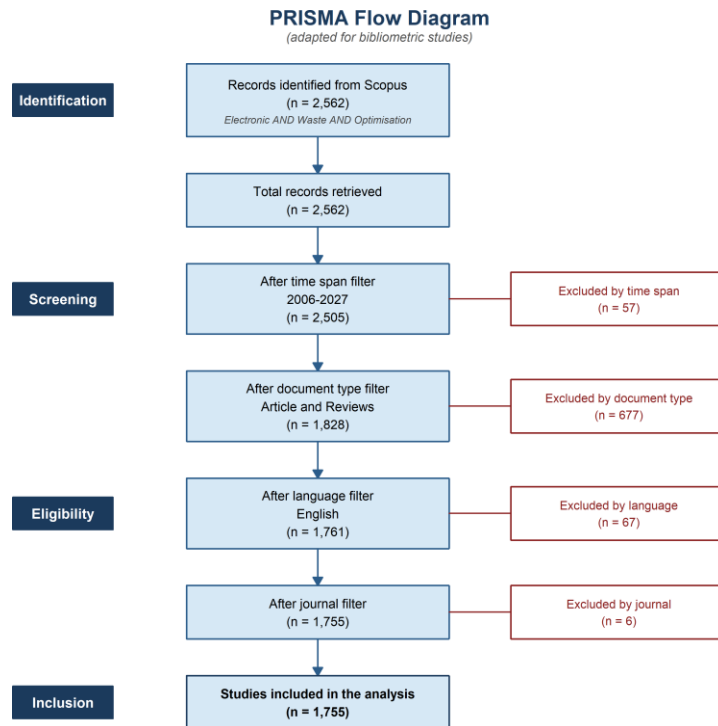


Figure -1: PRISMA flow diagram (adapted for bibliometric studies).

4. DATA ANALYSIS

Trends in Electronic Waste Management Optimisation

4.1 Main information

To understand how research on optimization in electronic waste (e-waste) management and resource recovery has developed, a bibliometric analysis was carried out using the Bibliometrix R-package and its Biblioshiny interface. The final dataset contains 1,755 documents published in 624 different sources between 2006 and 2027. The fact that these papers are spread across so many journals suggests that the topic does not belong to a single discipline. Instead, it draws on waste management, environmental science, chemical engineering, energy engineering and operations research (Achillas et al., 2010; Champier, 2017; Mossali et al., 2020). The few 2027 records are papers that have already been released online ahead of their official publication year.

At first sight, the annual growth rate of 1.38% appears surprisingly low for a field that is clearly expanding. However, this figure should be interpreted with caution. The growth rate is calculated only from the first and the last year of the dataset, and the last year, 2027, contains just 8 early-access papers. If 2026 is taken as the end point instead, output rises from 6 documents in 2006 to 450 documents in 2026, which works out to a compound growth of roughly 24% per year. This is well above the 10% level that is commonly treated as a sign of a fast-growing research area, and it matches the steep curve seen in the Annual Scientific Production chart.

A total of 5,889 authors contributed to this body of work, yet only 37 of them wrote papers on their own. On average, each document has 5.08 co-authors, which shows that research in this area is almost entirely team-based. This is not surprising, since most studies combine laboratory work, process modelling and optimization, which usually needs experts from different backgrounds (Xu et al., 2021). About 26.55% of the papers involve authors from more than one country. This means that roughly one in four studies is an international collaboration, while the majority are still carried out within national research groups, a pattern that becomes clearer in the Three-Field Plot.

The dataset also contains 5,409 unique author keywords, which reflects the wide range of topics covered, from metal leaching and spent lithium-ion batteries to reverse logistics networks and thermoelectric generators (Dutta et al., 2020; Lv et al., 2018). The average document age is only 3.66 years, so most of the research is very recent. Even so, each document has received an average of 28.53 citations, which is high for such a young collection and indicates that the field is being actively read and built upon.

4.2 Annual Production Chart

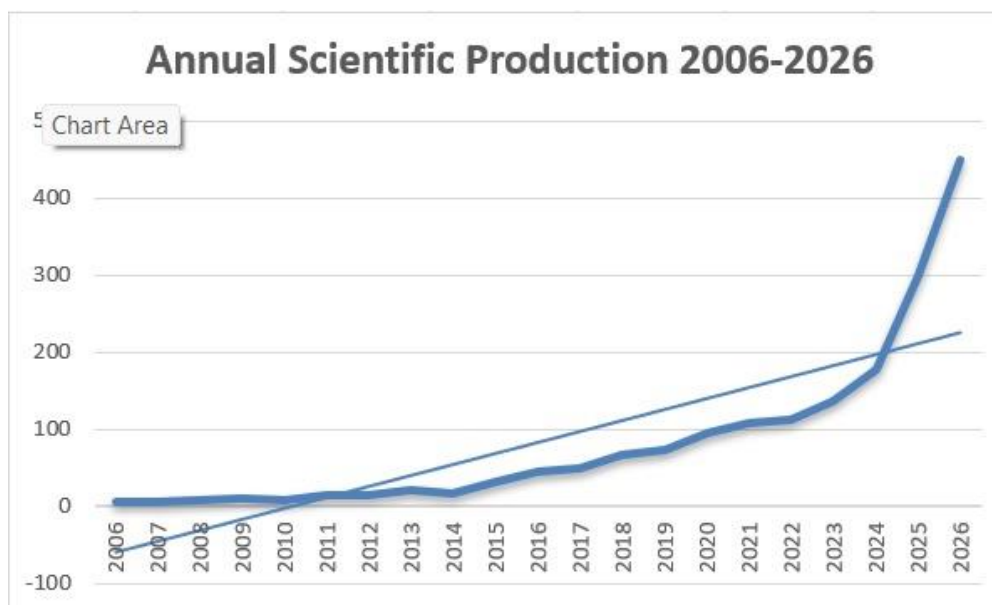


Figure -2: Annual publication output on optimization in e-waste management and resource recovery, 2006–2026.

The Annual Scientific Production chart shows how many papers were published each year on optimization in e-waste management and resource recovery between 2006 and 2026. As can be seen from the chart, the field has passed through three fairly clear stages of growth.

From 2006 to 2014, output stayed very low, with fewer than 25 papers a year. Early work in this period focused mainly on recovering metals from electronic scrap and on designing efficient disassembly and recovery processes (Hagelüken, 2006; Xanthopoulos & Iakovou, 2009). The topic was still small, and optimization was applied to only a handful of specific problems.

Between 2015 and 2022, there was a steady increase, from 31 papers in 2015 to 112 in 2022. A possible explanation for this rise is the growing volume of e-waste worldwide, together with new take-back and subsidy policies for waste electrical and electronic equipment (WEEE) and the rapid spread of lithium-ion batteries, all of which created new recovery problems to optimize (Yu et al., 2014; Lv et al., 2018).

What stands out in this chart is the sharp increase after 2023. Output rose from 137 papers in 2023 to 178 in 2024, then jumped to 300 in 2025 and 450 in 2026. In other words, 2025 and 2026 alone account for 750 papers, or about 43% of the entire dataset. The straight trend line helps to show this: it runs above the actual values in the early years, even dipping below zero, and then falls well below them after 2024. This means the growth is not linear but accelerating, which is typical of a research area that is still in its expansion phase.

