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TRENDS AND INSIGHTS IN MACHINE LEARNING FOR WASTE MANAGEMENT: A DECADE OF BIBLIOMETRIC ANALYSIS

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Abstract

This article investigates the evolving landscape of machine learning and its application in waste management from 2014 to 2024, utilizing data from Scopus and employing the VOSviewer software for bibliometric analysis. The research identified 217 articles related to machine learning in waste management. Our analysis aimed to assess metrics such as yearly publication trends, citation rates, top publishing countries, and the most influential authors in the field. Additionally, we examined the evolution of research on machine learning in waste management, focusing on highly cited articles, leading journals, authors' keywords, co-citation patterns, and co-authorship networks among countries and organizations. This comprehensive review provides a deeper understanding of the growth and collaborative nature of the field. The results indicate a notable rise in machine learning publications in waste management, increasing from 1 in 2016 to 62 in 2024, for a total of 217 publications. China, India, and South Korea led the research output, contributing 19.35%, 15.67%, and 10.60%, respectively. Leading journals such as the Journal of Cleaner Production, Waste Management, and Sustainability Switzerland emerged as critical contributors. A sharp increase in publications was observed post-2020, especially in the Journal of Cleaner Production. One of the most notable findings was the high citation rate of research on machine learning techniques in waste management, underscoring their practical relevance and mathematical significance in optimizing waste handling and reduction. Frequently occurring keywords included "machine learning", "waste management", and "deep learning". The VOSviewer visualizations indicated strong international collaboration networks, highlighting a robust global research framework. Our study emphasizes the growing influence of machine learning in waste management, marked by increasing research activity and international cooperation, and showcases the transformative potential of machine learning driven models in improving global waste management practices.

***Key words**: Bibliometric Analysis, Machine Learning, Scopus, VOSviewer Software, Waste Management.*

INTRODUCTION

The rapid pace of urbanization and industrialization in recent years has intensified challenges in waste management (WM), with an increase in waste generation necessitating innovative approaches to ensure sustainable waste handling practices that effectively mitigate environmental impacts. Traditional WM practices generally follow linear processes that include collection, transportation, and disposal, resulting in inefficiencies, higher costs, and low recycling rates. These conventional methods often rely on manual sorting and fixed collection schedules, which limit their ability to effectively manage the complexities of contemporary waste generation. In contrast, Machine learning (ML) has emerged as a transformative tool in response to these pressing challenges, capable of enhancing various facets of waste management. ML techniques have gained substantial attention due to their potential to optimize waste management processes, including waste sorting, predictive modeling, and recycling efficiency. ML has notably enhanced the accuracy of waste generation forecasts across various waste types, such as construction waste (Cha et al., 2021), municipal solid waste (Ayeleru et al., 2021), hospital waste (Golbaz et al., 2019), food industry waste (Garre et al., 2020), and more. By leveraging advanced algorithms, researchers are developing models that facilitate more effective WM. The application of data-driven planning through machine learning not only enhances the efficiency and sustainability of waste management practices but also contributes to the development of smarter, more resilient urban environments (Ahmad et al., 2020).

Moreover, integrating ML with the Internet of Things (IoT) has opened new avenues for efficient WM. Recent explorations into IoT-enabled solutions emphasize the potential of real-time data collection and analysis to promote cleaner, more sustainable urban environments (Rutqvist et al., 2019; Cheah et al., 2022; Patil & Gidde, 2023).

This study performs a bibliometric analysis that focuses on exploring and analyzing the development of ML technologies in WM. This investigation can lead to sophisticated ML models designed to address the complexities associated with WM, such as predicting waste production, sorting automation, and improving collection route efficiency. The bibliometric analysis of ML applications in this field yields important insights into its evolution, identifies major research contributions, and highlights gaps for future investigations. Additionally, it offers an in-depth view of these technologies and the dynamics of international collaborations within this domain over time, showcasing how different organizations and countries contribute to advancing the field. This research utilizes publications and data from Scopus and employs VOSviewer software to create graphical representations that examine keyword co-occurrences, citation patterns, bibliographic links, and co-authorship relationships. These findings can help the researchers with effective strategies and innovations in sustainable WM.

This study is organized as follows: Section 2 reviews the specialized literature on machine learning in waste management, highlighting key advancements and methodologies used in recent research. Section 3 outlines the methodology used for this bibliometric analysis, detailing the criteria for selecting publications and the analytical tools applied. Section 4 presents the findings along with their interpretations, revealing significant trends in the application of machine learning technologies and their impact on WM practices. Drawing on the trends identified in the results section, Section 5 will engage in discussions regarding these trends, addressing the implications for future research directions. Finally, Section 6 will summarize the key conclusions and provide recommendations for further exploration in the field, emphasizing the importance of continuous innovation in sustainable WM practices.

Literature review

Effective WM is essential for environmental sustainability, resource conservation, and public health protection. WM encompasses a range of processes focused on the collection, transportation, treatment, reuse, and disposal of waste materials. As urban populations grow, the volume and complexity of waste generated have increased, creating a need for more efficient and effective WM strategies. ML, a branch of artificial intelligence (AI), focuses on developing algorithms that allow computers to learn from data and make informed predictions. Its application in WM has significant potential to optimize processes, enhance decision-making, and improve sustainability outcomes. A key application of ML in WM is the classification and segregation of waste materials. Traditional sorting methods often rely on manual labor, which can be time-consuming, error-prone, and inefficient. For example, Nnamoko et al. (2022) introduced an optimized five-layer convolutional neural network (CNN) for classifying organic and recyclable waste, which reduces computational demands by using lower-resolution images, ultimately outperforming both higher-resolution models and baseline classifiers. Recent literature (Al Duhayyim et al., 2023; Ali et al., 2024; Nezerka et al., 2024) highlights substantial advancements in WM through machine learning, employing sophisticated algorithms such as custom CNNs, K-nearest neighbors (KNN), and ensemble learning models to achieve greater classification accuracy and efficiency. These studies emphasize ML's transformative role in automating sorting processes, reducing errors, and supporting a more sustainable future. Additionally, studies (Gondal et al., 2021; Carrera et al., 2022; Mohammed et al., 2023; Jin et al., 2023) address various waste types for improved classification and recycling. Techniques include using infrared spectrums for plastic identification, applying artificial neural networks (ANN) to urban waste sorting, deploying hybrid CNN models for real-time metal and non-metal sorting, and enhancing

