Applied Research in Science and Technology 6(1): 191-210 2026

Contents lists available at openscie.com
E-ISSN: 2776-7205
Applied Research in Science and Technology
DOI: 10.33292/areste.v6i1.163
Journal homepage: https://areste.org/index.php/oai

A Systematic Literature Review on Multimodal and Uncertainty-Based Fusion in Urban Waste Analytics

Adelin Adelin[1,2*], Wendi Usino[1], Arief Wibowo[1]

[1]Faculty of Information Technology, Budi Luhur University, Jakarta, Indonesia
[2] Institut Teknologi dan Bisnis Palcomtech, Palembang, Indonesia

*Correspondence E-mail: 241100038@student.budiluhur.ac.id

ARTICLE INFO

Received 29 July 2026
Revised 16 October 2026
Accepted 22 October 2026
Published 28 October 2026

Keywords:
Decision support,
Multimodal fusion,
Systematic literature review,
Uncertainty-based fusion,
Urban waste analytics.

ABSTRACT

Background: Urban waste studies now use many types of data, such as images, sensor readings, process records, geographic data, and operational records. However, many studies have not clearly evaluated data reliability, missing data, and uncertainty when these sources are combined.
Aims: This systematic literature review maps the data sources and integration methods used in urban waste analytics. It also examines how the studies handle uncertainty and source reliability and identifies the conditions needed to support decisions that can be traced
Methods: A Scopus search found 118 records published between 2020 and 2026. After applying language and document type filters, 105 records remained. The screening of titles and abstracts selected 59 reports for full text assessment. Fifty eight reports were obtained and examined. One overlapping report was removed, resulting in 57 studies for the final synthesis. Each study was coded separately and checked using five reporting completeness items.
Results: The review found 20 studies using direct multimodal or multisensor integration, 14 using feature or model fusion within one main modality, 15 using multisource platforms or decision support integration, and 8 using uncertainty, multicriteria decision making, or optimization without direct multimodal fusion. Forty nine studies directly supported RQ1. For RQ2, 28 studies provided direct support and one provided partial support. For RQ3, 56 studies provided direct support and one provided indirect support. Data integration has been applied to various waste management activities. However, uncertainty calibration and source reliability were not regularly evaluated.
Recommendation: Future research should test data integration when some sources are missing or have poor quality. Researchers should also compare confidence values with actual errors, explain the alignment of data across time and location, and relate model results to clear operational decisions and risks.

To cite this article: Adelin, A., Usino, W., Wibowo, A. (2026). A Systematic Literature Review on Multimodal and Uncertainty-Based Fusion in Urban Waste Analytics. *Applied Research in Science and Technology*, 6(1), 191-210.

This article is under a Creative Commons Attribution-ShareAlike 4.0 International (**CC BY-SA 4.0**) License. Creative Commons Attribution-ShareAlike 4.0 International License Copyright ©2026 by author/s

1. Introduction

Municipal solid waste management includes several connected activities. These activities cover waste generation, collection, transportation, sorting, treatment, disposal, and planning. Each activity uses different types of data and may require decisions at different times. Previous reviews reported that digital technology and artificial intelligence have been used for waste prediction, bin monitoring, route planning, waste sorting, treatment, and system planning (Abdallah *et al.,* 2020; Esmaeilian *et al.,* 2018; Ihsanullah *et al.,* 2022). Therefore, waste data are no longer used only for documentation. They are also used for daily monitoring and decision support.

Urban waste systems now use data from many sources. For example, smart waste systems may use fill level, weight, location, and environmental sensors to monitor waste bins and collection needs (Henaien *et al.,* 2024). Landfill monitoring may combine images from unmanned aerial vehicles, geospatial data, and sensor information (Hassan *et al.,* 2023; Y. Liu *et al.,* 2024). In municipal solid waste incineration, researchers also use process data, furnace images, and operating data to monitor combustion and emissions (Hua *et al.,* 2026; Xia *et al.,* 2024). In these applications, the result depends not only on the prediction model. It also depends on how data from different sources are prepared, aligned, and combined.

Waste sorting is one example of data integration in waste management. Some deep learning studies combine visual and geometric information, features from different network levels, or sensor readings with image classification *(Lu et al., 2022; Mohammed et al.,* 2023; Pan *et al.,* 2023). Other studies use hyperspectral data, optical and radar images, or several types of sensors to identify waste materials and support automatic sorting (Akomolafe *et al.,* 2026; Teng *et al.,* 2026; Vatsala *et al.,* 2025). These studies indicate that data fusion has already been applied in waste analytics. However, the sources and integration methods are different for each application.

Data integration is not limited to waste detection and sorting. Geographic information systems, multicriteria analysis, fuzzy methods, life cycle assessment, and digital platforms have been used to combine operational, spatial, environmental, and expert information. These methods support landfill selection, collection planning, technology assessment, and risk evaluation (Alvi *et al.,* 2026; Eghtesadifard *et al.,* 2020; Pamučar *et al.,* 2022; Saraiva *et al.,* 2021). In waste incineration studies, Bayesian models and feature-fusion methods have also been used to study abnormal emissions and combustion conditions (Cui *et al.,* 2026; Huang *et al.,* 2021). For this reason, direct multimodal fusion needs to be distinguished from feature fusion within one main data type and from integration at the decision level.

However, the use of many data sources does not always produce a reliable decision. Operational data may be incomplete or collected at different times. Sensor performance may also decrease, and each source may provide a different level of detail. Previous review discussed the effect of incomplete data in municipal solid waste assessment (Dangi *et al.,* 2023). Previous studies also showed that a high confidence score from a prediction model does not always represent a low prediction error (Guo *et al.,* 2017) . Therefore, a fusion method should not be evaluated only from its accuracy. The evaluation should also consider missing data, uncertainty, source reliability, and how the model output is used in an operational decision.

Previous reviews have discussed smart city infrastructure and connected waste systems (Esmaeilian *et al.,* 2018), the use of artificial intelligence in solid waste management (Abdallah *et al.,* 2020), and AI methods for prediction and optimization (Ihsanullah *et al.,* 2022). These reviews show that digital technology has an important role in modern waste management. However, most of them organize the literature based on application areas or computational methods. They do not specifically compare how different data sources are combined, how uncertainty and reliability are handled, and how the results support decisions that can be traced and explained.

The studies reviewed in this paper show two related areas that are not always studied together. The first area focuses on combining images, sensor readings, process variables, and spatial data. However, several studies in this area still use fixed thresholds or model confidence to represent reliability. The second area applies fuzzy sets, Bayesian networks, sensitivity analysis, or scenario analysis to represent uncertainty. However, these methods are not always applied to direct multimodal fusion. A systematic comparison is needed to understand where these two areas are connected, where they remain separate, and what conditions are needed for their application in urban waste management.