4.3 Average Citations per Year

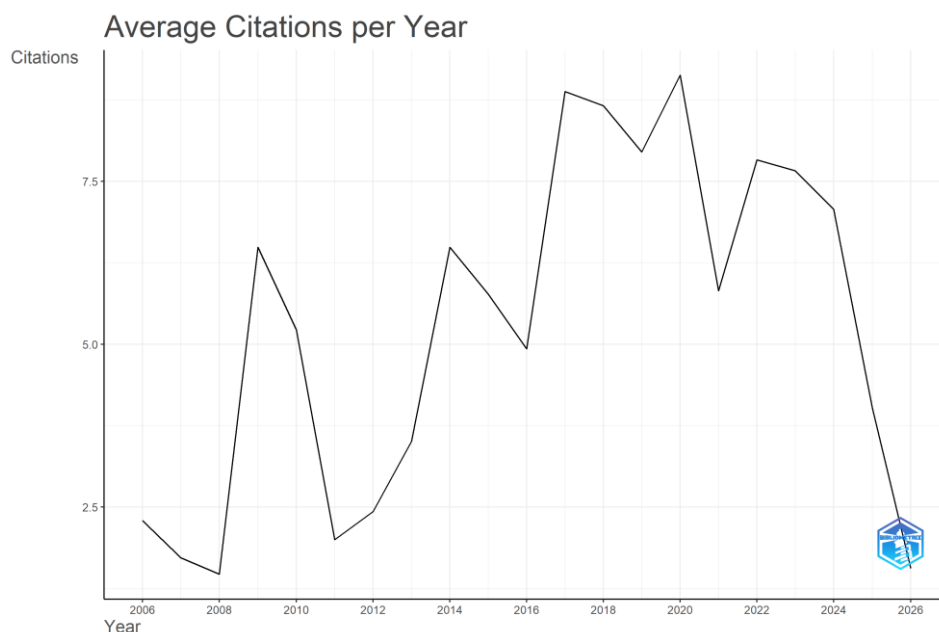


Figure -3: Average citations per year (2006–2026).

The Average Citations per Year chart shows how influential the papers from each publication year have been. For each year, the average number of citations is divided by the number of years the papers have been available, so older and newer papers can be compared more fairly. This is different from the Annual Scientific Production chart, which only counted how many papers were published.

Between 2006 and 2013, the values move up and down sharply, from a low of about 1.5 in 2008 to about 6.5 in 2009. These swings should be interpreted with caution, as very few papers were published in these years and a single highly cited study can lift the whole average. For example, the 2009 peak is largely driven by work on precious metal flows during WEEE pre-processing (Chancerel et al., 2009), and the similar peak in 2014 by studies on the systematic optimization of waste-heat power cycles (Maraver et al., 2014).

The most influential period is clearly 2017 to 2020, when the average stays between about 8 and 9.1 citations per year and reaches its highest point in 2020. This window includes the most cited paper in the whole dataset, a review of thermoelectric generator applications with over 1,300 citations (Champier, 2017), as well as widely cited reviews on recycling spent lithium-ion batteries (Lv et al., 2018; Mossali et al., 2020). Papers from these years appear to have laid the foundations that later studies build on.

After a dip in 2021, the average recovers to around 7 to 8 between 2022 and 2024, and then falls steeply to about 4 in 2025 and 1.6 in 2026. This decline does not mean that recent research is weaker. Instead, it reflects citation lag: new papers simply have not had enough time to be read and cited by other researchers, so their averages will naturally rise over the next few years.

4.4 Three Fields Plot

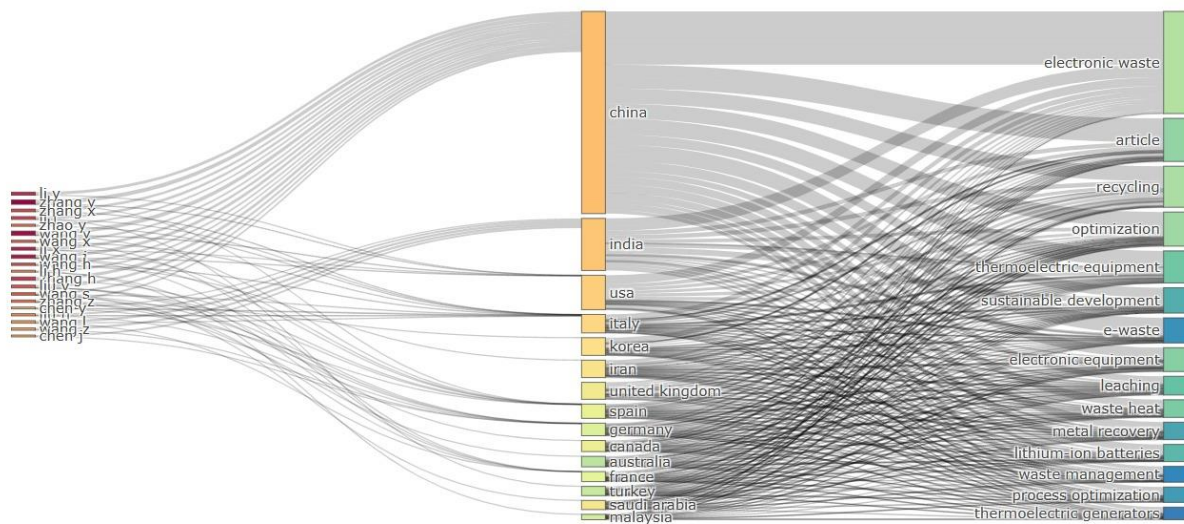


Figure -4: Three-Fields Plot showing the relationship between authors, countries and keywords.

The Three-Fields Plot links three dimensions of the dataset: authors on the left, countries in the middle and keywords on the right. The thickness of each band shows how often these elements are connected, giving an overall picture of who is publishing, where they are based and what they are studying.

1. Leading countries: China has by far the largest block, followed by India and the USA, with Italy, South Korea, Iran, the United Kingdom and Spain forming the next group (Liang et al., 2024; Priya & Hait, 2017). Smaller but visible contributions come from Germany, Canada, Australia, France, Turkey, Saudi Arabia and Malaysia. This spread across Asia, Europe, North America and the Middle East shows that e-waste and resource recovery are treated as global problems rather than regional ones.

2. Author–country links: All twenty of the most productive author names (such as Li Y., Zhang Y. and Wang X.) are Chinese, and most of their bands flow directly into China, which confirms the dominance of Chinese research groups. A few thinner bands run to the USA, South Korea and other countries, showing some international collaboration. However, these results should be read with care, as short name forms like Li Y. or Wang J. are shared by many different researchers, so each entry may combine the work of several people.

3. Core and specialised topics: On the keyword side, electronic waste, recycling and optimization form the shared core of the field. The keyword “article” is simply a database indexing tag rather than a research theme. Beyond the core, two distinct streams can be seen: a materials-recovery stream (leaching, lithium-ion batteries) and an energy-recovery stream (waste heat, thermoelectric equipment, thermoelectric generators). Process optimization is the common thread linking both (Gou et al., 2010; Lv et al., 2018).

