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A Quantitative Systematic Literature Review and Meta-synthesis of Internet of Things-enabled Smart Waste Management Technologies for Automated Waste Segregation, Real-time Fill-level Monitoring, Dynamic Collection Scheduling, Spillover Prevention, and Sustainable Smart City Implementation

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ABSTRACT

In this study a number of research publications on smart waste management are reviewed. We concentrated on four areas: sorting trash, tracking how full bins are, organizing collection routes and preventing bins from overflowing. We gathered and synthesized numbers and results from 100 studies published between 2021 and 2026. These studies were from Google Scholar, Scopus, IEEE Xplore and ScienceDirect. Our intentions were simple: We wanted to find out what frequently goes wrong with manual trash management, what smart technologies are commonly employed, how accurate ML models are at garbage sorting, how effectively ultrasonic sensors monitor the actual bin levels, and what the current research gaps are. We used a famous guide known as PRISMA for choosing and filtering studies to ensure we did things properly. We also extracted crucial information using a uniform form and utilized a checklist to assess the quality of each study. For the numbers we used basic statistics like averages, percentages and standard deviations. We then ran some deeper tests to measure our findings against predicted standards. So, what did we discover? The most common concerns with manual waste systems were bin overflowing (78% of studies cited this), improper garbage sorting by people (72%), delayed collections (65%) and workers being exposed to hazardous waste (58%). When it came to technology, machine learning algorithms that sort trash hit an average accuracy of 89.4%. In the meantime, IoT sensors that monitor bin fullness revealed a good link between the sensor reading and the bin contents, with an average correlation of 0.92. Here's a fun fact: only 2% of the research we reviewed included systems that changed collecting schedules depending on real-time data. And none of them had an automatic trash wrapping or sealing option. In conclusion, machine intelligence and IoT do make trash management more efficient. But looking ahead, we need solutions that pull it all together: sorting, monitoring, packaging, and smart scheduling, all on one platform.

Keywords: Internet of Things (IoT); Machine Learning; Deep Learning; Smart Waste Management; Waste Segregation; Fill-level Monitoring; Smart Bins; Collection Scheduling; Cloud Computing; Computer Vision; YOLO Object Detection; Environmental Sustainability; Circular Economy; Smart City Applications.

1.0. Introduction

Cities are growing, and more people are migrating into them. As a result, the world is generating more waste than ever before. Garbage that is not disposed of properly can cause serious difficulties, including pollution, toxic gases, contaminated water, and disease. In many developing nations, such as the Philippines, local administrations still face the same persistent problems: overflowing bins, garbage trucks that do not arrive on time, and citizens who do not sort their waste properly.

Conventional garbage systems are based mainly on visual inspections by personnel who walk around and check containers. Sanitation staff must look into each container to see whether it is full. This typically means either arriving too late or wasting time checking bins that are still empty. During peak seasons, bins may fill up long before the scheduled pickup.

However, technology is changing the picture. Thanks to technologies such as the Internet of Things (IoT), Machine Learning (ML), computer vision, and cloud computing, building smarter waste systems has become a real possibility. These systems handle sorting automatically, monitor bin levels in real time, and identify the most efficient time to collect. Based on the research conducted so far, they appear to perform well.

There are still some gaps, however. Most research focuses on one aspect at a time, such as sorting or monitoring. Very few studies combine several smart features into one complete solution, and there is hardly any work on areas such as automatic waste packaging or pickup schedules that adjust based on real data.

This is why the present study was undertaken. A Quantitative Systematic Literature Review (QSLR) was conducted to gather the data and results of published studies on smart waste management systems from the years 2021 to 2026.

1.1. Study Objectives

This study aims to:

1) Identify the major operational problems associated with conventional waste management systems.
2) Determine the smart waste management technologies most frequently implemented in existing studies.
3) Evaluate the average classification accuracy of machine learning-based waste segregation systems.
4) Assess the reliability of Internet of Things-enabled fill-level monitoring technologies.
5) Identify research gaps related to adaptive scheduling, waste containment, and integrated smart waste platforms.
6) Provide evidence-based recommendations for future smart waste management research and implementation.