Based on this research gap, this systematic literature review examines studies published from 2020 to 2026 on multimodal, multisource, and uncertainty aware analytics in urban waste management. The review has three objectives. First, it maps the data sources and fusion methods used in urban waste applications. Second, it examines how the studies handle uncertainty, confidence, missing data, and source reliability. Third, it identifies the conditions needed for integrated evidence to support traceable decisions. This review contributes by connecting the study selection process, article level coding, thematic findings, and research questions in one transparent synthesis.

2. Methods

2.1 Study Design

This study used a systematic literature review to find, assess, and summarize studies related to multimodal, multisource, and uncertainty analysis in urban waste management. The review process followed PRISMA 2020 and PRISMA-S to report the search, screening, and study selection stages in a clear way (Page *et al.,* 2021; Rethlefsen *et al.,* 2021). The selected studies used different tasks, datasets, and evaluation methods. Therefore, statistical pooling was not suitable for this review. Each article was coded separately, and the findings were summarized using narrative synthesis.

2.2 Research Questions

RQ1: What data sources and fusion methods are used in urban waste analytics? RQ2: How do the included studies address uncertainty, confidence, missing data, and source reliability? RQ3: What conditions are required for integrated evidence to support traceable decisions in urban waste management?

2.3 Search Strategy

The literature search was conducted using Scopus Advanced Search on October 4, 2026. The records shown in the PRISMA flowchart were obtained from this search. Scopus was used because it covers publications from computing, engineering, and environmental management. It also includes journal articles and conference papers.

The search query used waste related terms in the title. Terms related to fusion, integration, analytics, and decision support were searched in the title, abstract, or keywords. The publication period was limited from 2020 to 2026. This period was selected to include recent studies on artificial intelligence, the Internet of Things, sensor integration, and decision support in urban waste management.

The search produced 118 records. After the English language and document type filters were applied, 105 records remained. The selected document types were journal articles and conference papers. Duplicate checking was conducted using DOI, EID, and normalized article titles. No duplicate record was found among the 105 records. The complete Scopus query is presented below Table 1 so that the search process can be repeated.

Table 1. Search keyword groups and their relationship to the research questions.

Group	Example terms in the query	Related RQ
Waste domain	municipal solid waste; urban waste; household waste; waste sorting; smart waste; smart bin	RQ1
Fusion and integration	multimodal; multisource; data fusion; sensor fusion; feature fusion; decision fusion	RQ1, RQ2
Analytics	machine learning; deep learning; artificial intelligence; prediction; detection; classification	RQ1
Decision	decision support; risk; decision making; early warning	RQ2, RQ3

Table 1 presents the groups of terms used in the query. The terms "uncertainty," "reliability," and "confidence level" were not used as search terms. These aspects were examined during screening so that studies were not selected only because they used the same terms as RQ2.

The complete Scopus query was:

TITLE("municipal solid waste" OR "urban waste" OR "household waste" OR "solid waste management" OR "waste accumulation" OR "waste sorting" OR "waste monitoring" OR "smart waste" OR "smart bin" OR "smart bins") AND TITLE-ABS-KEY(multimodal OR "multi-modal" OR multisource OR "multi-source" OR "data fusion" OR "information fusion" OR "sensor fusion" OR "feature fusion" OR "model fusion" OR "score fusion" OR "decision fusion" OR "decision support") AND TITLE-ABS-KEY("machine learning" OR "deep learning" OR "artificial intelligence" OR prediction OR predictive OR detection OR classification OR monitoring OR risk OR "decision making" OR "early warning") AND PUBYEAR > 2019 AND PUBYEAR < 2027

The publication-year limit (2020-2026) was applied in the query. The Scopus result filters were English language and the Article and Conference Paper document types.

2.4 Literature Selection Criteria

The inclusion and exclusion criteria were defined before title and abstract screening. These criteria kept the selected articles within waste management and ensured that each article reported methods or results relevant to at least one research question.

Table 2. Article inclusion and exclusion criteria.

Aspect	Inclusion Criteria	Exclusion Criteria
Document type and year	Journal articles or conference papers, 2020-2026	Editorials, notes, book reviews, reviews, and non scientific documents
Language and access	English and full text available for review	Non English publication or full text unavailable
Subject coverage	Municipal, urban, household, or solid waste	Studies not related to waste, wastewater, or applications outside of waste management
Method scope	Applying fusion, integration, multi-source, multimodal, or decision support	Mere mention of general terms without specific methods or application results
Sufficiency of information	Data, methods, results, or evaluations are available for at least one RQ	Incomplete metadata or reports that overlap with more comprehensive publications

Table 2 shows that article selection was not based solely on keyword matches. Articles also had to be relevant to the field of waste management, employ verifiable methods, and provide sufficient information to answer at least one research question.

2.5 Study Selection Process

The titles and abstracts of all 105 records were examined. The records were not ranked and no priority score was used. A record was retained when it discussed urban waste management and applied data integration, data fusion, or decision support using clearly identified data sources. When the information in the title and abstract was not sufficient, the record was continued to the full text assessment. At this stage, 46 records were excluded and 59 reports were selected for full text assessment.

To make the records easier to manage, each article was given an internal code. The code started with "UW," which means "Urban Waste," followed by a sequence number, such as UW001 or UW002. This code was used only for record tracking. It did not replace the author name or article title.

Of the 59 reports selected for retrieval, 58 reports were obtained. Report UW093 could not be obtained, so its content was not assessed. For the 58 available reports, the methods, data, results, discussion, and conclusion were examined.

UW020 and UW040 were found to report the same study. Both reports used the same plant, data collection period, and data processing procedures. UW040 contained more complete information, so this report was retained. UW020 was excluded to prevent the same study from being counted twice. After this process, 57 studies were included in the final synthesis.

Two assessors independently conducted the title and abstract screening and the full text assessment using the same predefined criteria. Their decisions were compared, and any differences were resolved through discussion and consensus.

Figure 1 shows the complete study selection process, while Table 3 summarizes the checks conducted at each stage. From the 118 records identified in Scopus, 105 records remained after filtering. A total of 59 reports were selected for retrieval, 58 reports were assessed using their full text, and 57 studies were included in the final synthesis. These 57 studies were used as the basis for the coding and thematic analysis.