4.5 Most Relevant Sources

WASTE MANAGEMENT	113
JOURNAL OF CLEANER PRODUCTION	54
JOURNAL OF ENVIRONMENTAL MANAGEMENT	40
ENERGY CONVERSION AND MANAGEMENT	39
ENERGY	37
RESOURCES, CONSERVATION AND RECYCLING	32
APPLIED ENERGY	28
APPLIED THERMAL ENGINEERING	28
JOURNAL OF ENVIRONMENTAL CHEMICAL ENGINEERING	27
SEPARATION AND PURIFICATION TECHNOLOGY	26
JOURNAL OF HAZARDOUS MATERIALS	24
ENERGIES	23
SUSTAINABILITY (SWITZERLAND)	21
JOURNAL OF ENERGY STORAGE	20
CHEMICAL ENGINEERING JOURNAL	18
WASTE MANAGEMENT AND RESEARCH	17
ACS SUSTAINABLE CHEMISTRY AND ENGINEERING	15
ENVIRONMENTAL SCIENCE AND TECHNOLOGY	13
JOURNAL OF ELECTRONIC MATERIALS	13
RENEWABLE AND SUSTAINABLE ENERGY REVIEWS	12

Figure -5: Most Relevant Sources by Document Volume.

This table lists the twenty most productive journals in the dataset, each with at least 12 papers, showing where the core research on this topic is being shared.

1. The dominant core journal: Waste Management leads by a wide margin with 113 papers, more than twice as many as any other journal. It has been a home for this topic since the early years, publishing work on disassembly optimization and the recovery of metals from printed circuit boards (Birloaga et al., 2013; Xanthopoulos & Iakovou, 2009).

2. Sustainability and environmental outlets: The second tier is led by the Journal of Cleaner Production (54), followed by the Journal of Environmental Management (40) and Resources, Conservation and Recycling (32). These journals publish much of the operations research side of the field, such as multi-objective reverse logistics and network design models (Dutta et al., 2020; Safdar et al., 2020).

3. Energy journals: A strong group of energy journals appears, including Energy Conversion and Management (39), Energy (37), Applied Energy (28), Applied Thermal Engineering (28), Energies (23), the Journal of Energy Storage (20) and Renewable and Sustainable Energy Reviews (12). This group reflects the thermoelectric and waste-heat recovery stream of the literature (Champier, 2017; Chen et al., 2022).

4. Chemical and process engineering journals: Journals such as the Journal of Environmental Chemical Engineering (27), Separation and Purification Technology (26), the Journal of Hazardous Materials (24) and ACS Sustainable Chemistry and Engineering (15) cover the chemistry of recovery, especially leaching and battery recycling (Lv et al., 2018).

5. Bradford's Law and interdisciplinarity: Together, these twenty journals account for 600 papers, or about one-third of the dataset, while the remaining two-thirds are spread across more than 600 other sources, many of which published only a single paper. This pattern, with a small core of highly productive journals and a long tail of less productive ones, is consistent with Bradford's Law. The mix of waste, environmental, energy and chemical journals also confirms that the field is genuinely interdisciplinary.

Overall, the source analysis shows that research on this topic is anchored in waste management journals but is increasingly spreading into energy and chemical engineering outlets.

4.6 Production Overtime

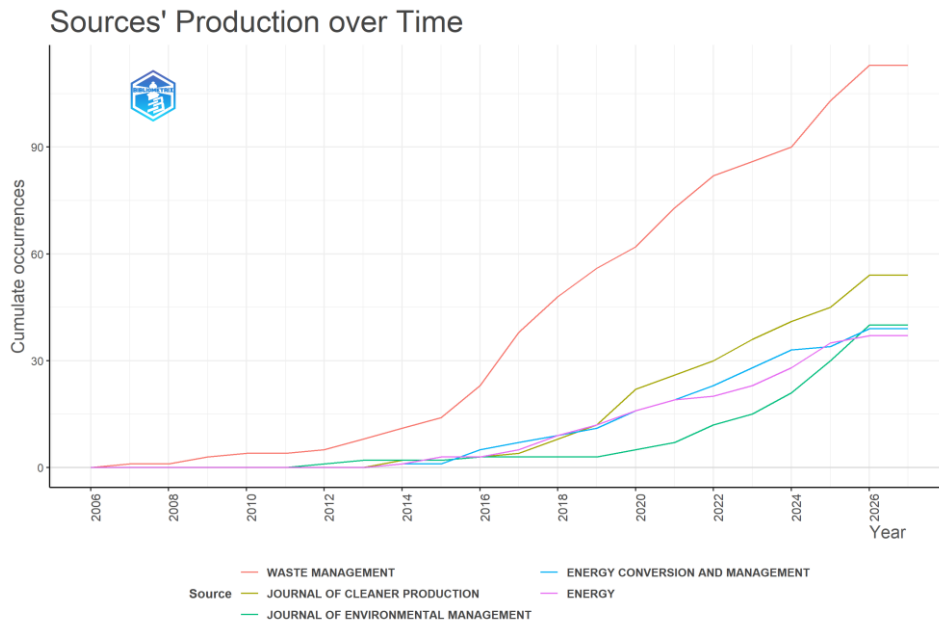


Figure -6: Cumulative number of publications in the top five journals (2006–2027).

The Sources' Production over Time chart shows how the cumulative number of papers in the five leading journals grew between 2006 and 2027. It reveals not only which journal is largest today, but also when each one became important.

Waste Management was the earliest and most consistent contributor. It published its first paper in 2007 and grew slowly until 2015, when it had 14 papers. It then rose sharply to 38 papers by 2017 and kept growing steadily to reach 113 by 2026, remaining the leading journal throughout the whole period.

The Journal of Cleaner Production did not publish on the topic until 2014, but it grew quickly after 2019, with its total almost doubling from 12 to 22 papers in a single year (2020). By 2026 it had reached 54 papers, securing a clear second place. This jump coincides with the growth of sustainability-focused reverse logistics research (Dutta et al., 2020; Safdar et al., 2020).

Energy Conversion and Management and Energy entered the field around 2014 and have grown almost in parallel ever since, ending with 39 and 37 papers respectively. Their similar paths reflect the steady development of the thermoelectric and waste-heat recovery stream (Champier, 2017).

Interestingly, the Journal of Environmental Management shows the most dramatic change. It stayed at just 3 papers from 2016 to 2019, but after 2021 it accelerated rapidly, reaching 40 papers by 2026 and overtaking both energy journals in the final year.

4.7 Countries Production Overtime

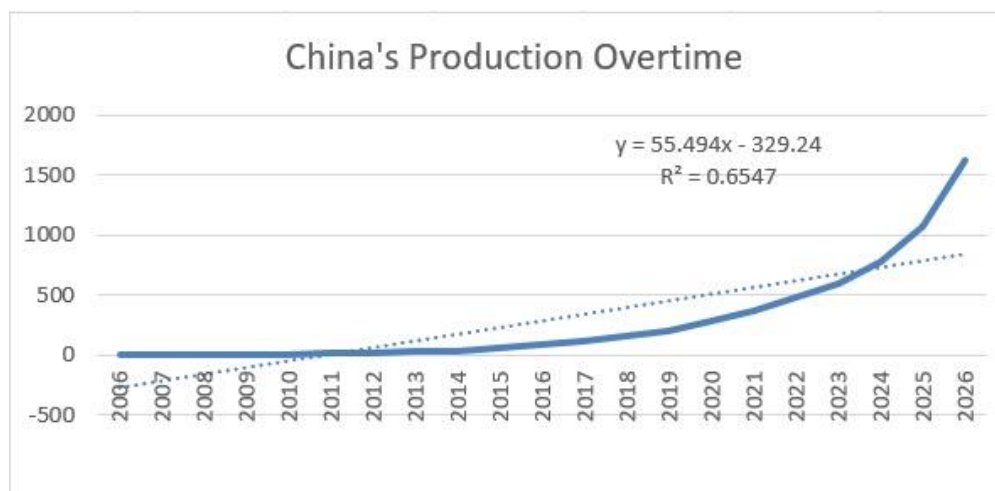


Figure -7: Cumulative publication output of China.