MobileNetV2 models with attention mechanisms to improve classification accuracy.
ML-driven predictive analytics has become an essential tool for anticipating waste generation patterns. By examining historical data, these models can detect trends and forecast future waste production. Namoun et al. (2022) discussed an optimized ensemble learning model for predicting urban household waste generation, which supports more effective waste management in smart cities. In the literature (Cha et al., 2020; Cha et al., 2022; Cha et al., 2022; Cha et al., 2024), advanced machine learning models, including ANN, support vector machines (SVM), and random forests (RF), have been applied to accurately predict construction and demolition waste production. Furthermore, ML models enhance the forecasting of municipal waste production by leveraging socioeconomic data, with optimization techniques improving accuracy. Many researchers (Oguz-Ekim et al., 2021; Yang et al., 2021; Zhang et al., 2022; Munir et al., 2023; Singh et al., 2023) utilize ML algorithms like XGBoost, and RF to predict municipal solid waste (MSW), highlighting population and gross domestic product (GDP) as key indicators.
Huang and Koroteev (2021) analyzed an ML framework to optimize waste and energy management, achieving a 90% reduction in waste processing time, a 40% decrease in landfill dependency, and a 15% reduction in transportation costs by predicting waste volumes and adapting to fluctuations in energy markets. Altarazi F. (2024) explores EcoEfficientNet, an advanced ML tool for sustainable manufacturing that uses deep learning to analyze production data and identify waste reduction opportunities. Through continuous learning, EcoEfficientNet adapts to new data and evolving production conditions, achieving up to a 30% reduction in waste generation. ML models are increasingly essential for enhancing waste-to-energy (WTE) processes by reliably forecasting the energy potential and volume of MSW based on diverse factors. Studies indicate that advanced techniques, including ANNs, SVMs, and ensemble approaches, improve WM efficiency and support the strategic siting of WTE facilities, as shown in the literature (Kaya et al., 2021; Al-Ruzouq et al., 2022; Taki & Rohani, 2022; Yatim et al., 2022).
In references (Mookkaiah et al., 2022; Belsare et al., 2024; Chavhan et al., 2024), artificial intelligence (AI), IoT, and ML have driven innovative solutions, utilizing CNN models like ResNet for precise automated classification of MSW, thereby improving sorting accuracy and promoting sustainable WTE practices. Moreover, numerous scholars (Mudannayake et al., 2022; Zia et al., 2022; AlJamal et al., 2024; Hossen et al., 2024; Mishra et al., 2024) have implemented AI and ML models such as GCDN-Net and DenseNet-121 - SVM to achieve highly accurate automated waste classification, enhancing recycling processes and supporting sustainable WM amid the challenges of urbanization.
Literature (Medina-Mijangos & Seguí-Amórtegui, 2020) offers a comprehensive bibliometric analysis of the economic dimensions of MSW management. This methodology has gained substantial traction across various disciplines, primarily due to its capacity to deliver intricate scientific mappings over specified temporal frameworks. Such analyses illuminate emerging trends that decision-makers can strategically utilize in diverse contexts (Tamala et al., 2022; Oladinrin et al., 2023; Martins et al.,2024). Recent studies (Negrete-Cardoso et al., 2022; Sohail et al., 2023) highlight, through bibliometric analyses, waste management strategies based on multi-criteria decision-making methods and circular economy principles, emphasizing current research trends in the field.

MATERIALS AND METHODS

In this study, data from the Scopus (Elsevier, accessed 17 October 2024). database is utilized. Scopus is a multidisciplinary citation database managed by Elsevier, widely recognized, and commonly used for analyzing research output. The database includes content from various subjects, including science, technology, medicine, and social sciences. Scopus provides detailed statistics and visualizations for assessing data on research areas, document types, countries, authors, institutions, publication timelines, and universities. Additionally, it allows users to export publication records in formats such as CSV or Excel, which are compatible with data visualization and analysis tools like VOSviewer or Bibliometrix. Besides journal articles, Scopus also indexes conference proceedings, book series, and patents, offering a comprehensive view of the global research landscape.

A key challenge in bibliometric research is defining the boundaries of the specific field being analyzed. To gain a broader perspective on publications related to ML in waste management systems, searches were conducted using the key words: "waste", "management", and "machine", "learning." The search was limited to publications from 2014 to 2024, and the data was collected on 17 October 2024. The objective of this search was to identify articles that explored the application of ML in waste management. A total of 217 results were found. To map and analyze the network, the full records which primarily included the titles, sources, authors, affiliations, abstracts of the research articles, and the cited references were downloaded in CSV format. Figure 1 illustrates the methodology employed for searching, data collection, and information processing.

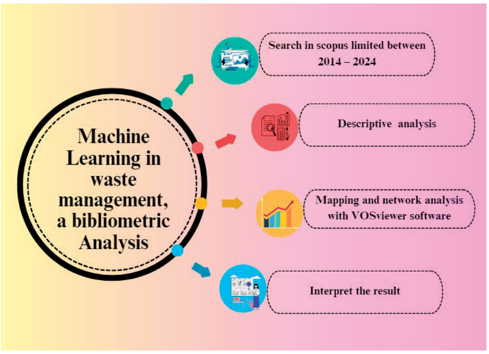

Figure 1. Methodology employed in this study

An exploratory analysis was conducted to examine and highlight the most impactful journals, authors, countries, and articles within the database. In reference (Seguí-Amortegui et al., 2019), the research employed bibliometric measures, including (i) productivity, determined by the total count of publications (Reuters, 2008); (ii) impact, analyzed by the total citation count (Reuters, 2008); (iii) the H-index (Hirsch index), which indicates that N publications have received at least N citations, providing a combined measure of both productivity and impact in a single figure (Reuters, 2008; Hirsch, 2005); and (iv) the impact factor (IF), a metric used to evaluate journals by calculating the average number of citations for articles published within a two-year period (Reuters, 2008).

The research employed VOSviewer software, developed by Leiden University, to map and analyze networks of scientific publications, including journals, institutions, countries, authors, and keywords (Van Eck & Waltman, 2016). Analyzing these networks creates a graphical representation that visualizes the relationships within the data (Ji, 2018). These networks allow for the viewing and exploration of maps by connecting the articles through citations, authorship, co-occurrence, bibliographic links, or co-citation connections (Van Eck & Waltman, 2016).

VOSviewer software represents the interest of items, such as publications, authors, sources, or keywords, using nodes; larger nodes indicate greater weight or significance of the item. A link refers to the connection between two objects, displaying the count of articles where one particular object is found alongside another. The thickest lines exhibit more frequent co-occurrence or higher levels of cooperation (Seguí-Amortegui et al., 2019; Van Eck & Waltman, 2016). The distance between the nodes also reflects their co-occurrence. Elements are grouped by colour to signify their connection to research topics, with elements sharing the same colour referred to as clusters (Van Eck & Waltman, 2016).

RESULTS AND DISCUSSIONS

First, we highlighted key research trends, including annual publication numbers, citation rates per article and field, leading countries in publication output, and the most prominent authors (Seguí-Amortegui et al., 2019). Next, we examined the current state and evolution of research on ML in waste management, analyzing 217 articles. In the second section, we focused on the most cited articles on ML in waste management. The third section examined the leading journals in this area. The fourth section investigated the overlap of authors' keywords in ML within waste management. The article then analyzed the co-citation patterns of references, sources, and authors related to ML in waste management. Finally, it explored the networks of co-authorship among countries and organizations involved in ML in waste management research.

Significant trends

In 2014 and 2015, no articles were published in Scopus on ML in waste management. However, from 2016 to 2024, the number of publications shows a significant increase, beginning with one publication in 2016 and rising to 62 in 2024. Despite a slight decline in 2024, with the number dropping to around 60, the overall trend indicates a substantial rise in research activity during this period, totalling 217 publications. This growth highlights the growing interest and contributions to the field over the years. Figure 2 illustrates the yearly publication count on ML in waste management as indexed in Scopus.