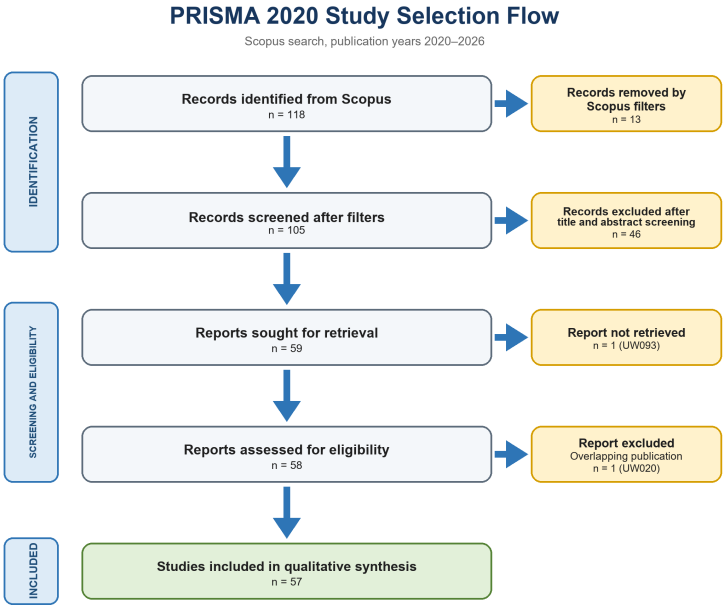

Figure 1. PRISMA 2020 study selection flowchart

Table 3. Summary of the study selection process audit.

Screening stage	n reviewed	Results	Controls and audit trail
Initial Scopus Results	118	13 excluded; 105 remaining	Year limited in the query; language and document type applied as Scopus filters
Duplicate check	105	No bibliographic duplicates found	DOI, EID, and normalized titles
Title and abstract	105	46 excluded; 59 included	Inclusion and exclusion criteria; reasons recorded per record
Fulltext search	59	58 obtained; 1 not obtained	UW093 was recorded as a manuscript that could not be obtained
Eligibility of full text manuscripts	58	1 overlapping report was excluded	UW020 was compared with UW040; the more complete report was retained
Final synthesis	57	57 studies were coded	Synthesis categories, RQ support, and reporting completeness
Assessment procedures	105/58	Two independent assessors; differences resolved by consensus	Decisions, reasons, dates, status, and location of evidence were recorded

Table 3 summarizes the checks at each selection stage. No duplicate records were found based on DOI, EID, and normalized titles. One report could not be obtained, and one overlapping report was excluded during full-text assessment because a more complete journal article was available. The complete audit log is retained by the corresponding author.

2.6 Data Extraction, Coding, and Reporting Completeness

The data extraction form included the study identifier, method, data or evidence sources, level of integration, handling of uncertainty or reliability, evaluation, support for each RQ, evidence location, and relevant notes. Each study was assigned to one primary category: direct multimodal or multisensor integration; feature or model fusion within one primary modality; multisource platform or decision-support integration; or uncertainty, multicriteria decision making, or optimization without direct multimodal fusion. A study could support more than one RQ. Support was coded as direct, partial, indirect, or no support. When a classification was unclear, the decision was based on the methods and results rather than keywords in the title.

Five items were scored as 0 or 1 to assess reporting completeness: clarity of objectives, description of data or evidence, explanation of methods or integration, reporting of evaluation, and discussion of limitations or applicability. A score of 5 was classified as high, 3-4 as moderate, and 0-2 as low reporting completeness. These scores guided the interpretation of results and were not used to exclude studies. The five items are not a validated risk of bias instrument and were not used to assess causal effect estimates.

Table 4. Operational coding rules for the synthesis.

Field	Operational Rule	Control of interpretation
Evidence Category	A single category based on the primary form of integration that is actually applied	Single modality feature fusion is not referred to as multimodal
RQ Support	Direct, partial, indirect, or no support	Partial and indirect evidence are not combined with direct support

Uncertainty or reliability	Described methods, backup rules, handling of missing data, sensitivity, calibration, or source quality	Confidence scores are not automatically considered calibrated uncertainty
Completeness of reporting	Five items of reporting completeness with a score of 0 or 1	Used to limit interpretation, not for automatic exclusion
Evidence trail	Location of sections or pages and critical notes	Allows claims to be cross checked against the full text

Table 4 outlines the rules used to ensure that each article is evaluated consistently. These rules distinguish multimodal evidence from the fusion of evidence within a single modality, differentiate levels of support for RQs, and prevent confidence scores from being directly interpreted as a calibrated measure of uncertainty.

2.7 Data Synthesis

Statistical pooling was not performed because the tasks, data, and outcome measures across studies varied widely. The number of studies was used to describe the coding results. A narrative synthesis was used to compare methods, strength of evidence, and conditions of use within each category. Research gaps were identified based on the results of reading and coding the full texts, not merely on the frequency of keyword occurrences.

3. Results and Discussions

3.1 Profile of the Included Studies

After the study selection, 57 studies were included in the synthesis. This process is explained in Section 2.5. The selected studies consisted of 39 journal articles and 18 conference papers. Four studies were published in 2020, two in 2021, three in 2022, four in 2023, four in 2024, ten in 2025, and 30 in 2026. Most studies were published in 2025 and 2026. This shows growing research activity in this area. However, because many studies are still recent, there has been limited time for their methods to be tested again by other researchers.

Reporting completeness was examined to help us interpret the findings. It was not used to remove studies from the review.

Table 5. Assessment of reporting completeness for 57 studies.

Criteria	Number of studies	Percentage
QA1 Objectives clearly stated	57/57	100.0%
QA2 Data or evidence is described	47/57	82.5%
QA3 Methods or integration explained	57/57	100.0%
QA4 Evaluation reported	56/57	98.2%
QA5 Limitations or application discussed	53/57	93.0%
High completeness of reporting	43	75.4%
Moderate reporting completeness	14	24.6%
Low reporting completeness	0	0.0%

Table 5 presents the five reporting items and the completeness results for all 57 studies. Among them, 43 studies met all five items, while 14 studies met three or four items. The main weaknesses were unclear descriptions of the data sources and limited explanation of how the methods could be implemented. For this reason, we interpreted the reported performance carefully when the sample size, research setting, or comparison method was not clearly described.

The coding results show that 49 studies provided direct evidence for RQ1. For RQ2, 28 studies provided direct evidence and one study provided partial evidence. For RQ3, 56 studies provided direct

evidence and one study provided indirect evidence. These numbers show how much evidence was available for each research question. They do not measure the effect size or the methodological quality of the studies.

3.2 Data Sources and Waste Application Areas

To answer RQ1, we compared the application area and the data sources used in each study. The applications covered waste sorting, smart bins and waste collection, landfill and spatial monitoring, waste incineration, and planning at the system level. In many studies, images were combined with depth data, sound, weight, spectral data, or process variables. Studies related to decision making used operational records, geographic data, life cycle information, scenarios, and expert opinions. Table 6 presents the common patterns and several representative studies. The application groups are used for description, and some studies may belong to more than one group.

Table 6. Data sources and integration patterns across urban waste applications.