China's trend line, $y = 55.494x - 329.24$, has the steepest slope of all four countries, meaning that China adds about 55 publications per year on average. However, the R^2 value of 0.6547 is only moderate, which shows that a straight line does not describe China's growth very well. The actual curve stays close to zero until around 2014 and then rises faster every year, reaching roughly 1,600 by 2026. This is almost double the value of about 836 that the trend line predicts for 2026, which confirms that China's growth is accelerating rather than steady (Liang et al., 2024; Yu et al., 2014).

India's Production Overtime

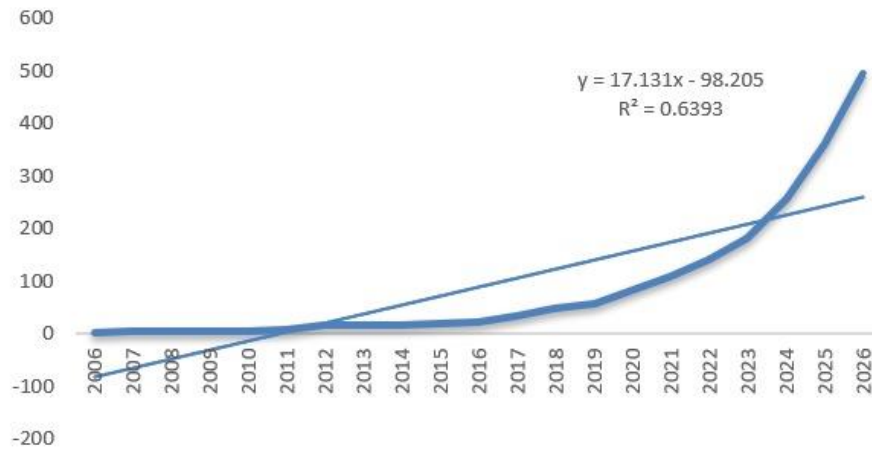


Figure -8: Cumulative publication output of India.

India's trend line, $y = 17.131x - 98.205$, has the second-highest slope but the lowest R^2 value (0.6393) of the four countries. This is because India's output was almost flat until about 2016 and has grown very quickly since then, reaching around 495 by 2026 compared with a predicted value of about 262. India's growth is therefore the most concentrated in recent years, driven by work on bioleaching, reverse logistics and AI-based e-waste management (Dutta et al., 2020; Priya & Hait, 2017; Ramya et al., 2023). Notably, India appears to have overtaken the USA around 2023.

USA's Production Overtime

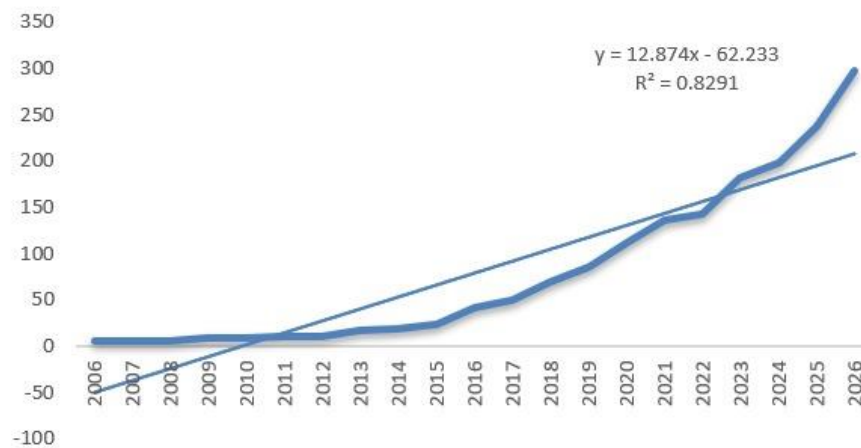


Figure -9: Cumulative publication output of the USA.

The USA's trend line, $y = 12.874x - 62.233$, has the strongest fit of the four countries, with an R^2 value of 0.8291. This indicates that the USA's output has grown in a steadier and more gradual way than that of China or India, starting to rise from around 2015 and reaching roughly 297 by 2026. Even so, the actual values in recent years sit above the trend line (about 208 predicted for 2026), showing that growth has also picked up in the USA, particularly in battery recycling research (Xu et al., 2021).

Italy's Production Overtime

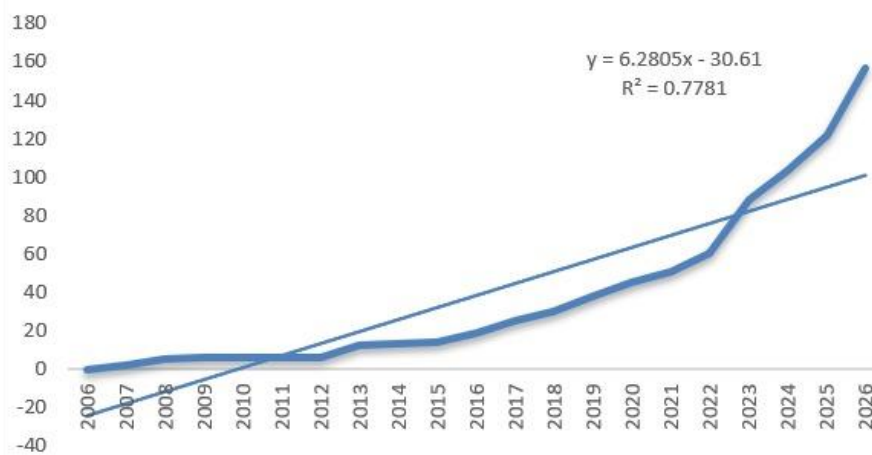


Figure -10: Cumulative publication output of Italy.

Italy's trend line, $y = 6.2805x - 30.61$, has the smallest slope, reflecting its smaller overall output of about 157 by 2026. The R^2 value of 0.7781 is fairly strong, showing reasonably steady growth, although there is a noticeable jump between 2022 and 2023, when the total rose from around 60 to nearly 90. Italian research has contributed notably to metal recovery from printed circuit boards, disassembly line optimization and battery recycling (Birloaga et al., 2013; Mossali et al., 2020; Pistolesi et al., 2018).

Taken together, these charts show that all four countries follow a similar accelerating pattern, which a straight line can only partly capture. Countries with lower R^2 values, such as China and India, have experienced the most recent and explosive growth, while the USA and Italy have grown more steadily over a longer period.