1.2. Significance of the Study

The results of this study provide local government units (LGUs), researchers, planners, and technology developers with concrete figures on how well smart waste technologies perform. The findings also build on the existing body of research on smart-city technology and environmental sustainability.

1.3. Scope and Limitations

The studies reviewed were published between 2021 and 2026. They were located using four main databases: Google Scholar, Scopus, IEEE Xplore, and ScienceDirect. Only English-language studies that reported actual numerical results on smart waste management technologies were retained. This study did not involve building any system or running original tests. No prototypes were developed, no surveys were distributed, no interviews were conducted, and no experiments were performed. The work consisted solely of reviewing what other researchers had already published.

1.4. Statement of the Problem

Manual waste management systems continue to experience operational inefficiencies, such as delayed collection, improper segregation, waste overflow, and exposure of sanitation workers to hazardous materials. Although smart waste management technologies have increasingly been proposed, limited quantitative synthesis exists regarding their effectiveness and the research gaps that remain. This study therefore aimed to review existing research and consolidate the numerical findings of published studies on smart waste management technologies.

1.5. Research Questions

1. What common operational problems of manual waste management systems are reported in published studies?
2. What smart waste management technologies are commonly implemented in existing studies?
3. What is the average classification accuracy reported in ML-based waste segregation systems?
4. How accurately do ultrasonic sensors estimate the correct bin fill level?
5. What research gaps remain across the studies conducted so far on smart waste technologies?

2.0. Review of Related Literature

2.1. Technology Acceptance Model (TAM)

In 1989, Davis introduced the Technology Acceptance Model (TAM). It holds that whether people decide to use a new technology depends mainly on two things. First, whether they believe it actually helps them perform their work better is what researchers call perceived usefulness. Second, whether people find the technology easy to use without too much effort perceived ease of use. When both conditions are met, people tend to be more willing to accept the technology and put it to use.

In smart waste management systems, TAM is relevant because sanitation personnel, LGUs, and the public are more likely to adopt automated waste technologies when those systems are efficient, reliable, and user-friendly. A number of studies found that real-time monitoring and automated sorting systems make waste management more effective and reduce the need to handle waste manually, which in turn makes users more willing to accept and use smart waste technologies. This theory therefore supports the use of IoT monitoring, mobile alerts, and ML for waste sorting, because they make waste management far less burdensome and help users make better decisions as they go.

2.2. IoT-Enabled Service Optimization Theory

This theory holds that embedding sensors and communication tools into physical assets such as bins or pipes makes it possible to monitor live conditions, set up automation, and deliver better service. In smart cities, IoT keeps operations running smoothly by continuously gathering fresh data and delivering it where it is needed.

In current waste management systems, bins are fitted with ultrasonic sensors, Global System for Mobile Communications (GSM) modules, cloud platforms, and wireless communication. These tools allow bins to report how full they are to monitoring systems in real time. Collection can then be scheduled based on actual need rather than a fixed calendar, and overflow problems become far less common. Several studies found that IoT-based waste monitoring systems make collection more efficient, reduce unnecessary trips, and lower operating costs. The theory thus supports the use of sensor-based monitoring and automated scheduling in smart waste management.

2.3. Automation Complementarity Theory

According to Automation Complementarity Theory, automation performs best when it supports human workers rather than replacing them entirely. Machines handle the dull, dangerous, or slow tasks, which frees people to make decisions, monitor operations, and carry out any needed repairs. In this context, ML sorts the waste on its own, while IoT sensors track bin levels and trigger collection alerts. This does not remove people from the process. Sanitation workers remain essential: they handle waste pickup, perform repairs, and oversee the entire process from start to finish. The theory therefore supports the use of automated sorting and monitoring, since these systems protect workers from hazardous materials while helping operations run more smoothly and quickly.