Application area	Common data sources	Typical integration	Representative studies
Waste sorting and material classification	RGB or RGB-D images, acoustic signals, weight, material sensors, and hyperspectral data	Feature, decision, and sensor level fusion	(Akomolafe *et al.*, 2026; Lu *et al.*, 2022; Mohammed *et al.*, 2023; Vatsala *et al.*, 2025)
Smart bins and waste collection	Fill level, load, object presence, location, historical records, and routes	IoT sensor integration, forecasting, routing, and digital twin support	(Alfaidz *et al.*, 2025; Alvi *et al.*, 2026; Henaien *et al.*, 2024; Ram Nivas *et al.*, 2026)
Landfill and spatial monitoring	UAV, optical and SAR images, GIS layers, land use, and environmental indicators	Sensor or spatial fusion and GIS based multicriteria analysis	(Eghtesadifard *et al.*, 2020; Hassan *et al.*, 2023; Kumar *et al.*, 2026; Teng *et al.*, 2026)
Incineration and process monitoring	Process variables, furnace images, emissions, and operational records	Multimodal datasets, feature fusion, Bayesian reasoning, and process platforms	(Huang *et al.*, 2021; Pan *et al.*, 2023; Tang *et al.*, 2025; Xia *et al.*, 2024)
Planning, sustainability, and risk assessment	Operational, spatial, environmental, lifecycle, scenario, and expert information	MCDM, fuzzy models, lifecycle assessment, indicators, and scenario analysis	(Dangi *et al.*, 2023; Pamučar *et al.*, 2022; Saraiva *et al.*, 2021; Swan *et al.*, 2026)

Table 6 also shows that data integration has different meanings in different applications. Waste sorting studies usually combine several signals that describe the same waste item. In contrast, collection and planning studies combine information obtained from different times, locations, or organizational levels. Therefore, the method for assessing data alignment, reliability, and uncertainty also needs to follow the characteristics of each application.

3.3 Fusion Methods in Urban Waste Analytics

Each of the 57 studies was placed in one main category based on the integration method used in the study. This classification distinguishes feature fusion in a single image source from the integration of separate sensors or operational data sources. Table 7 presents every included study according to its main category. This arrangement allows the evidence to be traced back to each article.

3.3.1 Direct Multimodal and Multisensor Integration

Twenty studies directly combined different types of input data. Their applications included the use of RGB images and depth or sound data for waste sorting, visual and weight data in smart bins, UAV images combined with sensor or spatial data, optical and SAR images for waste mapping, hyperspectral sensing, and the combination of process variables and images for incineration monitoring (Akomolafe *et al.,* 2026; Hassan *et al.,* 2023; Lu *et al.,* 2022; Teng *et al.,* 2026; Xia *et al.,* 2024) . These studies provide direct evidence of multimodal or multisource integration. However, their results are still related to the specific task, dataset, and operating condition examined in each study.

3.3.2 Feature and Model Fusion within a Single Modality

Fourteen studies combined features, different scales, model outputs, or detection stages, but mainly used one type of data. Examples include the combination of combustion image features from several levels, improved features for object detection, ensemble classifiers, and image representations at different scales (Cui *et al.,* 2026; Mohammed *et al.,* 2023; Pan *et al.,* 2023; K. Ren *et al.,* 2024). These methods may improve prediction performance. However, they do not show the integration of separate physical sensors or operational data sources.

3.3.3 Multisource Platforms and Decision Support

Fifteen studies combined operational records, geographic layers, demographic or environmental indicators, routes, lifecycle information, or expert judgments. The methods included GIS-based analysis, multicriteria decision making, lifecycle assessment, digital twins, and end-edge-cloud platforms (Alvi *et al.,* 2026; Eghtesadifard *et al.,* 2020; Saraiva *et al.,* 2021; Tang *et al.,* 2025). Integration in this group mainly occurred at the platform or decision level and therefore depended on transparent criteria and a clear connection to the action being supported.

3.3.4 Uncertainty-Aware Decision Methods

Eight studies focused on uncertainty, multicriteria decision making, or optimization without direct multimodal fusion. Fuzzy demand, Bayesian networks, scenario analysis, sensitivity analysis, and robust or fuzzy aggregation were used to represent uncertain conditions *(Ali et al., 2026; Babaee Tirkolaee et al*., 2020; Huang *et al*., 2021; Pamučar *et al*., 2022) . These methods represent uncertainty more explicitly than a single confidence score, but they rarely estimate source-specific reliability for use in fusion weights.

Table 7. Study level grouping by integration category, research question support, and reporting completeness.

Studies	Cat.	RQ1	RQ2	RQ3	RC
(Akomolafe *et al.,* 2026; Bharathi *et al.,* 2025; Jonuzi & Mishkovski, 2026; Vatsala *et al.,* 2025; Xia *et al.,* 2024)	MM	Dir.	Dir.	Dir.	High
(Frinifa Babu *et al.,* 2025; Sharanya *et al.,* 2025)	MM	Dir.	Dir.	Dir.	Mod.
(Hua *et al.,* 2026)	MM	Dir.	Dir.	Ind.	High
(Alfaidz *et al.,* 2025)	MM	Dir.	Part.	Dir.	High

Studies	Cat.	RQ1	RQ2	RQ3	RC
(Hassan *et al.*, 2023; Lu *et al.*, 2022; Paulo *et al.*, 2026; Teng *et al.*, 2026)	MM	Dir.	—	Dir.	High
(Deepa *et al.*, 2026; Guo *et al.*, 2025; X. Liu & Zhai, 2022; Ram Nivas *et al.*, 2026; Wei *et al.*, 2026; Yu *et al.*, 2020, 2025)	MM	Dir.	—	Dir.	Mod.
(Cui *et al.*, 2026; Gnanavelu & Murugan, 2026; Mohammed *et al.*, 2023)	FM	Dir.	Dir.	Dir.	High
(Bao *et al.*, 2025; Chandran & Babu, 2026; Y. Liu *et al.*, 2024; Navya *et al.*, 2025; Pan *et al.*, 2023; K. Ren *et al.*, 2024; M. Ren *et al.*, 2026; Song *et al.*, 2026; Wu & Yang, 2026; Zhang, 2026)	FM	Dir.	—	Dir.	High
(Gomathi *et al.*, 2026)	FM	Dir.	—	Dir.	Mod.
(Alvi *et al.*, 2026; Eghtesadifard *et al.*, 2020; Kumar *et al.*, 2026; Saraiva *et al.*, 2021; Shbool *et al.*, 2026; Swan *et al.*, 2026; Vohra & Mishra, 2026)	PD	Dir.	Dir.	Dir.	High
(Aitimbetova & Pernebayev, 2026; De-la-Mata-Moratilla *et al.*, 2026; Henaien *et al.*, 2024; Ma & Liu, 2026; Martínez-Ramón *et al.*, 2026; Tang *et al.*, 2025)	PD	Dir.	—	Dir.	High
(Dangi *et al.*, 2023; Kirilchuk *et al.*, 2020)	PD	—	Dir.	Dir.	High
(Paulose & Augustin, 2026)	KU	Dir.	Dir.	Dir.	High
(Huang *et al.*, 2021)	KU	Dir.	Dir.	Dir.	Mod.
(Babaee Tirkolaee *et al.*, 2020; Mondal *et al.*, 2026; Pamučar *et al.*, 2022)	KU	—	Dir.	Dir.	High
(Ali *et al.*, 2026; Behera & Panda, 2026; Khan *et al.*, 2026)	KU	—	Dir.	Dir.	Mod.