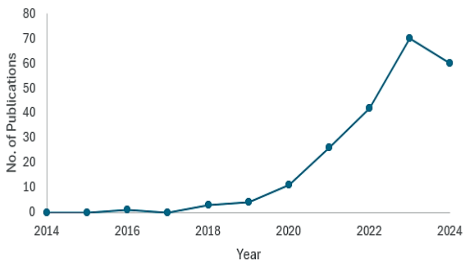

Figure 2. Yearly publication counts on ML in waste management

The bar chart in Figure 3 highlights the countries with the highest number of publications focused on ML in waste management. The x-axis represents the number of publications, ranging from 0 to 45, while the y-axis lists the countries involved. The analysis shows that China leads with 42 articles, followed by India with 34 and South Korea with 23. Iran has the fewest publications among the listed countries. In total, 62 countries have contributed to the production of 217 publications, corresponding to 19.35%, 15.67%, and 10.60% of the total publications on the topic, respectively. This visual representation effectively demonstrates the comparative research contributions of different nations.

Figure 3. Publications in Scopus on ML in waste management, categorized by country

The horizontal bar chart visually represents the number of publications by different authors in the field. The x-axis indicates the number of publications, ranging from 0 to 8, while the y-axis lists the authors' names. Figure 4 shows that the top authors in ML research in waste management are Cha, G.W. with 8 publications, Kim, Y.C. with 6 publications, and Hong, W.H. with 5 publications. These figures represent 3.69%, 2.76%, and 2.30% of the 217 total publications in this area, respectively.

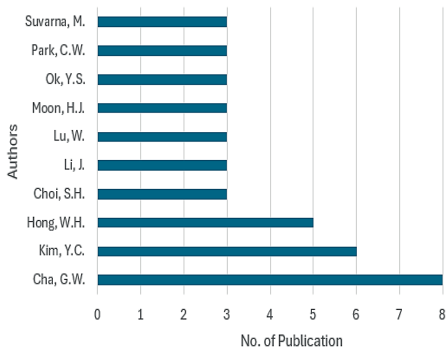

Figure 4. Publications in Scopus on ML in waste management, categorized by author

Citation counts provide a clear measure of an article's impact. Table 1 provides a detailed breakdown of articles based on their citation count, offering insights into the citation performance of publications related to ML in waste management. Only 1 article (0.46%) has more than 251 citations, and articles with 151 to 250 citations represent 0.92% of the total. Moderately cited articles (51 to 100 citations) account for 6.45%, while a larger portion has fewer citations: 12.91% (26 to 50 citations) and 17.06% (11 to 25 citations). Notably, 44.23% of the articles have fewer than 11 citations, and 16.12% have not been cited at all, indicating that many publications have relatively low visibility and impact in the academic community. Overall, this highlights a significant opportunity for increased recognition and dissemination of research in this field.

Table 1. Overview of Citation Distribution on ML in waste management

Citation Count	Number of Articles	Accumulated Articles	% Articles	% Accumulated Articles
≥251	1	1	0.46%	0.46%
≥201	0	1	0%	0.46%
≥151	2	3	0.92%	1.38%
≥101	4	7	1.84%	3.22%
≥51	14	21	6.45%	9.66%
≥26	28	49	12.91%	22.61%
≥11	37	86	17.06%	39.63%
<11	96	182	44.23%	83.89%
0	35	217	16.12%	100%

Most-cited publications on ML in waste management

Table 2 provides a ranking of influential articles that apply ML to waste management, detailing important factors such as the reference, year of publication, country of origin, journal source, article title, and the number of citations each work has received. This ranking helps to highlight the most impactful contributions in this research area. At the top of the list is the work by Abbasi & El Hanandeh (2016) from Australia, which has garnered 276 citations. Following closely is the study by Palansooriya et al. (2022) from South Korea, with 195 citations. Another notable contribution comes from Yuan et al. (2021) from South Korea, which has received 173 citations. These top-cited articles illustrate the critical role of ML in addressing global waste management challenges, with each contributing to advancements in predictive modeling and sustainable practices within the field.

Table 2. Most-Cited Articles

Rank	Reference	Country	Journal source	Title	Citations
1	Abbasi & El Hanandeh (2016)	Australia	*Waste Management*	Forecasting municipal solid waste generation using artificial intelligence modelling approaches	276
2	Palansooriya et al. (2022)	South Korea	*Environmental Science and Technology*	Prediction of soil heavy metal immobilization by biochar using machine learning	195
3	Yuan et al. (2021)	South Korea	*Environmental Science and Technology*	Applied machine learning for prediction of CO 2 adsorption on biomass waste-derived porous carbons	173
4	Kumar et al. (2018)	India	*Waste Management*	Estimation of the generation rate of different types of plastic wastes and possible revenue recovery from informal recycling	123
5	Anh Khoa et al. (2020)	Vietnam	*Wireless Communications and Mobile Computing*	Waste management system using iot-based machine learning in university	118
6	Kontokosta et al. (2018)	United States	*Computers, Environment and Urban Systems*	Using machine learning and small area estimation to predict building-level municipal solid waste generation in cities	106

Rank	Reference	Country	Journal source	Title	Citations
7	Yu et al. (2021)	United Kingdom	*Environmental Impact Assessment Review*	Environmental planning based on reduce, reuse, recycle and recover using artificial intelligence	103
8	Nguyen et al. (2021)	Vietnam	*Resources, Conservation and Recycling*	Development of machine learning - based models to forecast solid waste generation in residential areas: a case study from Vietnam	95
9	Vu et al. (2019)	Canada	*Waste Management*	Time-lagged effects of weekly climatic and socio-economic factors on ANN municipal yard waste prediction models	90
10	Lu et al. (2021)	Australia	*Waste Management*	Estimating construction waste generation in the Greater Bay Area, China using machine learning	77

Analysis of the Research Journals in ML in Waste Management

In this bibliometric analysis, Table 3 highlights the top 10 local sources that play a significant role in assessing the influence and relevance of research in the field of ML in waste management. Among these, the *Journal of Cleaner Production* stands out as a particularly impactful source. With an H-index of 9 and a G-index of 14, this journal demonstrates a strong influence in the domain, reflecting that many of its articles have significantly contributed to the research community. Its M-index of 1.5 suggests an average of 1.5 citations per article, further emphasizing its academic value. Since 2019, this journal has published 14 papers on ML in waste management, contributing a total of 302 citations to the field. Next in line is the *Waste Management Journal*, with an H-index of 9 and a G-index of 12. It has been a prominent contributor since 2016, with 12 articles accumulating an impressive 714 total citations, making it a highly referenced source in the field, even though its M-index is slightly lower at 1.

The *Journal of Environmental Management*, active in this area since 2021, also makes a notable contribution with an H-index of 6 and a G-index of 9, featuring an M-index of 1.5. Despite having published only 9 papers, it has garnered 177 citations, indicating that the work published here is also well-regarded in the academic community.