2.4. Smart Waste Management Systems

Smart waste systems combine several kinds of technology, including IoT sensors, cloud platforms, ML, mobile applications, and automation. Their goal is to make waste collection more effective, reduce overflowing bins, and sort garbage correctly. Cities are gradually adopting these systems because they return live information, allowing waste managers to decide what to do based on actual conditions rather than a schedule fixed months earlier.

According to Pardini et al. (2020), smart waste management systems improve collection efficiency considerably, mainly because they allow real-time tracking of waste levels and reduce unnecessary collection runs. Similarly, Ahmed et al. (2022) stated that deep learning paired with predictive monitoring supports better waste collection planning and helps prevent overflow before it occurs.

Several studies also highlighted the weaknesses of the traditional waste management approach. For example, Dela Cruz and Santos (2021) reported that in several Philippine urban centers, manual systems often result in delayed pickup schedules, overflowing bins, and occasionally improper segregation practices. These everyday operational problems contribute to environmental pollution and public-health concerns.

Cheema et al. (2022) further emphasized that smart waste management setups improve sustainability by adding automation tools that classify waste, maintain continuous monitoring, and optimize collection operations. However, the same study noted that many of these systems remain confined to laboratory environments and do not reach full deployment in real-world settings. Although existing smart waste management systems offer significant operational improvements, many studies focus only on isolated features, such as segregation or monitoring, rather than comprehensive, integrated systems.

2.5. Machine Learning-Based Waste Segregation

ML-based waste segregation systems rely on computer vision, image recognition, neural networks, and deep learning algorithms to sort waste materials automatically. With these approaches, segregation accuracy tends to increase, and the need for manual sorting is reduced.

Usha and Mahesh (2022) developed an ML garbage-detection system and reported 85.7% classification accuracy, with neural networks performing most of the work. Their results showed that automated image processing can identify recyclable and non-recyclable waste categories in a practical way.

Mortos et al. (2024) introduced SMARTSORT, a You Only Look Once version 4 (YOLOv4)-driven waste-sorting system, and reported 98.34% classification accuracy. They also noted that object-detection setups such as YOLOv4 improve not only classification precision but also processing speed.

Similarly, Gunaseelan et al. (2023) designed a deep-learning-based segregation system capable of recognizing several waste categories. They reported high reliability and argued that deep learning tends to outperform simpler image-classification approaches, mainly because it can capture subtle object details that are easy to miss.

Wahyutama and Hwang (2022) reported that YOLO-based object-detection systems can classify recyclable materials effectively while simultaneously tracking waste capacity. Their work highlighted how computer vision is becoming increasingly central to automated waste management systems. Even so, although many studies report strong classification accuracy, researchers also noted certain limitations, including dataset imbalance, sensitivity to lighting, and weaker results in outdoor settings. These issues suggest that further research is required, especially for real-world deployment, environmental adaptation, and robustness.

2.6. IoT-Based Fill-Level Monitoring Systems

IoT-enabled waste monitoring systems often rely on ultrasonic sensors, GSM modules, Wi-Fi communication, cloud platforms, and mobile applications to track waste levels in real time. In practice, these setups allow waste bins to relay information about their current fill status, making collection planning more efficient and less reliant on guesswork.

According to Khan et al. (2024), IoT-supported waste collection improved operational efficiency by reducing unnecessary trips and simplifying route optimization. Their results also showed that sensor-based monitoring helps the overall process respond faster and can lower the number of overflow events.

Prakash et al. (2022) created an IoT "smart dustbin" setup that monitors waste levels with ultrasonic sensors and sends the readings to cloud dashboards. They concluded that automating observation tends to increase collection-scheduling efficiency while also reducing the overall monitoring cost.

Longo et al. (2021) deployed a fifth-generation (5G)-enabled smart waste management system in a university-campus setting. They showed that faster communication networks improve real-time monitoring reliability and enhance data-transmission outcomes.