Table 7 presents the assessment results for the 57 included studies. Studies are placed in the same row when they have the same integration category, the same type of support for RQ1 to RQ3, and the same reporting completeness level. This grouping makes the table easier to read. Each study can still be identified through its author and year citation.

The code MM refers to direct multimodal or multisensor integration. FM refers to feature or model fusion within one main modality. PD refers to multisource platform or decision support integration. KU refers to uncertainty, multicriteria decision making, or optimization without direct multimodal fusion. Dir., Part., and Ind. indicate direct, partial, and indirect support. A dash means that the study does not support the related research question. RC refers to reporting completeness. These categories show the coverage of evidence and the completeness of reporting. They do not show effect size or risk of bias. In the RC column, High means that all five criteria were met, while Mod. means that three or four criteria were met.

3.4 Handling of Uncertainty and Reliability

RQ2 was directly supported by 28 studies and partially supported by one. The reported approaches ranged from preprocessing and fallback rules to fuzzy, probabilistic, sensitivity, and scenario based methods. Table 8 compares these approaches. The review distinguishes calibrated uncertainty from model confidence because a high confidence value does not necessarily correspond to a low probability of error.

Table 8. Approaches used to address uncertainty and reliability.

Approach	How it was used	Interpretation	Representative studies
Confidence thresholds and fallback rules	Model confidence, voting, or a threshold determined whether another sensor or rule was used	Useful for handling ambiguous predictions, but the thresholds were rarely calibrated against observed error	(Bharathi *et al.*, 2025; Frinifa Babu *et al.*, 2025; Vatsala *et al.*, 2025)
Missing data, preprocessing, and alignment	Incomplete records, synchronization, or preprocessing were handled before integration	Supports data usability, but systematic tests under sensor degradation were uncommon	(Dangi *et al.*, 2023; Hua *et al.*, 2026; Xia *et al.*, 2024)
Fuzzy and multicriteria methods	Linguistic judgments, criterion weights, and fuzzy aggregation represented imprecision	Makes decision uncertainty explicit, but does not by itself estimate the reliability of each sensor or source	(Ali *et al.*, 2026; Behera & Panda, 2026; Khan *et al.*, 2026; Pamučar *et al.*, 2022)
Probabilistic, sensitivity, and scenario analysis	Bayesian networks, sensitivity analysis, scenarios, and lifecycle comparisons examined uncertain conditions	Quantifies decision uncertainty, but rarely feeds source-specific reliability back into fusion weights	(Aitimbetova & Pernebayev, 2026; Huang *et al.*, 2021; Mondal *et al.*, 2026; Saraiva *et al.*, 2021)
Performance variation or model confidence	Repeated tests, cross-validation variation, or confidence scores were reported	Provides performance context, but should not be treated as calibrated uncertainty without a calibration test	(Jonuzi & Mishkovski, 2026; Lu *et al.*, 2022; Paulo *et al.*, 2026)

Table 8 indicates that uncertainty is considered in several forms, but the approaches are not equivalent. Missing data handling and confidence thresholds address operational ambiguity, whereas fuzzy and probabilistic methods represent uncertainty in decision models. Only limited evidence links an estimated reliability value for each source to the weight assigned during fusion and then validates the result as source quality decreases.

3.5 Implementation Conditions for Decision Support

RQ3 received direct support from 56 studies and indirect support from one. Across the studies, five implementation conditions repeatedly affected whether integrated evidence could support a traceable decision. These conditions concern compatibility, alignment, missing or degraded sources, calibration, and the link from model output to operational action, as summarized in Table 9.

Table 9. Conditions for implementing integrated evidence in decision support.

Implementation condition	Why it matters	Evidence pattern in the reviewed studies	Representative studies
Comparable outcomes or label spaces	Sources cannot be fused meaningfully when they describe incompatible targets	Sorting and mapping studies aligned modalities around the same class, object, or spatial target	(Lu *et al.*, 2022; Teng *et al.*, 2026; Xia *et al.*, 2024)

Implementation condition	Why it matters	Evidence pattern in the reviewed studies	Representative studies
Temporal and spatial alignment	Signals collected at different times or locations may describe different events	Multimodal datasets, UAV monitoring, and process platforms required alignment before interpretation	(Hassan *et al.*, 2023; Hua *et al.*, 2026; Tang *et al.*, 2025)
Realistic missing-data and sensor degradation tests	Operational systems must remain interpretable when one source is unavailable or unreliable	Incomplete data and fallback rules were reported, but broad degradation tests were limited	(Bharathi *et al.*, 2025; Dangi *et al.*, 2023; Vatsala *et al.*, 2025)
Calibration against observed error	A confidence value is useful only if it corresponds to the likelihood of being correct	Several studies used confidence or accuracy, whereas explicit calibration was rarely reported	(Bharathi *et al.*, 2025; Guo *et al.*, 2025; Paulo *et al.*, 2026)
Connection to actions, thresholds, or risks	Decision support requires an operational response, not only a prediction score	Collection planning, process control, and risk studies linked evidence to specific decisions	(Alvi *et al.*, 2026; Henaien *et al.*, 2024; Huang *et al.*, 2021; Saraiva *et al.*, 2021)

The conditions in Table 9 are synthesis findings rather than a validated checklist. They show that implementation cannot be assessed from predictive accuracy alone. A model may perform well in a controlled test but remain difficult to use if its sources are misaligned, its confidence is uncalibrated, or its output is not connected to an identifiable action and risk.

3.6 Research Gaps and Future Directions

The comparison across RQ1-RQ3 identified gaps that recur across application areas. The central gap is not the absence of fusion methods, but the limited connection among source quality, uncertainty estimation, fusion behaviour, and operational consequences. Table 10 states each gap together with the evaluation needed to address it. These gaps were derived from full-text coding and comparison, not from the absence of particular keywords.

Table 10. Research gaps and corresponding evaluation needs.