Table 3. Influence of Research Journal

Source	H_index	G_index	M_index	TC	NP	PY_start
Journal of Cleaner Production	9	14	1.5	302	14	2019
Waste Management	9	12	1	714	12	2016
Journal of Environmental Management	6	9	1.5	177	9	2021
Sustainability (Switzerland)	5	6	1.667	48	9	2022
International Journal of Environmental Research and Public Health	4	4	0.8	119	4	2020
Sensors	4	5	1	122	5	2021
Environmental Science and Technology	3	4	0.75	393	4	2021

Keyword analysis

Keywords typically signify the main topics and themes of a research article, highlighting key trends and essential subjects within a particular field (Segui-Amortegui et al., 2019). An analysis of 217 articles on ML in waste management identified 779 unique keywords. Figure 5 illustrates the network map of keywords in ML for waste management. The central node, machine learning (blue), connects to several related terms, such as artificial intelligence (red), deep learning (green), solid waste management (yellow), municipal solid waste (orange), sustainability (purple), and artificial neural network (teal).

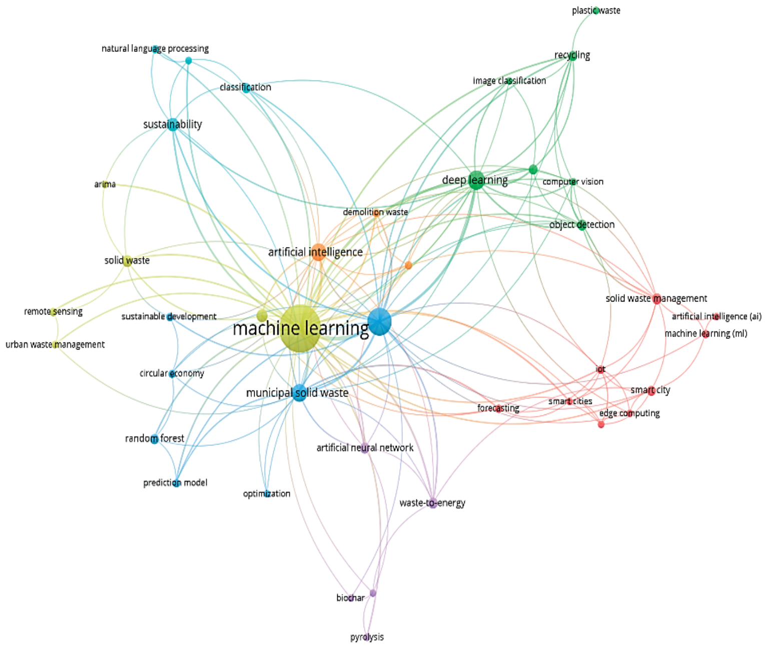

Figure 5. Author keywords network of co-occurrence. The figure showcases the 41 most frequently occurring keywords out of a total of 779 keywords, each meeting a minimum occurrence threshold of 3

The top 10 keywords highlighted in this analysis emphasize the integration of ML within waste management. Keywords such as machine learning, deep learning, and artificial intelligence underscore the role of advanced algorithms in improving waste processing systems. Terms like municipal solid waste and waste classification reflect efforts to optimize waste handling and categorization through technology. Additionally, the inclusion of object detection and recycling highlights the importance of automation in enhancing sorting processes, while sustainability and prediction emphasize the commitment to sustainable practices and the anticipation of waste trends to inform better management strategies.

Table 4 presents the 10 most prominent keywords, along with their occurrences and link strengths.

VOSviewer offers powerful density visualizations, as shown in Figure 4. In the keyword density plot, each node is colored according to the concentration of elements around it, making patterns in the data easily identifiable.

Table 4. The top 10 keywords of the ML in waste management

Rank	Keywords	Occurrences	Link strength
1	Machine learning	109	121
2	Waste management	37	67
3	Deep learning	19	36
4	Municipal solid waste	15	35
5	Artificial intelligence	15	27
6	Object detection	6	15
7	Recycling	5	15
8	Sustainability	9	15
9	Prediction	8	14
10	Waste classification	5	14

In other words, a node's color reflects the number of surrounding objects, with denser areas showing higher concentrations of keywords. Keywords highlighted in red occur more frequently, indicating major areas of focus, while those in yellow are less common and represent peripheral topics. Density visualizations are particularly useful for gaining a quick overview of the distribution of research trends, identifying clusters, and detecting key themes.

As demonstrated in Figure 6, this method provides a clear and intuitive view of the primary research areas in machine learning within WM systems. Keywords such as "machine learning", "waste management", "deep learning", "municipal solid waste", and “artificial intelligence” emerge as significant.

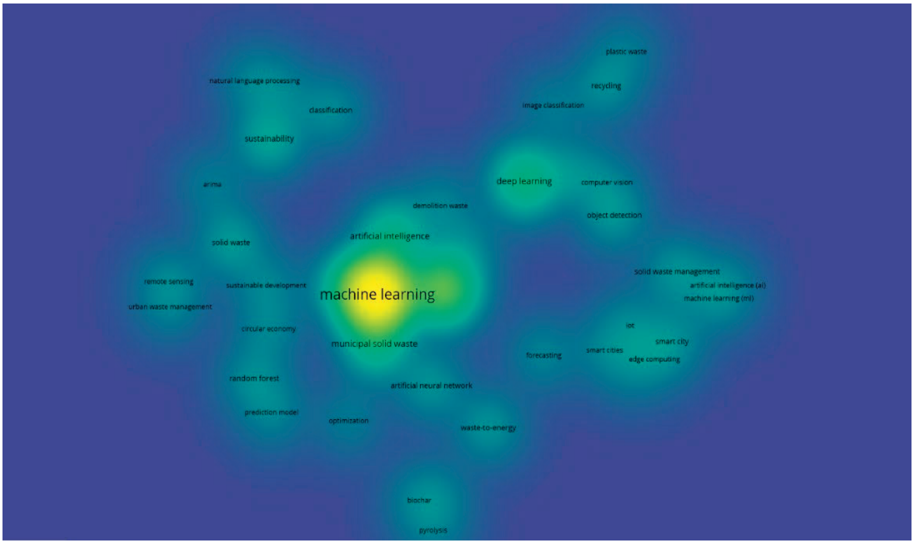

Figure 6. A density map illustrating the keyword distribution in publications related to ML in waste management

Analysis of co-citations for authors, references, and research journals

This section focused on the concept of co-citation among authors, references, and research journals. Co-citation occurs when two documents are cited in tandem by a third source, reflecting how frequently these items (authors, research journals, or references) are jointly referenced, thus forming a co-citation link between them (Small, 1973). A co-citation link connects two elements that are cited within the same document. Here, the proximity between two authors, references, or research journals indicates the strength of their relationship based on shared citation links. Generally, nodes that are closer together indicate a stronger relationship. Connections between nodes are also depicted with lines, highlighting the strongest co-citation (Van Eck & Waltman, 2016).

The initial analysis focused on author co-citation patterns. The network of author co-citations illustrated in Figure 7 identifies three main clusters: a red cluster, which is the largest, containing 70 authors; a green cluster with 46 authors; and a blue cluster with 7 authors. Key authors include Li J., who has 109 citations along with a link strength of 6,425; Wang X., who has 105 citations along with a link strength of 5,622; and Wang Y., who has 102 citations along with a link strength of 4,796.