Kumaravel and Ilankumaran (2022) described a solar-powered waste monitoring setup that sends fill-level warnings through GSM. Their work emphasized the benefits of using renewable energy, showing that green electricity can be integrated into more intelligent waste management systems. Across the reviewed studies, researchers consistently found strong links between ultrasonic sensor readings and the actual waste level. Nevertheless, they noted drawbacks such as reduced accuracy outdoors, environmental interference, and power-consumption concerns that can affect performance over time.

2.7. Cloud-Based Monitoring and Mobile Notification Systems

Cloud computing and mobile technology are increasingly being combined in smart waste management frameworks, allowing operators to perform centralized monitoring and remote access to real-time waste information. Ahmed et al. (2022) reported that cloud-linked waste monitoring systems improved prediction precision and collection planning through centralized data analytics. They highlighted that cloud platforms can support large-scale waste monitoring across smart cities.

In addition, many studies implemented mobile applications that send alerts when bins approach a critical, near-overflowing fill level. This allows sanitation staff to react faster instead of waiting too long, and it helps fine-tune the collection schedule. Cheema et al. (2022) further explained that cloud-based monitoring platforms improve scalability, mainly because several waste bins can be tracked at once through a centralized dashboard interface. Even with these benefits, cloud solutions can encounter issues such as unstable internet connectivity, cybersecurity threats, and ongoing infrastructure costs.

2.8. Responsive Collection Scheduling Systems

Responsive collection scheduling systems use real-time monitoring data to adjust collection routes on the fly and cut down on unnecessary trips. In doing so, they improve fuel efficiency, lower labor costs, and keep overflow far more contained.

Ikram et al. (2023) built an intelligent waste management application using IoT technology and a fuzzy inference system, with the goal of optimizing schedules. They reported that dynamic scheduling methods can noticeably improve operational efficiency, especially when conditions change. Likewise, some Long-Range Wide Area Network (LoRaWAN)-based waste management research showed that adaptive scheduling approaches can improve communication efficiency while reducing energy use within IoT waste monitoring setups.

Even so, although responsive scheduling delivers clear operational benefits, only a small number of the reviewed studies actually embedded adaptive scheduling within their complete systems. Much of the existing work stopped at monitoring and did not extend into automated route optimization. This overall gap suggests that responsive scheduling remains an underdeveloped component in many smart waste management systems.

2.9. Automatic Waste Wrapping and Spillover Prevention

Automatic waste wrapping and spillover-prevention systems are among the least explored areas in smart waste management research. Most reviewed studies concentrate on segregation and monitoring technologies but tend to overlook the physical waste-containment aspect.

Overflowing bins remain a major operational issue in public places and urban settings. When waste is not contained properly, it can produce strong odors, contaminate the surroundings, trigger pest infestation, and raise public-health concerns. Despite the importance of spillover prevention, none of the reviewed studies implemented automatic drawstring-bag sealing or any automated wrapping mechanism. Instead, most existing solutions rely on the manual replacement of waste bags once the bin reaches full capacity. This gap represents a clear and valuable opportunity for future research, particularly work that combines automated containment systems with real-time monitoring technologies.

2.10. Local and International Studies

International studies consistently reported good results for ML-based segregation and IoT-enabled monitoring systems. Researchers from various countries showed that smart waste management solutions can improve operational efficiency, reduce overflow incidents, and generally improve waste-segregation performance.

In the Philippines, local studies highlighted operational challenges tied to manual waste management setups. Busa et al. (2025) developed an IoT-based system that monitors the amount of waste and detects the burning of plastics, while Cuarto et al. (2023) developed an automated infectious-waste segregation setup using microcontrollers together with sensor technologies. Despite these encouraging local results, much of the work remained at the laboratory stage or was tested only as a prototype. Few papers addressed large-scale public deployment or long-term operational evaluation, so the real-world picture remains limited. Overall, the findings suggest that smart waste management technology continues to advance worldwide, but more studies are needed on localized implementation and integration, specifically for Philippine public settings.