Research gap	Current evidence	Needed evaluation	Examples revealing the gap
Source reliability is rarely linked to fusion weights	Most systems use fixed weights, thresholds, or model confidence	Estimate reliability for each source and test whether adaptive weighting improves decisions	(Bharathi *et al.*, 2025; Vatsala *et al.*, 2025; Wei *et al.*, 2026)
Confidence calibration remains limited	Prediction confidence is often reported without showing whether it matches observed error	Report calibration curves or errors and evaluate decision thresholds	(Bharathi *et al.*, 2025; Guo *et al.*, 2025; Paulo *et al.*, 2026)
Robustness under missing or degraded sources is under-tested	A few studies discuss incomplete data or fallback rules, but	Remove, corrupt, or delay individual sources and measure performance and decision changes	(Dangi *et al.*, 2023; Hua *et al.*, 2026; Vatsala *et al.*, 2025)

Research gap	Current evidence	Needed evaluation	Examples revealing the gap
	systematic ablation is uncommon		
Spatiotemporal alignment is not consistently reported	Alignment is essential in UAV, process, and sensor systems but is described at different levels of detail	Document synchronization windows, spatial resolution, and alignment error	(Hassan *et al.*, 2023; Hua *et al.*, 2026; Xia *et al.*, 2024)
The path from model output to operational action is not always traceable	Some studies end with accuracy or a score without specifying its operational consequence	Define the action, threshold, accountable user, and risk of an incorrect decision	(Alvi *et al.*, 2026; Henaien *et al.*, 2024; Saraiva *et al.*, 2021)

Table 10 directs future work toward tests that can be observed and repeated. In particular, studies should report what happens when individual sources are missing or degraded, whether confidence matches observed error, and how a change in integrated evidence changes the supported decision.

3.7 Discussion

The synthesis shows that urban waste analytics uses several forms of data integration. However, each form addresses a different problem. Direct multimodal studies combine different observations about an object, location, or process. Feature fusion studies combine information within one main type of data to improve its representation. Platform and decision support studies bring together operational and contextual information. Studies on uncertainty mainly represent unclear or incomplete information in planning and risk analysis. Separating these categories helps us avoid making an excessive claim about the current development of multimodal decision support.

One common problem is that data fusion and reliability assessment are often studied separately. Systems that combine several sources commonly use fixed rules or confidence values that have not been calibrated. In contrast, studies with more detailed uncertainty methods do not always combine different types of data directly. Based on these findings, future research needs to test the reliability of each data source, confidence calibration, system performance when a source is missing, and the effect of data fusion on operational decisions. At this stage, the evidence supports further testing rather than the immediate development of a new framework.

The findings need to be understood within the coverage of this review. The search included English language records from Scopus published between 2020 and 2026. One report could not be obtained. Two assessors independently conducted the screening and full text assessment. Their decisions were compared, and any differences were resolved through discussion and consensus. All final screening and coding decisions were recorded in an audit log. The reporting completeness checklist helped us interpret the study reports more carefully. However, it was not used as a validated instrument for assessing risk of bias. The studies also used different tasks, datasets, and outcome measures. Therefore, we used narrative synthesis and did not combine the results through statistical analysis.

4. Conclusions

This review screened all 105 records that remained after the Scopus filters. The final synthesis included 57 studies. We identified four main forms of integration: direct multimodal or multisensor integration, feature or model fusion within one modality, multisource platform or decision support integration, and uncertainty based decision methods without direct multimodal fusion.

The findings show that data integration has been used in waste sorting, collection, spatial monitoring, incineration, planning, and risk assessment. However, the connection among source reliability,

uncertainty estimation, fusion behaviour, confidence calibration, and operational effects is still limited. Future studies should test data integration when some sources are missing or have lower quality. They should also examine whether confidence values match the actual errors, explain how data are aligned across time and location, and relate model results to specific operational decisions and risks

5. Acknowledgment and Funding Information

The authors gratefully acknowledge the Faculty of Information Technology, Budi Luhur University, Jakarta, Indonesia, and Institut Teknologi dan Bisnis Palcomtech, Palembang, Indonesia, for the institutional support and academic facilities provided during the preparation of this article. This research received no specific grant from any funding agency in the public, commercial, or nonprofit sectors

6. Conflict of Interest Declaration

The authors declare that there are no conflicts of interest related to the publication of this article. The authors also confirm that this manuscript is original, free from plagiarism, and is not currently under consideration for publication by another journal or publisher.

7. Author Contribution Statement

This journal uses Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Adelin Adelin	x	x		x	x	x	x	x	x	x	x		x	
Wendi Usino				x						x		x		
Arief Wibowo				x						x		x		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

8. Generative AI Statement

During the preparation and revision of this manuscript, the authors used Grammarly and DeepL to assist with English grammar correction, translation, language refinement, and improvement of clarity and readability. All suggestions generated by these tools were critically reviewed, edited, and validated by the authors to ensure accuracy, originality, and scientific integrity. Grammarly and DeepL were used solely as supportive language tools and were not involved in literature searching, study selection, data extraction, coding, synthesis, or interpreting research findings. The authors take full responsibility for the accuracy, integrity, and final content of the manuscript, and these tools are not credited with authorship.

9. References

Abdallah, M., Abu Talib, M., Feroz, S., Nasir, Q., Abdalla, H., & Mahfood, B. (2020). Artificial Intelligence Applications in Solid Waste Management: A Systematic Research Review. *Waste Management*, *109*, 231–246. https://doi.org/10.1016/j.wasman.2020.04.057

Aitimbetova, A., & Pernebayev, Z. (2026). Sustainable Municipal Solid Waste Treatment in a Central Asian City: A Geographic Information System and Scenario-Based Framework for Technology Prioritization in Shymkent, Kazakhstan. *Sustainability (Switzerland)*, *18*(11), 5318. https://doi.org/10.3390/su18115318

Akomolafe, D., Klinger, J., Saha, N., Kuns, M., Linck, M., El Zahab, Z., & Bhattacharyya, D. (2026). ClassNMSW- a real-time classification approach for non-recycled municipal solid waste using hyperspectral imaging. *Computers and Chemical Engineering*, *213*, 109742. https://doi.org/10.1016/j.compchemeng.2026.109742

Alfaidz, A. M., Avansyah, H. Z., & Rosmiati, M. (2025). Revolutionizing Waste Management with an IoT Smart Bin Featuring App and Sensor Fusion for Waste Segregation. *ICONS-IoT 2025 - International Conference on Networking, Intelligent Systems, and IoT*, 135–141. https://doi.org/10.1109/ICONS-IoT65216.2025.11210903

Ali, U., Li, J., Ahmad, Y., Tolasa, F. T., & Senapati, T. (2026). A Decision Support Model for Artificial Intelligence-Based Solid Waste Management Through CRITIC-TOPSIS and Complex Fermatean Fuzzy Structure. *International Journal of Computational Intelligence Systems*, *19*(1), 330. https://doi.org/10.1007/s44196-026-01372-2