The network of reference co-citations presented in (Figure 8) reveals three primary clusters: a red cluster, the most extensive, which includes 8 references; a green cluster comprising 7 references; and a blue cluster featuring 3 references. The red cluster may represent the most influential or foundational works in the field, while the green and blue clusters highlight additional areas of research that are interconnected but perhaps less frequently cited. This visualization aids in understanding the relationships between key references and their contributions to the overall scholarly discourse.

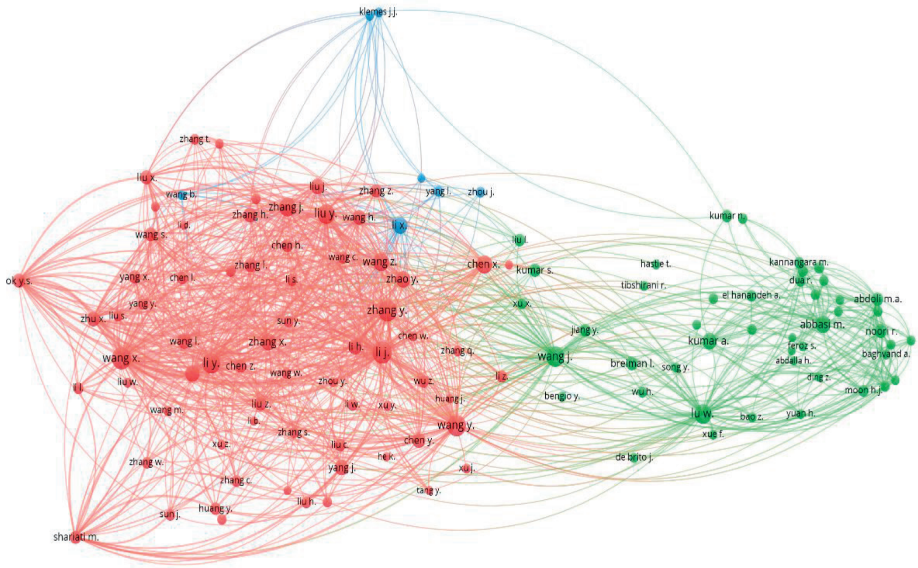

Figure 7. Network of author co-citations, highlighting 123 authors out of 25,398 cited authors who meet the minimum threshold of 20 citations each

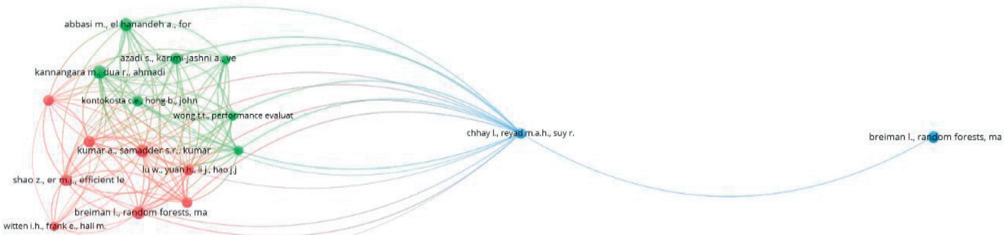

Figure 8. Co-citation of references, 19 references from a total of 11,490 that meet the minimum citation threshold of 5

Concerning journal co-citation patterns, the network discussed in Figure 9 identifies seven clusters. The first three clusters are as follows: The red cluster, the largest, includes 10 research journals, with the *Journal of Cleaner Production* as the most prominent source, having 223 citations and a link strength of 5,875. This cluster consists of interdisciplinary journals addressing topics related to environmental sustainability. The second cluster is green, also containing 10 research journals, with *Waste Management* as the leading source, having 181 citations and a link strength of 3,755. This cluster covers journals on various aspects of WM, including generation, features, reduction, gathering, sorting, treatment, and disposal. The third cluster is blue and includes 8 research journals, with *Sustainability* as a key source, showing 104 citations and a link strength of 2,090. This cluster features journals that publish research on sustainability, including topics such as energy production, conversion, and utilization. The remaining clusters include yellow and purple with 7 journals, light blue with 5 journals, and orange with 2 journals.

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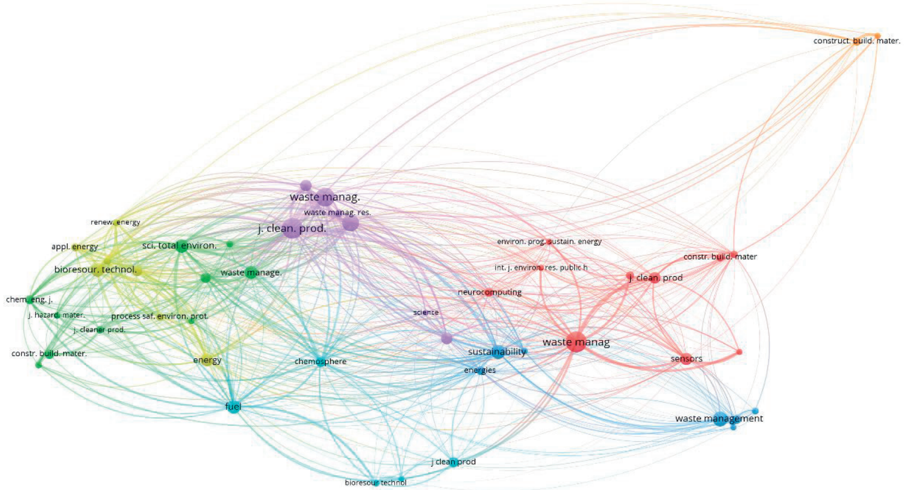

Figure 9. Network of journal co-citations 49 core journals from a total of 5,262 that meet the minimum citation threshold of 20

Authors' bibliographical coupling

The analysis of bibliographic coupling among authors enabled us to determine whether authors A and B reference the works of author C. This means that two authors sharing common citations are more interconnected and likely have comparable research interests (Gazni & Didegah, 2016). The bibliographic coupling of authors (Figure 10) revealed two clusters consisting of 10 authors in total. The primary cluster is red, featuring 6 authors, with the most notable being Cha, Gi-Wook. The green cluster contains 4 authors, with Li, Jie being the most prominent. The authors with the highest number of publications include Cha, Gi-Wook (155 citations), who has 8 publications in Scopus; Kim, Young-Chan (136 citations), who has 6 publications; and Hong, Won-Hwa (72 citations) has 5 publications.

Figure 10. Authors' bibliographical coupling: 10 authors out of 928 meet the minimum threshold of 3 documents per author

Analysis of co-authors by country and institution

Co-authorship among cities and Institution was examined, with node size representing the importance of Institution or countries and the spacing indicates the extent of their collaboration.

Examining the co-authorship connections among countries reveals a network of 20 countries divided into 5 clusters (Figure 11). The cluster of red includes 7 countries, with China as the most prominent (42 documents, 745 citations), followed by Hong Kong (7 documents, 323 citations) and South Korea (23 documents, 842 citations). The cluster of green comprises 4 countries, with Saudi Arabia as the leading country (20 documents, 210 citations), along with Pakistan (8 documents, 135 citations) and Poland (8 documents, 166 citations). In the cluster of blue, which includes 3 countries, the United States is the primary contributor (23 documents, 426 citations), followed by Bangladesh (5 documents, 67 citations) and Canada (6 documents, 121 citations). The cluster of yellow is made up of 3 countries, led by India (35 documents, 516 citations), while the cluster of purple also contains 3 countries, led by the United Kingdom (16 documents, 59 citations). The countries with the highest number of publications and citations are China, Saudi Arabia, and the United Kingdom.