2.11. Synthesis of Literature

The reviewed literature makes it clear that ML, IoT monitoring, cloud computing, and automation technologies contribute substantially to waste management efficiency. Most existing studies reach similar conclusions, reporting high waste-classification accuracy and fairly reliable fill-level monitoring, even when the setups differ.

ML-based solutions showed a solid ability to automate waste sorting and segregation, especially through deep learning and computer-vision approaches. IoT-enabled monitoring systems, in turn, improved how quickly collection teams could respond, mainly because sensors provided real-time status updates.

The papers also identified several important limitations. Many studies examined single features, such as either sorting or monitoring, rather than complete, integrated smart waste management systems. In addition, responsive scheduling and automatic waste-containment systems appear underdeveloped; they are frequently mentioned but rarely implemented. Another recurring observation is that many systems were tested only under laboratory conditions, which makes it harder to predict their long-term behavior in public environments, where conditions are messier and less predictable. Overall, these results suggest that future smart waste management systems should bring segregation, monitoring, scheduling, and spillover prevention together into one unified platform.

2.12. Research Gaps

The review identified several significant research gaps, summarized in Table 1.

Table 1. Summary of the research gaps identified across the reviewed studies on smart waste management, with a brief description of each gap.

Research Gap Description

Research Gap	Description
Lack of automatic wrapping systems	No reviewed study implemented automatic drawstring waste wrapping
Limited feature integration	Most systems focused only on one functionality
Limited field deployment	Many studies were laboratory-based
Limited responsive scheduling	Very few systems implemented adaptive collection scheduling
Limited quantitative synthesis	Few studies synthesized quantitative findings systematically
Limited Philippine public environment studies	Few studies evaluated systems in local public plazas

As shown in Table 1, the identified gaps indicate the need for future smart waste management systems that integrate ML, IoT monitoring, responsive scheduling, and spillover prevention into comprehensive platforms.

3.0. Research Methodology

3.1. Research Design

This study employed a Quantitative Systematic Literature Review (QSLR) design. The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework in searching for, screening, assessing, and selecting relevant studies. The overall selection process is presented in Figure**.**

Figure 1 illustrates the PRISMA study selection process.

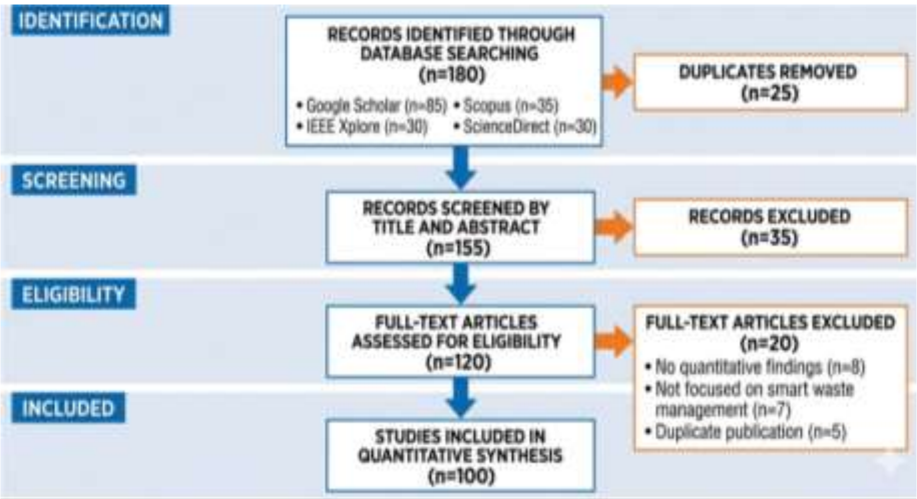

Figure 1. PRISMA flow diagram showing the identification, screening, eligibility, and inclusion stages used to select the 100 studies analyzed in this review. (Adapted from Page et al., 2021, the PRISMA 2020 statement includes this attribution only if the diagram template is taken from that source.)