Alvi, M., Minerva, R., Dutta, H., Herath, M., & Crespi, N. (2026). A Decision-Support Digital Twin Framework for Sustainable Urban Waste Collection Planning. *Process Integration and Optimization for Sustainability*. https://doi.org/10.1007/s41660-026-00818-6

Babaee Tirkolaee, E., Mahdavi, I., Seyyed Esfahani, M. M., & Weber, G.-W. (2020). A hybrid augmented ant colony optimization for the multi-trip capacitated arc routing problem under fuzzy demands for urban solid waste management. *Waste Management and Research*, *38*(2), 156–172. https://doi.org/10.1177/0734242X19865782

Bao, L., Zhang, Y., Xue, F., & Zhang, X. (2025). LiteWaste-YOLO: A Super-Resolution-Aware Framework for Urban Waste Detection in Remote Sensing Imagery. *2025 6th International Conference on Big Data, Artificial Intelligence and Internet of Things Engineering, ICBAIE 2025*, 285–290. https://doi.org/10.1109/ICBAIE66852.2025.11326552

Behera, M., & Panda, A. C. (2026). A q-rung orthopair fuzzy Gaussian aggregation-based decision-making framework for sustainable solid waste management. *Applied Soft Computing*, *199*, 115381. https://doi.org/10.1016/j.asoc.2026.115381

Bharathi, M., Joshwin Antony, J., Refin, R., & Yokesh, A. (2025). IoT-Based Smart Waste Segregation System with Real-Time Data Analytics and AI for Efficient Waste Management and Recycling. *Proceedings ICECONF 2025 - 2025 2nd International Conference on Artificial Intelligence and Knowledge Discovery in Concurrent Engineering*. https://doi.org/10.1109/ICECONF65644.2025.11379597

Chandran, N., & Babu, N. R. (2026). Quantum-inspired deep learning model for organic municipal solid waste classification toward a circular bioeconomy. *Journal of Environmental Management*, *404*, 129331. https://doi.org/10.1016/j.jenvman.2026.129331

Cui, C., Yao, J., & Xia, H. (2026). Multilevel Feature Fusion and Nonparametric Detection of Furnace Temperature States in Municipal Solid Waste Incineration Systems. *IEEE Transactions on Industrial Informatics*, *22*(8), 7541–7552. https://doi.org/10.1109/TII.2026.3687100

Dangi, M. B., Malla, O. B., Cohen, R. R. H., Khatiwada, N. R., & Budhathoki, S. (2023). Life cycle assessment of municipal solid waste management in Kathmandu city, Nepal – An impact of an incomplete data set. *Habitat International*, *139*, 102895. https://doi.org/10.1016/j.habitatint.2023.102895

Deepa, T., Kumar, S. N., Kumar, R. H., Lokesh, K., & Joyrishi, T. R. (2026). IoT-based Intelligent Waste Monitoring System using a Hybrid CNN-LSTM Deep Learning Model. *Proceedings of 9th International Conference on Inventive Computation Technologies, ICICT 2026*, 524–531. https://doi.org/10.1109/ICICT68280.2026.11510935

De-la-Mata-Moratilla, S., Castillo-Martinez, A., Gutierrez-Martinez, J.-M., Ramirez-Velarde, R., & Ferrer-Oliva, M. (2026). Enhancing municipal solid waste management through artificial neural

network based forecasting of discharge point behaviour. *Knowledge-Based Systems*, *350*, 116600. https://doi.org/10.1016/j.knosys.2026.116600

Eghtesadifard, M., Afkhami, P., & Bazyar, A. (2020). An integrated approach to the selection of municipal solid waste landfills through GIS, K-Means and multi-criteria decision analysis. *Environmental Research*, *185*, 109348. https://doi.org/10.1016/j.envres.2020.109348

Esmaeilian, B., Wang, B., Lewis, K., Duarte, F., Ratti, C., & Behdad, S. (2018). The Future of Waste Management in Smart and Sustainable Cities: A Review and Concept Paper. *Waste Management*, *81*, 177–195. https://doi.org/10.1016/j.wasman.2018.09.047

Frinifa Babu, B. M., Aarthi, M., Priscilla, R., & Patturose, J. G. B. (2025). YOLO-GreenBin: A Real-Time Multi-Modal Smart Waste Monitoring System using YOLOv8 and Sensor Fusion with Live Geo-Mapping. *Proceedings of the 6th International Conference on Electronics and Sustainable Communication Systems, ICESC 2025*, 1342–1347. https://doi.org/10.1109/ICESC65114.2025.11212305

Gnanavelu, B., & Murugan, J. (2026). Hybrid fuzzy machine learning model for municipal solid waste forecasting in India. *Discover Environment*, *4*(1), 377. https://doi.org/10.1007/s44274-026-00841-x

Gomathi, P., Anfinston, F. D., Manikandan, S., Gopi, R., Robert, R., & Joseph, S. S. (2026). Hybrid YOLO-CNN Architectures for High-Performance Real-Time Waste Classification in Smart Waste-Management System. *ADSSSC 2026 - International Conference on AI-Driven Solutions for Sustainable Smart Cities: Challenges and Opportunities*, 566–571. https://doi.org/10.1109/ADSSSC67751.2026.11581951

Guo, C., Zan, I., & Ye, I. (2025). Intelligent Waste Sorting System Based on YOLO-Enhanced Deep Learning Models. *Proceedings - 2025 International Conference on Artificial Intelligence, Digital Media Technology and Social Computing, ICAIDS 2025*, 87–90. https://doi.org/10.1109/ICAIDS67687.2025.00026

Hassan, S. Z., Sun, P., Gokgoz, M., Chen, J., Reinhart, D. R., & Gustitus-Graham, S. (2023). UAV-based approach for municipal solid waste landfill monitoring and water ponding issue detection using sensor fusion. *Journal of Hydroinformatics*, *25*(6), 2107–2127. https://doi.org/10.2166/hydro.2023.195

Henaien, A., Ben Elhadj, H., & Chaari Fourati, L. (2024). A sustainable smart IoT-based solid waste management system. *Future Generation Computer Systems*, *157*, 587–602. https://doi.org/10.1016/j.future.2024.03.056

Hua, Y., Tang, J., & Tian, H. (2026). Benchmark Operational Condition Multimodal Dataset Construction for the Municipal Solid Waste Incineration Process. *Sustainability (Switzerland)*, *18*(5). https://doi.org/10.3390/su18052282

Huang, W., Li, H., Fan, H., & Qian, Y. (2021). Causation mechanism analysis of excess emission of flue gas pollutants from municipal solid waste incineration power plants by employing the Fault Tree combined with Bayesian Network: A case study in Dongguan. *Journal of Cleaner Production*, *327*, 129533. https://doi.org/10.1016/j.jclepro.2021.129533