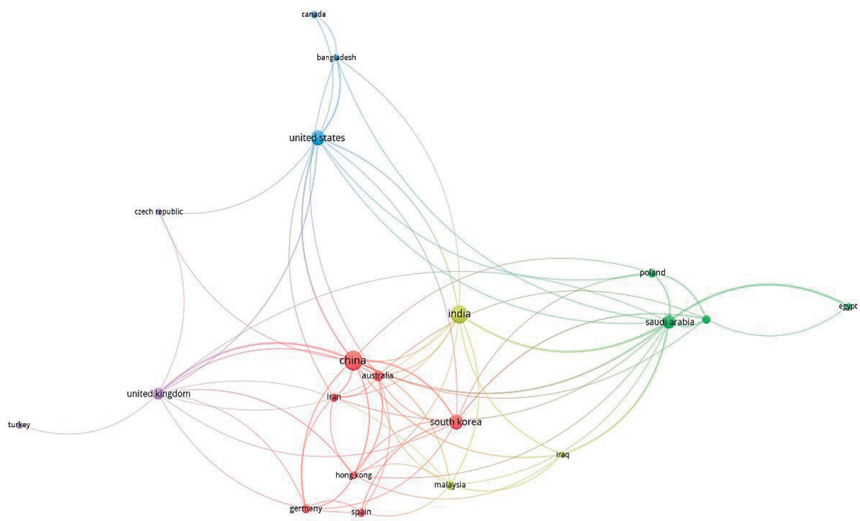

Figure 11. Co-authorship network of countries: 20 countries out of 63 meet the minimum threshold of 5 papers per country

Finally, the co-authorship network of institutions Figure 12 reveals that there is limited collaboration among different organizations that satisfy the threshold of having at least 2 published documents. Out of the 608 universities listed, the largest group comprises only 5, divided into two clusters: the cluster of red consists of 3 organizations, while the cluster of green includes 2 organizations. A notable organization is the School of Science and Technology in Acceleration Engineering at Kyungpook, National University in Daegu, South Korea, which has 4 documents and 27 citations.

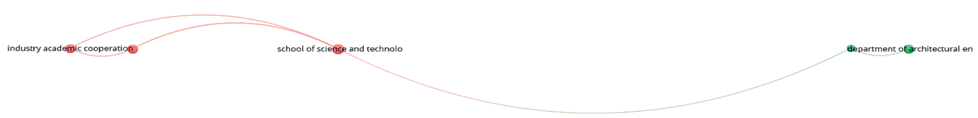

Figure 12. Co-authorship network of organizations: 5 organizations out of 608 meet the minimum threshold of 2 documents

This study examined the application of ML in waste management to understand how these advanced algorithms can enhance decision-making processes and improve WM outcomes. The results highlight several critical factors that could advance the field and help scholars make more informed decisions. This paper also explores how ML integration impacts current practices and influences future developments in waste management. China, India, and South Korea lead in the highest number of publications in this area. Keyword analysis indicates a strong focus on specific waste types, including "solid waste", "demolition waste", and "organic waste". Research on these types of waste is essential, as they represent the most generated waste worldwide and pose multiple potential negative impacts (economic, sustainability, and environmental) if not managed properly.

In general, there is a noticeable rise in publications focused on WTE. Recovering energy from waste through incineration plants offers a way to reduce the volume of waste directed to landfills. Moreover, it can aid in decreasing reliance on energy produced from fossil fuels, which are often imported. However, the increase in publications does not align with the waste hierarchy outlined by organizations like the European Parliament. This hierarchy emphasizes the importance of implementing strategies to minimize waste generation, enhance efforts for recycling and reuse, and discourage reliance on landfills and incinerators, which remain common in certain areas of Europe and other parts of the world. Evaluating WM systems (collection and processing) is crucial because they can help minimize waste generation and enhance opportunities for recycling and reuse instead of relying on landfills and incineration.

The present study can help researchers identify various concepts and their interconnections, paving the way for further research opportunities. In this context, the article reveals several trends within the research landscape. The first trend is the growing importance of machine learning in waste management, as demonstrated by the increase of publications in Scopus. Additionally, there is heightened interest in researching WTE technologies. Another significant point is the need for collaboration among various universities across different countries, as limited cooperation has been observed. Such collaboration would facilitate knowledge sharing and the development of improved WM systems. Ultimately, there is a pressing need for increased research in this area on a global scale.

CONCLUSIONS

This bibliometric analysis highlights the application of ML in waste management from 2014 to 2024, covering trends and developments that underscore the growing importance of ML in this field. The significance of this study lies in its being the first bibliometric analysis to examine the role of ML in waste management. The data reveals substantial growth in ML-related studies within waste management, increasing from a single publication in 2016 to 62 in 2024, culminating in 217 publications. China, India, and South Korea have emerged as leading contributors to global research, driving significant advancements in the application of ML to waste management. The recognition of key journals, including the Journal of Cleaner Production and Waste Management, further underscores the academic significance of research in this domain. We also analyzed the evolution of research by examining highly cited papers, top journals, authors' keywords, co-citation patterns, and co-authorship networks among countries and organisation. This analysis highlights the ongoing need for further exploration and application of ML in waste management. VOSviewer visualizations revealed extensive international collaboration, emphasizing a robust research framework. However, the study has limitations. The use of broad keywords like "machine learning in waste management" could be refined to focus more specifically on waste-related topics. Additionally, the reliance on the Scopus database, while favored for its wide coverage and credibility in bibliometric studies, limits the study’s overall scope. Overall, this bibliometric analysis provides a comprehensive overview of the evolving role of ML within waste management, it highlights the field's rapid growth, the strength of international collaborations, and the rising significance of

ML techniques in enhancing waste management processes. In the near future, research could investigate a comparison between conventional bibliometric methods and machine learning-driven bibliometric models in waste management. Expanding this comparison over several decades may reveal trends in the development and effectiveness of these approaches. This approach helps researchers identify various concepts and their connections, paving the way for new research directions.

REFERENCES

Abbasi, M., & El Hanandeh, A. (2016). Forecasting municipal solid waste generation using artificial intelligence modelling approaches. *Waste management*, *56*, 13-22.

Ahmad, S., & Kim, D.H. (2020). Quantum GIS based descriptive and predictive data analysis for effective planning of waste management. *IEEE Access*, *8*, 46193-46205.

Al Duhayyim, M., Alotaibi, S.S., Al-Otaibi, S., Al-Wesabi, F.N., Othman, M., Yaseen, I., & Motwakel, A. (2023). An Intelligent Hazardous Waste Detection and Classification Model Using Ensemble Learning Techniques. *Computers, Materials & Continua*, *74*(2).

Ali, Z., Jamil, Y., Anwar, H., & Sarfraz, R.A. (2024). Classification of e-waste using machine learning-assisted laser-induced breakdown spectroscopy. *Waste Management & Research*, 0734242X241248730.