4.8 Thematic Evolution

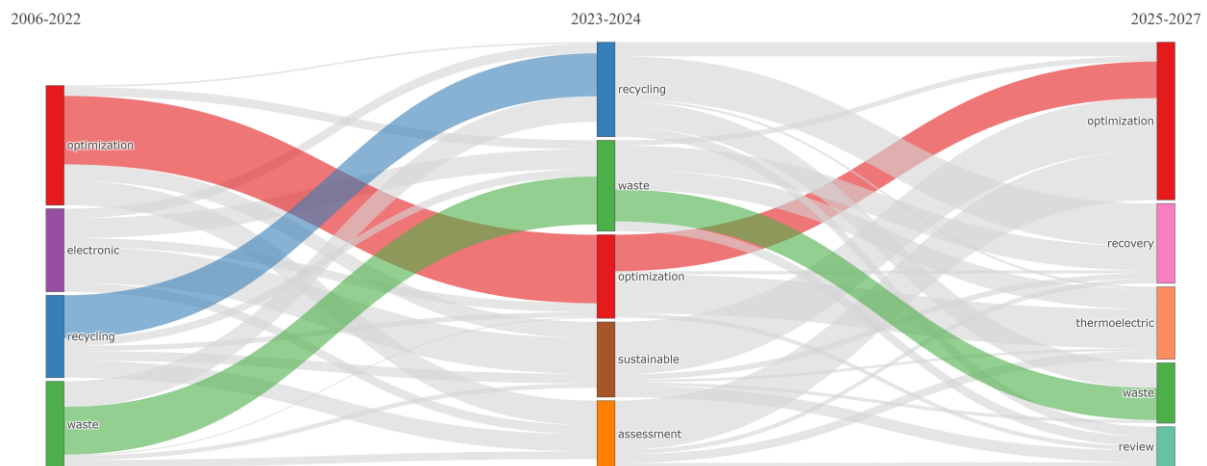


Figure -11: Thematic evolution of research across three periods (2006–2022, 2023–2024 and 2025–2027).

The Thematic Evolution chart shows how the main research themes have changed across three periods: 2006–2022, 2023–2024 and 2025–2027. The size of each box shows how important a theme was in that period, while the thickness of each flow shows how strongly a theme in one period is connected to a theme in the next.

In the first period (2006–2022), the field was organised around four themes: optimization, electronic, recycling and waste, with optimization being the largest. The most striking feature of the whole chart is that optimization is the only theme that continues as a thick, unbroken flow across all three periods. This suggests that optimization is the backbone of the field, applied to problems ranging from waste collection routes to thermoelectric system design (Gou et al., 2010; Nowakowski et al., 2018).

In the second period (2023–2024), recycling and waste continue from the earlier period, while two new themes appear: sustainable and assessment. The “electronic” theme no longer stands alone. Instead, its flows are spread across several of the new themes, which suggests that e-waste has become the shared context of the field rather than a separate topic. The rise of “assessment” reflects the growing use of life cycle and environmental assessment to compare recovery technologies (Villares et al., 2017).

In the third period (2025–2027), the themes are optimization, recovery, thermoelectric, waste and review. Recycling no longer appears as a separate label; its flows now feed mainly into recovery and optimization. This indicates a shift from recycling in general towards recovering specific high-value materials, especially from spent batteries (Xu et al., 2021). Thermoelectric research re-emerges as a theme of its own, and the appearance of “review” shows that researchers are increasingly summarising the rapidly growing literature (Erkmen et al., 2025; Tabakh et al., 2026).

4.9 Time Slice

4.9.1 2006–2022 Time Slice

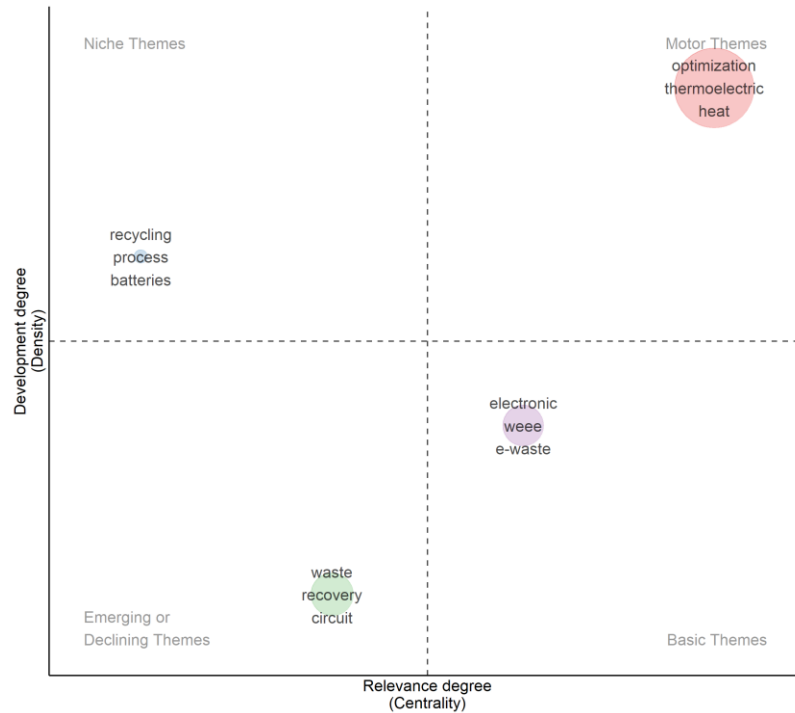


Figure -12: Thematic map (Time Slice: 2006–2022).

In this early period, the only motor theme, and also the largest, was optimization, thermoelectric and heat. This shows that the optimization of thermoelectric waste-heat recovery systems was the most developed and central research stream at the time (Champier, 2017; Gou et al., 2010). The e-waste and WEEE theme sat in the basic themes quadrant, meaning it was central to the field but not yet well developed internally. Recycling of batteries formed a small niche theme, while the recovery of metals from circuit boards appeared in the emerging or declining quadrant (Birloaga et al., 2013). Overall, this period shows a field in which energy recovery was more mature than materials recovery.

4.9.2 2023–2024 Time Slice

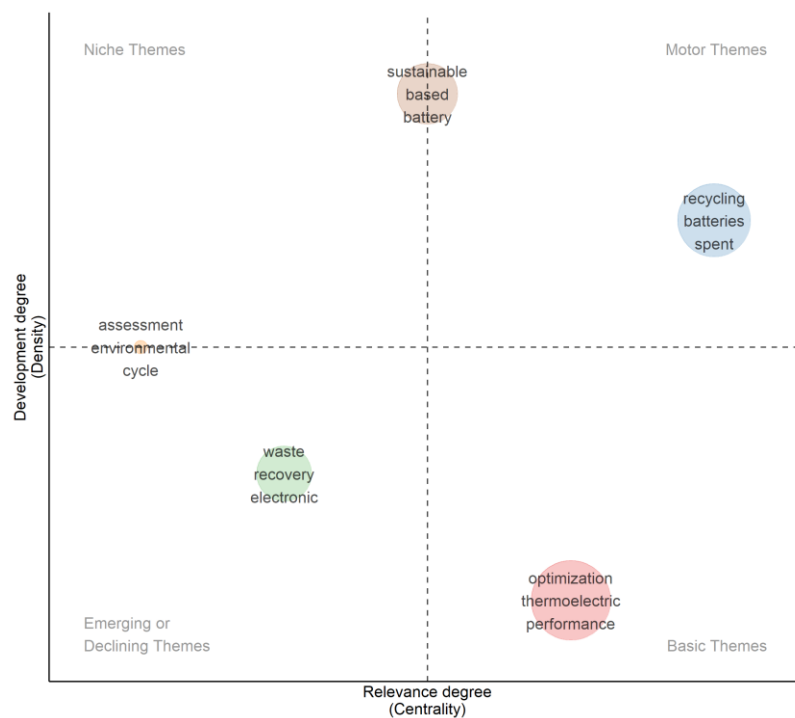


Figure -13: Thematic map (Time Slice: 2023–2024).