3.2. Search Strategy

The following databases were searched:

- Google Scholar
- Scopus
- IEEE Xplore
- ScienceDirect

The following Boolean search strings were used:

- (“smart waste management” OR “smart bin”) AND (IoT OR “machine learning”) AND (segregation OR monitoring OR scheduling)
- (“waste segregation” AND “machine learning”)
- (“IoT waste monitoring” AND sensors)

3.3. Inclusion and Exclusion Criteria

- Inclusion Criteria

a. Published between 2021 and 2026. b. Written in English. c. Peer-reviewed journal or conference paper. d. Focused on smart waste management technologies. e. Reported quantitative findings.

Exclusion Criteria

i. Purely qualitative studies. ii. Duplicate studies. iii. non-English studies. iv. Studies unrelated to smart waste management.

3.4. Quality Assessment

A modified quality-assessment checklist was used to evaluate (1) clarity of methodology; (2) validity of findings; (3) completeness of data reporting; (4) relevance to smart waste management; and (5) reliability of statistical analysis. Only studies meeting acceptable quality standards were included.

3.5. Data Extraction

A structured data-extraction table was used to record the author, year, technology, and key findings of each included study. A representative sample of the extracted data is shown in Table 2.

Table 2. Representative sample of the structured data-extraction table, showing the author, publication year, core technology, and key quantitative findings for selected studies.

Author	Year	Technology	Key Findings
Usha and Mahesh	2022	Neural Network	85.7% classification accuracy
Mortos et al.	2024	YOLOv4	98.34% classification accuracy
Khan et al.	2024	IoT Monitoring	Improved collection efficiency

3.6. Data Analysis

Descriptive statistics, including frequency, percentage, mean, and standard deviation, were computed. The aggregated quantitative findings were then analyzed using inferential statistics to determine whether the synthesized findings differed significantly from benchmark values. The Shapiro-Wilk test was used to assess normality.

4.0. Results & Discussion

4.1. Results

Common Operational Problems

The frequency of the operational problems reported for manual waste management systems is presented in Table 3.

Table 3. Frequency of common operational problems reported for manual waste management systems across the reviewed studies.

Problem	Frequency
Overflowing bins	78%
Improper segregation	72%
Delayed collection	65%
Hazard exposure	58%

As shown in Table 3, these findings indicate that manual waste management systems continue to experience substantial operational inefficiencies.

Smart Waste Management Technologies

The frequency with which each smart waste management technology was implemented is summarized in Table 4.

Table 4. Frequency of the smart waste management technologies implemented across the reviewed studies.

Technology	Frequency
Machine learning classification	45%
IoT monitoring systems	32%
Cloud-based platforms	28%
Mobile scheduling systems	15%
Automatic wrapping systems	1%

Table 4 shows that ML and IoT monitoring technologies were the most commonly implemented solutions.

Classification Accuracy

A total of 45 studies reported classification-accuracy values. The summary statistics are presented in Table 5.

Table 5. Summary statistics of the classification-accuracy values reported in the 45machine learning-based waste-segregation studies.

Statistic	Value
Mean Accuracy	89.4%
Standard Deviation	6.2%
Minimum	70%
Maximum	98.9%

As presented in Table 5, ML-based systems achieved an average classification accuracy of 89.4%.

Fill-Level Monitoring Correlation

A total of 28 studies reported correlation coefficients between sensor readings and actual fill levels. The summary statistics are presented in Table 6.

Table 6. Summary statistics of the correlation coefficients reported in the 28 IoT-based fill-level monitoring studies.

Statistic	**Value**
Mean Correlation	0.92
Standard Deviation	0.05

The values in Table 6 indicate the strong reliability of IoT-based fill-level monitoring systems.

Research Gaps

The frequency of the two least-implemented features is shown in Table 7.