AlJamal, M., Mughaid, A., Bani-Salameh, H., Alzubi, S., & Abualigah, L. (2024). Optimizing risk mitigation: A simulation-based model for detecting fake IoT clients in smart city environments. *Sustainable Computing: Informatics and Systems*, *43*, 101019.

Al-Ruzouq, R., Abdallah, M., Shanableh, A., Alani, S., Obaid, L., & Gibril, M.B.A. (2022). Waste to energy spatial suitability analysis using hybrid multi-criteria machine learning approach. *Environmental Science and Pollution Research*, *29*, 2613-2628.

Altarazi, F. (2024). Optimizing Waste Reduction in Manufacturing Processes Utilizing IoT Data with Machine Learning Approach for Sustainable Production. *Scalable Computing: Practice and Experience*, *25*(5), 4192-4204.

Anh Khoa, T., Phuc, C. H., Lam, P. D., Nhu, L. M. B., Trong, N. M., Phuong, N. T. H., ... & Duc, D. N. M. (2020). Waste Management System Using IoT-Based Machine Learning in University. *Wireless Communications and Mobile Computing*, *2020*(1), 6138637.

Ayeleru, O.O., Fajimi, L.I., Oboirien, B.O., & Olubambi, P.A. (2021). Forecasting municipal solid waste quantity using artificial neural network and supported vector machine techniques: A case study of Johannesburg, South Africa. *Journal of Cleaner Production*, *289*, 125671.

Belsare, K., Singh, M., Gandam, A., Malik, P.K., Agarwal, R., & Gehlot, A. (2024). An integrated approach of IoT and WSN using wavelet transform and machine learning for the solid waste image classification in smart cities. *Transactions on Emerging Telecommunications Technologies*, *35*(4), e4857.

Carrera, B., Piñol, V.L., Mata, J.B., & Kim, K. (2022). A machine learning based classification models for plastic recycling using different wavelength range spectrums. *Journal of Cleaner Production*, *374*, 133883.

Cha, G. W., Choi, S. H., Hong, W. H., & Park, C. W. (2022). Development of machine learning model for prediction of demolition waste generation rate of buildings in redevelopment areas. *International Journal of Environmental Research and Public Health*, *20*(1), 107.

Cha, G.W., Moon, H.J., & Kim, Y.C. (2021). Comparison of random forest and gradient boosting machine models for predicting demolition waste based on small datasets and categorical variables. *International Journal of Environmental Research and Public Health*, *18*(16), 8530.

Cha, G.W., Moon, H.J., & Kim, Y.C. (2022). A hybrid machine-learning model for predicting the waste generation rate of building demolition projects. *Journal of Cleaner Production*, *375*, 134096.

Cha, G.W., Moon, H.J., Kim, Y.M., Hong, W.H., Hwang, J.H., Park, W.J., & Kim, Y.C. (2020). Development of a prediction model for demolition waste generation using a random forest algorithm based on small datasets. *International Journal of Environmental Research and Public Health*, *17*(19), 6997.

Cha, G.W., Park, C.W., & Kim, Y.C. (2024). Optimal Machine Learning Model to Predict Demolition Waste Generation for a Circular Economy. *Sustainability*, *16*(16), 7064.

Chavhan, P.G., Khedka, V.N., Gupta, M., & Agarwal, K. (2024). Automatic Waste Segregator Based on IoT & ML Using Keras model and Streamlit. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(2), 787-799.

Cheah, C.G., Chia, W.Y., Lai, S.F., Chew, K.W., Chia, S.R., & Show, P.L. (2022). Innovation designs of industry 4.0 based solid waste management: Machinery and digital circular economy. *Environmental Research*, *213*, 113619.

Elsevier Scopus Database. Available online: https://www.elsevier.com/solutions/scopus/content (accessed on 17 October 2024).

Garre, A., Ruiz, M.C., & Hontoria, E. (2020). Application of Machine Learning to support production planning of a food industry in the context of waste generation under uncertainty. *Operations Research Perspectives*, *7*, 100147.

Gazni, A., & Didegah, F. (2016). The relationship between authors' bibliographic coupling and citation exchange: analyzing disciplinary differences. Scientometrics, *107,* 609-626.

Golbaz, S., Nabizadeh, R., & Sajadi, H.S. (2019). Comparative study of predicting hospital solid waste generation using multiple linear regression and artificial intelligence. *Journal of Environmental Health Science and Engineering*, *17*, 41-51.

Gondal, A.U., Sadiq, M.I., Ali, T., Irfan, M., Shaf, A., Aamir, M., & Kantoch, E. (2021). Real time multipurpose smart waste classification model for efficient recycling in smart cities using multilayer convolutional neural network and perceptron. *Sensors, 21*(14), 4916.

Hirsch, J.E. (2005). An index to quantify an individual's scientific research output. *Proceedings of the National academy of Sciences*, *102*(46), 16569-16572.

Hossen, M.M., Ashraf, A., Hasan, M., Majid, M.E., Nashbat, M., Kashem, S.B.A., & Chowdhury, M.E. (2024). GCDN-Net: Garbage classifier deep neural network for recyclable urban waste management. *Waste Management*, *174*, 439-450.

Huang, J., & Koroteev, D.D. (2021). Artificial intelligence for planning of energy and waste management. *Sustainable Energy Technologies and Assessments*, 47, 101426.

Ji, L., Liu, C., Huang, L., & Huang, G. (2018). The evolution of Resources Conservation and Recycling over the past 30 years: A bibliometric overview. *Resources, Conservation and Recycling*, *134*, 34-43.

Jin, S., Yang, Z., Królczykg, G., Liu, X., Gardoni, P., & Li, Z. (2023). Garbage detection and classification using a new deep learning-based machine vision system as a tool for sustainable waste recycling. *Waste Management*, *162*, 123-130.

Kaya, K., Ak, E., Yaslan, Y., & Oktug, SF. (2021). Waste-to-Energy Framework: An intelligent energy recycling management. *Sustainable Computing: Informatics and Systems*, *30*, 100548.

Kontokosta, C.E., Hong, B., Johnson, N.E., & Starobin, D. (2018). Using machine learning and small area estimation to predict building-level municipal solid waste generation in cities. *Computers, Environment and Urban Systems*, *70*, 151-162.

Kumar, A., Samadder, S.R., Kumar, N., & Singh, C. (2018). Estimation of the generation rate of different types of plastic wastes and possible revenue recovery from informal recycling. *Waste Management*, *79*, 781-790.

Lu, W., Lou, J., Webster, C., Xue, F., Bao, Z., & Chi, B. (2021). Estimating construction waste generation in the Greater Bay Area, China using machine learning. *Waste management*, *134*, 78-88.

Martins, J., Gonçalves, R., & Branco, F. (2024). A bibliometric analysis and visualization of e-learning adoption using VOSviewer. *Universal Access in the Information Society*, *23*(3), 1177-1191.

Medina-Mijangos, R., & Seguí-Amórtegui, L. (2020). Research trends in the economic analysis of municipal solid waste management systems: A bibliometric analysis from 1980 to 2019. *Sustainability*, *12*(20), 8509.

Mishra, S., Yaduvanshi, R., Rajpoot, P., Verma, S., Pandey, A.K., & Pandey, D. (2024). An integrated deep-learning model for smart waste classification. *Environmental Monitoring and Assessment*, *196*(3), 279.