This period shows a clear change in direction. The recycling of spent batteries moved from a small niche theme to a strong motor theme, becoming the main driver of the field (Lv et al., 2018; Mossali et al., 2020). At the same time, optimization, thermoelectric and performance moved from the motor quadrant into the basic themes quadrant. It remains highly central but less specialised, which suggests that optimization has become a general tool used across the field. A sustainability theme linked to batteries sits on the border between niche and motor themes, while environmental and life cycle assessment forms a small theme on the edge of the niche quadrant. Waste, recovery and electronic remain in the emerging or declining quadrant.

4.9.3 2025–2027 Time Slice

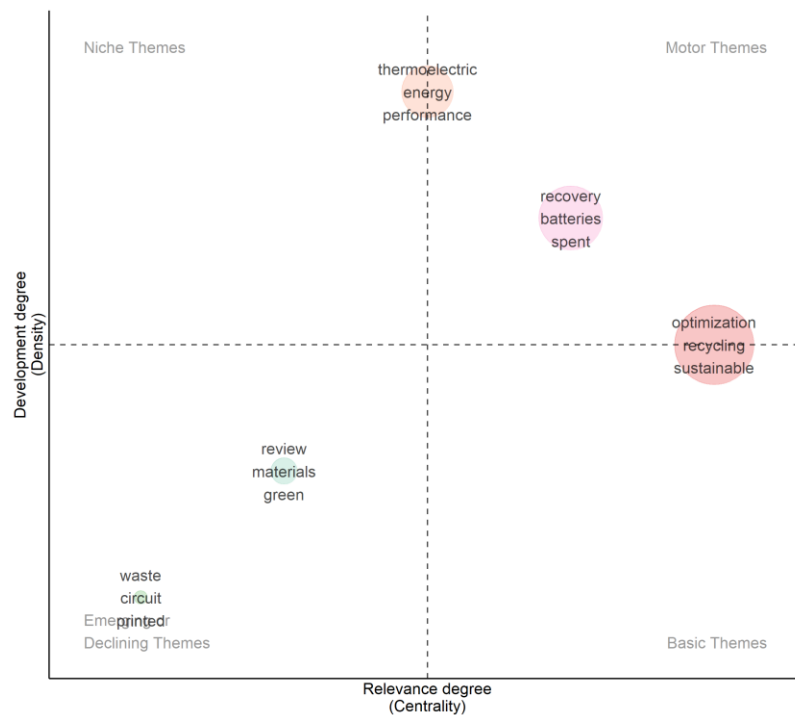


Figure -14: Thematic map (Time Slice: 2025–2027).

In the most recent period, optimization, recycling and sustainable have merged into one large theme with the highest centrality, placed on the border between motor and basic themes. This indicates that optimization and sustainable recycling are now treated as a single core topic. The recovery of spent batteries remains a strong motor theme, while thermoelectric energy performance has become a highly developed but more specialised stream on the edge of the niche quadrant (Chen et al., 2022). Review, materials and green appear in the emerging or declining quadrant, and given the recent interest in greener recovery methods such as bioleaching, this theme is more likely to be emerging (Erkmen et al., 2025). By contrast, the small printed circuit board theme seems to be declining as it is absorbed into broader recovery research.

5. FUTURE RESEARCH AGENDA

The bibliometric analysis of 1,755 documents and the accompanying literature review suggest that future research should give greater attention to how optimisation methods perform in working e-waste systems. The thematic maps connect materials recovery, sustainable decision making, process optimisation and energy efficiency, while the reviewed studies reveal a recurring need for validation beyond controlled experiments and simulations. These patterns provide a basis for selecting research priorities, although keyword prominence alone cannot establish the effectiveness of a technology or the absence of research on a topic.

The agenda below therefore links the report's findings to questions that can be investigated through plant trials, comparative assessments and field studies. Its central concern is whether improvements in individual processes translate into lower resource losses, affordable recovery and measurable environmental and social benefits across the waste lifecycle.

5.1 Validate digital systems under operating conditions

The first priority is to establish whether AI-assisted recycling retains its performance when waste composition and operating conditions change. The reviewed AI-integrated battery recycling framework uses benchmark datasets and simulations, while the IoT-based recovery study links sensing and process control to battery-material recovery. Together, these studies offer a basis for testing how digital methods transfer between facilities, feedstocks and scales of operation.

Comparative pilot trials should evaluate conventional process control, AI-assisted control and digital-twin-assisted control using comparable batches of waste. Training and evaluation data should be separated by collection period, facility and, where possible, product family to test performance on unfamiliar inputs. Trials should record recovery yield, product purity, throughput, energy use, downtime and the frequency of human intervention. Sensor failure, contaminated inputs and changes in battery chemistry should also be tested. Publishing operating conditions and failed trials would make it easier to judge when the added cost of a digital system is justified.

5.2 Test selective recovery with varied and mixed feedstocks

Selective recovery methods need to be assessed using the materials that recycling facilities actually receive. The review of supercritical-fluid recovery identifies scale-up and process integration as priorities, while the review of bioleaching and phytomining discusses constraints involving selectivity and processing time. A useful question is how these routes respond to mixed products, variable metal concentrations and contamination from earlier treatment stages.

Pilot studies should compare established treatment routes with supercritical-fluid, solvent-based, biological and hybrid alternatives on clearly characterised feedstocks. Repeated operating cycles are needed to measure reagent reuse, solvent degradation, corrosion, residence time and the accumulation of impurities. Researchers should distinguish extraction into solution from recovery as a usable final product and account for losses at every separation stage. For battery recycling, evaluation should

include the performance of regenerated materials in new cells. For circuit boards, it should also track low-concentration critical metals that may be missed when optimisation concentrates on bulk metal yield.

5.3 Assess environmental and economic performance together

High product purity does not by itself demonstrate an efficient or sustainable recovery route. The green-solvent cobalt recovery study, for example, reports a cobalt oxide/hydroxide product with 99.12% purity but a laboratory cobalt recovery efficiency of 57%. Its life cycle assessment identifies solvent preparation and the electricity used in leaching as important environmental hotspots. This distinction makes total material recovery and resource consumption essential parts of future evaluation.

Life cycle assessment should be combined with techno-economic analysis from the pilot stage, using measured inventories wherever possible. Comparisons should report impacts per unit of waste treated and per unit of recovered material meeting a stated quality specification. The boundaries should include collection, pretreatment, reagent manufacture, energy supply, wastewater treatment and residual disposal. Sensitivity analysis should examine electricity mix, solvent reuse, plant utilisation and metal prices. Employment measures should include job quality and occupational exposure where feasible. These assessments would help identify the conditions under which a technically successful route can also operate at an acceptable cost and environmental burden.