Table 7. Frequency of the least-implemented smart waste management features across the reviewed studies, highlighting major research gaps.

Feature	**Frequency**
Automatic waste wrapping	0%
Responsive scheduling	2%

As shown in Table 7, these findings reveal significant opportunities for future smart waste management research.

4.2. Discussion

The results show that adopting ML and IoT technologies greatly improves the efficiency of waste management. The high classification-accuracy results (Table 5) are consistent with prior studies that demonstrated the strong performance of deep-learning and computer-vision algorithms in waste segregation. The strong correlation between sensor readings and actual fill levels (Table 6) further supports the effectiveness of IoT-enabled monitoring systems.

Despite these advances, the reviewed studies rarely integrated multiple smart waste management functionalities into a single platform; most systems focused only on monitoring or segregation (Table 4). The absence of automatic waste-wrapping systems (Table 7) points to a major opportunity for future innovation.

5.0. Conclusion & Future Recommendations

5.1. Conclusion

This study conducted a Quantitative Systematic Literature Review on smart waste management technologies. The findings revealed that manual waste management systems commonly experience overflowing bins, delayed collection, and improper segregation. ML-based waste-segregation systems demonstrated high classification accuracy, while IoT-enabled monitoring systems showed strong reliability. Important gaps remain, however, in responsive collection scheduling and automatic waste-wrapping technologies. Future smart waste management systems should therefore integrate segregation, monitoring, scheduling, and waste containment into unified platforms.

5.2. Future Suggestions

Based on the findings, the following suggestions are offered for future work:

- Develop fully integrated smart waste management systems that combine ML segregation, IoT monitoring, responsive scheduling, and spillover prevention on a single platform.
- Design and test automatic waste-wrapping and drawstring-sealing mechanisms, which were entirely absent from the reviewed studies.
- Conduct large-scale, real-world field deployments and long-term operational evaluations, especially in Philippine public plazas and urban settings.
- Improve outdoor robustness of ML and sensor systems by addressing dataset imbalance, lighting sensitivity, environmental interference, and power consumption.
- Implement and validate adaptive, data-driven collection scheduling that adjusts routes using real-time bin data.
- Perform meta-analyses and effect-size evaluations in future reviews to strengthen the quantitative synthesis of smart waste management research.

5.3. Recommendations

For Future Researchers

- Develop integrated smart waste management systems.
- Conduct real-world field testing.
- Explore automatic waste-wrapping technologies.
- Perform meta-analysis and effect-size evaluation.

For Local Government Units (LGUs)

- Consider adopting IoT-enabled waste monitoring systems.
- Improve waste-segregation programs using smart technologies.

For Technology Developers

- Design reliable and user-friendly outdoor waste monitoring systems.
- Integrate monitoring and scheduling features into unified platforms.

Declarations

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Competing Interests Statement

The authors declare that they have no competing financial, professional, or personal interests.

Authors' Contributions

Warren Arias: Conceptualization, methodology, data collection, formal analysis, writing original draft. Ed Mai Mah Gyle P. Bayeta, Loren Limpahan, Evin Mae Berdon, Jomari Sunogan, Meaths Jambo, Eusibio Patria, Mark Angelo Dontar, Shiarah Rapirap and Femour Banawa: Literature screening, data extraction, validation, and manuscript review. Kim Cyrus Aurea: Supervision, project administration, manuscript review and editing.

Consent for Publication

All authors have read and approved the final manuscript and consent to its publication.

Informed Consent

Not applicable. This study did not involve human participants.

Availability of Data and Material

All data analyzed in this study were obtained from publicly available, previously published sources cited in the references. No new datasets were generated.

Institutional Review Board Statement

This study is a literature review and did not involve human or animal subjects.

Ethical Approval

Not applicable.

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Declaration of Artificial Intelligence

The authors used an AI-assisted tool only for language editing and formatting. All content, analysis, interpretation, and conclusions are the authors' own, and the authors take full responsibility for the integrity of the work.

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