Mohammed, M.A., Abdulhasan, M.J., Kumar, N.M., Abdulkareem, K.H., Mostafa, S.A., Maashi, M.S., & Chopra, S.S. (2023). Automated waste-sorting and recycling classification using artificial neural network and features fusion: A digital-enabled circular economy vision for smart cities. *Multimedia tools and applications*, *82*(25), 39617-39632.

Mookkaiah, S.S., Thangavelu, G., Hebbar, R., Haldar, N., & Singh, H. (2022). Design and development of smart Internet of Things–based solid waste management system using computer vision. *Environmental Science and Pollution Research*, *29*(43), 64871-64885.

Mudannayake, O., Rathnayake, D., Herath, J.D., Fernando, D.K., & Fernando, M. (2022). Exploring Machine Learning and Deep Learning Approaches for Multi-Step Forecasting in Municipal Solid Waste Generation. *IEEE Access*, *10*, 122570-122585.

Munir, M.T., Li, B., & Naqvi, M. (2023). Revolutionizing municipal solid waste management (MSWM) with machine learning as a clean resource: Opportunities, challenges and solutions. *Fuel*, *348*, 128548.

Namoun, A., Hussein, B.R., Tufail, A., Alrehaili, A., Syed, T.A., & BenRhouma, O. (2022). An ensemble learning based classification approach for the prediction of household solid waste generation. *Sensors, 22*(9), 3506.

Negrete-Cardoso, M., Rosano-Ortega, G., Álvarez-Aros, E.L., Tavera-Cortés, M.E., Vega-Lebrún, C.A., & Sánchez-Ruíz, F.J. (2022). Circular economy strategy and waste management: a bibliometric analysis in its contribution to sustainable development, toward a post-COVID-19 era. *Environmental Science and Pollution Research*, *29*(41), 61729-61746.

Nežerka, V., Zbíral, T., & Trejbal, J. (2024). Machine-learning-assisted classification of construction and demolition waste fragments using computer vision: convolution versus extraction of selected features. *Expert Systems with Applications*, *238*, 121568.

Nguyen, X.C., Nguyen, T.T.H., La, D.D., Kumar, G., Rene, E.R., Nguyen, D.D., & Nguyen, V.K. (2021). Development of machine learning-based models to forecast solid waste generation in residential areas: A case study from Vietnam. *Resources, Conservation and Recycling*, *167*, 105381.

Nnamoko, N., Barrowclough, J., & Procter, J. (2022). Solid waste image classification using deep convolutional neural network. *Infrastructures*, *7*(4), 47.

Oguz-Ekim, P. (2021). Machine learning approaches for municipal solid waste generation forecasting. *Environmental Engineering Science*, *38*(6), 489-499.

Oladinrin, O.T., Arif, M., Rana, M.Q., & Gyoh, L. (2023). Interrelations between construction ethics and innovation: A bibliometric analysis using VOSviewer. *Construction Innovation*, *23*(3), 505-523.

Palansooriya, K.N., Li, J., Dissanayake, P.D., Suvarna, M., Li, L., Yuan, X., & Ok, Y.S. (2022). Prediction of soil heavy metal immobilization by biochar using machine learning. *Environmental science & technology*, *56*(7), 4187-4198.

Patil, S.C., & Gidde, M.R. (2023). RFID and IoT Enabled Framework to Make Pune City an Eco-friendly Smart City. *Nature Environment and Pollution Technology*, *22*(2), 553-563.

Reuters, T. (2008). Whitepaper using bibliometrics. *Thomson Reuters*, *12*.

Rutqvist, D., Kleyko, D., & Blomstedt, F. (2019). An automated machine learning approach for smart waste management systems. *IEEE transactions on industrial informatics*, *16*(1), 384-392.

Seguí-Amortegui, L., Clemente-Almendros, J.A., Medina, R., & Grueso Gala, M. (2019). Sustainability and competitiveness in the tourism industry and tourist destinations: A bibliometric study. *Sustainability*, *11*(22), 6351.

Singh, T., & Uppaluri, R.V.S. (2023). Machine learning tool-based prediction and forecasting of municipal solid waste generation rate: a case study in Guwahati, Assam, India. *International Journal of Environmental Science and Technology*, *20*(11), 12207-12230.

Small, H. (1973). Co-citation in the scientific literature: A new measure of the relationship between two documents. *Journal of the American Society for information Science*, *24*(4), 265-269.

Sohail, S.S., Javed, Z., Nadeem, M., Anwer, F., Farhat, F., Hussain, A., & Madsen, D.Ø. (2023). Multi-criteria decision making-based waste management: A bibliometric analysis. *Heliyon*.

Taki, M., & Rohani, A. (2022). Machine learning models for prediction the Higher Heating Value (HHV) of Municipal Solid Waste (MSW) for waste-to-energy evaluation. *Case Studies in Thermal Engineering*, *31*, 101823.

Tamala, J.K., Maramag, E.I., Simeon, K.A., & Ignacio, J.J. (2022). A bibliometric analysis of sustainable oil and gas production research using VOSviewer. *Cleaner Engineering and Technology*, *7*, 100437.

Van Eck, N.J. & Waltman, L. (2016). VOSviewer Manual 1.6.11. Manual, No. Version 1.6.4, 2016, pp. 1–28. Available online: http://www.vosviewer.com/documentation/Manual_VOSviewer_1.5.4.pdf

Vu, H.L., Ng, K.T.W., & Bolingbroke, D. (2019). Time-lagged effects of weekly climatic and socio-economic factors on ANN municipal yard waste prediction models. *Waste Management*, *84*, 129-140.

Yang, L., Zhao, Y., Niu, X., Song, Z., Gao, Q., & Wu, J. (2021). Municipal solid waste forecasting in China based on machine learning models. *Frontiers in Energy Research, 9,* 763977.

Yatim, F.E., Boumanchar, I., Srhir, B., Chhiti, Y., Jama, C., & Alaoui, F.E.M.H. (2022). Waste-to-energy as a tool of circular economy: Prediction of higher heating value of biomass by artificial neural network (ANN) and multivariate linear regression (MLR). *Waste Management, 153,* 293-303.

Yu, K.H., Zhang, Y., Li, D., Montenegro-Marin, C.E., & Kumar, P.M. (2021). Environmental planning based on reduce, reuse, recycle and recover using artificial intelligence. *Environmental Impact Assessment Review*, *86*, 106492.

Yuan, X., Suvarna, M., Low, S., Dissanayake, P.D., Lee, K.B., Li, J., & Ok, Y.S. (2021). Applied machine learning for prediction of CO_2 adsorption on biomass waste-derived porous carbons. *Environmental Science & Technology*, *55*(17), 11925-11936.

Zhang, C., Dong, H., Geng, Y., Liang, H., & Liu, X. (2022). Machine learning based prediction for China's municipal solid waste under the shared socioeconomic pathways. *Journal of Environmental Management*, *312*, 114918.

Zia, H., Jawaid, M.U., Fatima, H.S., Hassan, I.U., Hussain, A., Shahzad, S., & Khurram, M. (2022). Plastic waste management through the development of a low cost and light weight deep learning based reverse vending machine. *Recycling*, *7*(5), 70.