5.4 Connect collection models with household and worker behaviour

Collection deserves attention alongside improvements inside recycling plants. The reviewed community collection study models collection and treatment centres to address limited access to certified reverse logistics networks. Its case provides a starting point for examining whether predicted collection gains occur after facilities are introduced and whether similar designs work in other settings.

Field studies could compare neighbourhood collection points, scheduled pickup, retailer take-back and financial incentives. Where practical, phased introduction across comparable communities would allow researchers to examine changes in verified returns rather than relying only on stated willingness to recycle. Interviews with households, repair businesses and informal collectors could explain how convenience, payment, trust and concerns about personal data affect participation. Research should also test arrangements that involve existing collectors in safer formal recovery systems, measuring income stability and working conditions alongside collection volume. Comparative work in India, China and less represented settings would help establish how local institutions and collection practices affect the transferability of network designs.

5.5 Integrate process and supply chain decisions under uncertainty

The report's clusters suggest a useful connection between recovery chemistry and supply chain optimisation. Changes in collection quality can affect sorting requirements, recovery yield and the value of the final output. Future models could represent these relationships explicitly, linking collection and disassembly choices to treatment capacity, process performance and demand for recovered materials. The reviewed sustainable and climate-responsive supply chain model provides a starting point through its multi-objective treatment of economic, environmental, social and risk-related outcomes.

A central question is whether an integrated model produces decisions that remain useful when return volumes, feedstock quality, energy costs or metal prices differ from expectations. Stochastic, robust and neutrosophic approaches should be compared on the same instances, with transparent assumptions, comparable computational budgets and clearly defined performance measures. Evaluation should include unseen operating periods and disruption scenarios, alongside solver runtime and solution quality. Researchers should report how trade-offs change with stakeholder priorities, rather than treating one set of objective weights as universally appropriate.

5.6 Extend the agenda to reuse and non-metallic fractions

Spent batteries are prominent in the recent thematic maps, but this prominence should not determine the entire research agenda. The reviewed work on electronic plastics identifies obstacles to commercial pyrolysis, including catalyst performance and energy optimisation. Further work should examine treatment routes for plastics, glass, resins and mixed residues alongside the recovery of valuable metals.

Comparative studies could evaluate mechanical separation, chemical treatment and thermal conversion using material balances and verified product destinations. For electronic plastics, evaluation should include the fate of flame retardants, contaminant removal, emissions control and the quality of recovered products. Upstream research should compare repair, refurbishment and component reuse with immediate material recovery, accounting for remaining service life, safety and displacement of new production. Optimisation models could then identify when preserving a device or component offers better outcomes than dismantling it. This would connect the report's recovery focus with waste prevention and retention of product value.

5.7 Establish the lifecycle value of energy harvesting

Thermoelectric and waste-heat research forms a distinct stream in the bibliometric analysis. Future studies should clarify how this stream contributes to the report's e-waste focus. Recovering heat during a product's use is different from managing discarded electronics, although the two can be connected through equipment design and lifecycle assessment. The reviewed energy-harvesting research examines ways to reduce dependence on batteries while recognising constraints involving power availability, storage and materials.

Long-duration trials could compare battery-powered sensors with energy-harvesting alternatives under realistic and variable energy conditions. Evaluation should measure avoided battery replacements, device reliability, maintenance and the environmental burden of manufacturing the additional components. For thermoelectric equipment used in recycling operations, net energy savings should include auxiliary power and maintenance requirements. These comparisons would establish whether a design reduces waste and lifecycle impacts over its service life, and identify the operating conditions required to achieve those benefits.

5.8 Strengthen the evidence base and comparative research

Future bibliometric work should test the sensitivity of the present findings to database coverage, search terminology and screening decisions. The current dataset uses English-language journal articles and reviews from Scopus. An expanded search could combine terms such as electronic waste, e-waste and WEEE with both optimisation and optimization and with relevant method names. Title and abstract screening should distinguish end-of-life equipment management from unrelated research on electronics or waste heat. Findings from other waste sectors should be treated as methodological context until tested on e-waste. Where access permits, comparison with another database and selected non-English records would help assess coverage bias.

The Scopus export is dated 17 September 2026 and includes eight records assigned to 2027. Subsequent analyses should identify these forward-dated records separately and avoid interpreting incomplete recent years as completed annual totals. Keyword cleaning, author disambiguation and alternative time slices should also be documented, particularly because the current slices differ substantially in length. Cluster labels and small keyword nodes should be checked against article content before being treated as emerging or neglected topics. Finally, shared datasets and common evaluation protocols could support replication across countries and facilities, addressing the variation in technologies and outcome measures identified in the review of digital technologies for circular waste management.

5.9 Priority research questions and evaluation measures

The questions below translate the agenda into testable comparisons. Research can begin with shared definitions and baseline data, proceed to pilot and field trials, and then examine whether the results transfer across facilities and regions.

Table -3: Priority research questions and evaluation measures

Priority	Research question	Evaluation measures
1.) Digital control	Do AI and digital twins improve recovery when the facility, feedstock or operating conditions change?	Usable recovery, purity, throughput, downtime, energy demand and human intervention on independent test data.
2.) Selective recovery	Which treatment routes maintain selective recovery over repeated cycles with mixed and contaminated inputs?	Complete material balances, impurity levels, reagent reuse, processing time and final product performance.
3.) Lifecycle value	Under which energy, price and scale conditions are recovery routes environmentally and economically preferable?	Lifecycle impacts and costs per stated unit, with quality specifications, uncertainty ranges and exposure measures.
4.) Collection	Which collection arrangements increase verified returns while supporting household access and collector livelihoods?	Return rates, cost per unit collected, participation, income stability and working conditions from field studies.
5.) Integrated models	Do linked process and network models improve decisions during changes in returns, prices and disruptions?	Performance in unseen periods, trade-offs between objectives, runtime and sensitivity to stakeholder priorities.
6.) Reuse and residues	When should products be reused, and which routes recover non-metallic fractions with acceptable residual impacts?	Remaining service life, avoided new production, recovered product quality, contaminant fate and residual disposal.
7.) Energy harvesting	Do energy-harvesting designs reduce waste and lifecycle burdens over a realistic equipment service life?	Avoided battery replacements, reliability, maintenance, additional material demand and net energy savings.
8.) Evidence quality	How stable are the mapped themes when search terms, databases, time slices and screening decisions change?	Screened relevance, coverage differences, cluster stability, author disambiguation and reproducibility of the analysis.

The strongest next study would combine a practical recovery or collection intervention with a clear baseline and an assessment of its wider consequences. Establishing where a method works, what resources it requires and how its benefits are distributed would give the field a firmer basis for scaling up e-waste optimisation.

6. CONCLUSION

E-waste has become an increasingly important environmental and resource-management challenge as the use of electronic products continues to expand. The problem is not limited to the safe disposal of unwanted devices. Electronic products contain valuable metals and other recoverable materials, but they can also contain hazardous substances that create environmental risks when they are poorly handled. Effective e-waste management therefore requires systems that can improve collection, sorting, recovery, transportation and treatment while balancing economic, environmental and social objectives.

A central conclusion is that optimisation has become an important way of addressing this complexity. Earlier research was more focused on individual recovery and process problems, whereas recent work increasingly considers the interaction between different stages of the waste lifecycle. Optimisation can be applied to collection routes, facility locations, disassembly, material recovery, energy use and supply-chain decisions. This broader approach is important because improvements at one stage can create disadvantages at another. A recycling process that produces a high recovery rate, for example, may still have a large environmental impact if it requires excessive energy or chemicals.

The research shows a particularly strong increase in recent activity. Publication output remained relatively low during the early years, with fewer than 25 papers annually between 2006 and 2014. It then increased steadily, reaching 112 papers in 2022. The

growth became much sharper after 2023, with 137 papers in 2023, 178 in 2024, 300 in 2025 and 450 in 2026. The large increase in recent publications indicates that e-waste optimisation is developing rapidly and attracting attention from several research communities. The high number of recent studies also means that many new methods have not yet had sufficient time to demonstrate their long-term impact.

The field has also become strongly interdisciplinary. Research is distributed across waste-management, environmental, energy, chemical-engineering and related journals. Waste Management is the largest source in the dataset, while the Journal of Cleaner Production and Journal of Environmental Management also make substantial contributions. Energy journals form an important stream because waste heat and thermoelectric systems have been studied alongside conventional material recovery. Chemical and process-engineering journals contribute research on leaching, separation and battery recycling. This distribution shows that e-waste optimisation cannot be treated as a problem belonging to one academic discipline.

Another important conclusion concerns the changing nature of resource recovery. Recent research places particular emphasis on spent lithium-ion batteries and the recovery of materials such as lithium, cobalt and other critical metals. Green solvents, hydrometallurgy and supercritical fluids are being investigated as alternatives or improvements to conventional recovery routes. Abdollahi Darestani et al., for example, reported lithium leaching efficiencies of 91.59% under subcritical conditions and 98.35% under supercritical conditions. Such results demonstrate the value of optimising operating conditions, but they should not be interpreted as proof that a process is automatically sustainable.

The importance of life-cycle assessment is therefore another major conclusion. Environmental performance needs to be considered alongside recovery efficiency and product purity. Mojtahedi et al. reported a cobalt recovery product with 99.12% purity, but their study also found that solvent production and electricity consumption were important sources of environmental impact, while laboratory recovery efficiency was 57%. This illustrates why optimisation should not focus on one output. A genuinely sustainable recovery process needs to consider material yield, energy consumption, emissions, chemical use, cost and other relevant impacts together.

Digital technologies provide an additional opportunity to improve these systems. Artificial intelligence, machine learning, the Internet of Things, blockchain, digital twins and big-data analytics can support monitoring, classification, traceability, prediction and process control. Sukmasetya et al. identifies these technologies as important enablers of smart circular waste management. Luo et al. combined IoT sensors, a holographic twin and automatic process control and reported a 95.2% recovery rate for cathode active materials. These developments indicate that digital tools can make waste systems more responsive and data-driven.

However, digitalisation should not be treated as a solution by itself. A digital system depends on reliable data, appropriate infrastructure, skilled personnel and coordination between stakeholders. Recent research also shows that some impressive AI and automation results are based on simulations or benchmark datasets. Lakshmaiya, for instance, reported high classification and simulated disassembly performance, but the results were not obtained from a fully operating industrial facility. The next stage of research therefore needs stronger real-world validation. Pilot-scale and industrial demonstrations are necessary to determine whether promising digital systems remain effective when exposed to variations in waste composition, operating conditions and economic constraints.

Reverse logistics is another essential part of optimisation. Recoverable material cannot be recycled if it does not enter an appropriate collection and treatment system. Collection points, transport routes, facility locations and the movement of materials between different actors all influence the final recovery outcome. Ni et al. highlighted the importance of the last mile in e-waste reverse logistics and showed how community collection and treatment centres can improve collection performance. This suggests that optimisation should begin before e-waste reaches a recycling facility. Consumer accessibility and the design of collection networks are important components of a circular system.

Supply-chain research further demonstrates the need for multi-objective decision making. E-waste systems involve competing goals such as profitability, emissions reduction, risk control, employment and material recovery. Saeed et al. incorporated profit, carbon dioxide emissions, job creation and risk into an e-waste supply-chain model. Such approaches are more realistic than models that maximise a single objective because real waste-management decisions involve trade-offs. The most efficient system economically may not be the best environmentally, and the highest recovery rate may not always correspond to the lowest overall impact.

The thematic development of the field supports this broader interpretation. In the earlier period, optimisation was strongly associated with thermoelectric and waste-heat research. During 2023–2024, spent-battery recycling became a strong research theme, while sustainability and environmental assessment became more visible. In the most recent period, optimisation and sustainable recycling increasingly appear together, while recovery remains particularly important for spent batteries. This indicates that the concept of recycling is gradually being expanded into a wider idea of resource recovery supported by optimisation and sustainability assessment.

The geographical pattern also shows that e-waste optimisation is a global research concern. China has the largest research output, followed by India and the USA, while countries such as Italy contribute specialised work in areas including metal recovery and battery recycling. India has experienced particularly rapid recent growth, with research involving bioleaching, reverse logistics and AI-based e-waste management. At the same time, international collaboration represents only about one-quarter of the publications. Greater international cooperation could strengthen the field because e-waste supply chains, critical-material markets and environmental impacts often cross national boundaries.

Several gaps remain despite the strong development of the field. One of the most important is the limited integration of technical recovery with complete lifecycle performance. Many studies focus on a specific process, while fewer evaluate the full chain from collection to recovery and reuse. Social factors also require greater attention. Community access, employment, consumer participation and the relationship between formal and informal recycling systems can strongly influence real-world outcomes. Technical optimisation alone cannot guarantee that a system will be adopted or used effectively.

Another major gap is the distance between research results and commercial implementation. Laboratory experiments and computer models are useful for identifying promising approaches, but industrial conditions are more variable and complex. Future studies should therefore combine process optimisation with economic assessment, life-cycle assessment and pilot-scale validation. Digital systems should be tested using real operational data, while recovery technologies should be evaluated under realistic energy, cost and material constraints.

Overall, the future of e-waste optimisation lies in integration rather than dependence on one technology. Advanced recovery chemistry, reverse logistics, artificial intelligence, IoT monitoring, digital twins, multi-objective optimisation and life-cycle assessment can complement one another. The strongest systems will be those that connect these capabilities across the entire e-waste lifecycle and evaluate performance using technical, environmental, economic and social criteria.

A practical optimisation framework should also recognise that e-waste systems operate within changing markets and regulatory environments. The value of recovered materials, availability of collection infrastructure, consumer behaviour and technological costs can change over time. Flexible models that can incorporate new data and changing conditions will therefore be more useful than static solutions. Continuous monitoring and periodic reassessment can help ensure that optimisation remains aligned with both environmental priorities and the economic realities of recovery operations.

E-waste optimisation should therefore be understood as a systems-level challenge. The goal is not simply to recover the maximum quantity of material, but to create a practical and sustainable system that recovers valuable resources while reducing environmental impacts, controlling costs and improving accessibility. Continued research, stronger real-world validation and closer cooperation between technological, industrial and policy stakeholders can help convert the rapid growth of research into effective circular-economy practices. In this way, e-waste can increasingly be managed as a valuable secondary resource rather than as a waste stream whose principal destination is disposal. This combined perspective keeps technical, environmental, economic and social considerations connected.

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