Ihsanullah, I., Alam, G., Jamal, A., & Shaik, F. (2022). Recent Advances in Applications of Artificial Intelligence in Solid Waste Management: A Review. *Chemosphere*, *309*, 136631. https://doi.org/10.1016/j.chemosphere.2022.136631

Jonuzi, V. M., & Mishkovski, I. (2026). A Multimodal Vision: Language Framework for Intelligent Detection and Semantic Interpretation of Urban Waste. *Informatics*, *13*(4), 57. https://doi.org/10.3390/informatics13040057

Khan, A., Ali, J., & Syam, M. I. (2026). Multi-stage decision support framework under cubic q-rung orthopair fuzzy environment for smart waste management technology selection. *Array*, *31*, 101094. https://doi.org/10.1016/j.array.2026.101094

Kirilchuk, I., Yushin, V., Barkov, A., & Iordanova, A. (2020). Information technologies for risk assessment to public health from emissions of municipal solid waste landfill. *International Multidisciplinary Scientific GeoConference Surveying Geology and Mining Ecology Management, SGEM, 2020-August(5.1)*, 455–462. https://doi.org/10.5593/sgem2020/5.1/s20.058

Kumar, P., Choudhary, M. P., & Mathur, A. K. (2026). Analyzing the relationship between municipal solid waste generation and urban land use using integrated geospatial and spatial statistical techniques. *Integrated Environmental Assessment and Management*, *22*(2), 448–462. https://doi.org/10.1093/inteam/vjaf128

Liu, X., & Zhai, J. (2022). Domestic Waste Sorting System Based on Deep Learning. In *Lecture Notes in Electrical Engineering: 803 LNEE* (pp. 38–47). https://doi.org/10.1007/978-981-16-6328-4_5

Liu, Y., Zhao, B., Zhang, X., Nie, W., Gou, P., Liao, J., & Wang, K. (2024). A Practical Deep Learning Architecture for Large-Area Solid Wastes Monitoring Based on UAV Imagery. *Applied Sciences (Switzerland)*, *14*(5), 2084. https://doi.org/10.3390/app14052084

Lu, G., Wang, Y. B., Xu, H. X., Yang, H. Y., & Zou, J. (2022). Deep multimodal learning for municipal solid waste sorting. *Science China Technological Sciences*, *65*(2), 324–335. https://doi.org/10.1007/s11431-021-1927-9

Ma, S., & Liu, C. (2026). A landscape-aware multi-objective ant colony optimization framework for urban waste collection vehicle routing. *Discover Artificial Intelligence*, *6*(1), 1088. https://doi.org/10.1007/s44163-026-02159-2

Martínez-Ramón, N., Díaz, I., Iribarren, D., & Dufour, J. (2026). Integrated modeling and assessment of municipal solid waste use for aviation decarbonization. *Energy Conversion and Management: X*, *30*, 101809. https://doi.org/10.1016/j.ecmx.2026.101809

Mohammed, M. A., Abdulhasan, M. J., Kumar, N. M., Abdulkareem, K. H., Mostafa, S. A., Maashi, M. S., Khalid, L. S., Abdulaali, H. 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. https://doi.org/10.1007/s11042-021-11537-0

Mondal, A., Reddy N.R, M., Dubey, B. K., & Yadav, V. (2026). Pathways to sustainable municipal solid waste management: An LCA of integrated approaches and product circularity in Nashik, India. *Journal of Environmental Management*, *398*, 128424. https://doi.org/10.1016/j.jenvman.2025.128424

Navya, N., Inumarthi, S., Snigdha, K., Divya, U., Guttula, T., & Rajesh, J. T. (2025). An Optimized Vision-based Smart Bin for Waste Management Classification System Using Enhanced YOLOv8 Segmentation and Feature Fusion Networks. *3rd International Conference on Emerging Applications of Material Science and Technology, ICEAMST 2025*, 1207–1214. https://doi.org/10.1109/ICEAMST67459.2025.11336006

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. In *BMJ* (Vol. 372). BMJ Publishing Group. https://doi.org/10.1136/bmj.n71

Pamučar, D., Behzad, M., Božanić, D., & Behzad, M. (2022). Designing a fuzzy decision support framework for assessing solid waste management in the South European region. *Environmental Science and Pollution Research*, *29*(28), 42862–42882. https://doi.org/10.1007/s11356-022-18891-y

Pan, X., Tang, J., Xia, H., & Wang, T. (2023). Online Combustion Status Recognition of Municipal Solid Waste Incineration Process Using DFC Based on Convolutional Multi-Layer Feature Fusion. *Sustainability (Switzerland)*, *15*(23), 16473. https://doi.org/10.3390/su152316473

Paulo, D. J., Martins, J., Proença, H., & Neves, J. C. (2026). StreetView-Waste: A Multi-Task Dataset for Urban Waste Management. *Proceedings - 2026 IEEE/CVF Winter Conference on Applications of Computer Vision, WACV 2026*, 3015–3025. https://doi.org/10.1109/WACV61042.2026.00295

Paulose, A. P., & Augustin, F. (2026). BiAPPSS: an enhanced bipolar fuzzy APPSS framework for sustainable solid waste management. *Frontiers in Environmental Science*, *14*, 1756874. https://doi.org/10.3389/fenvs.2026.1756874

Ram Nivas, D., Sanjeyan, B., Subakarini, S., & Matheshwaran, R. (2026). SmartBin Network: IoT based Waste Monitoring and Data-Driven Decision Support. *2026 International Conference on Innovations in Emerging Technologies for Sustainable Development: Empowering Innovation for a Sustainable Future, ICIETSD 2026 - Conference Proceedings*. https://doi.org/10.1109/ICIETSD68684.2026.11584895

Ren, K., Ren, F., & Han, H. (2024). One-Shot Municipal Solid Waste Detection via Object-Relevant Feature Enhancement and Category-Level Feature Fusion. In *Communications in Computer and Information Science: 1960 CCIS* (pp. 43–53). https://doi.org/10.1007/978-981-99-8761-0_5

Ren, M., Guan, Q., Sun, M., Liu, Y., Qiao, B., & Zhao, H. (2026). Automated detection of hazardous household waste in complex sorting scenarios: A lightweight and high-precision deep learning approach. *Waste Management*, *223*, 115720. https://doi.org/10.1016/j.wasman.2026.115720

Rethlefsen, M. L., Kirtley, S., Waffenschmidt, S., Ayala, A. P., Moher, D., Page, M. J., Koffel, J. B., Blunt, H., Brigham, T., Chang, S., Clark, J., Conway, A., Couban, R., de Kock, S., Farrah, K., Fehrmann, P., Foster, M., Fowler, S. A., Glanville, J., … Young, S. (2021). PRISMA-S: an extension to the PRISMA Statement for Reporting Literature Searches in Systematic Reviews. *Systematic Reviews*, *10*(1). https://doi.org/10.1186/s13643-020-01542-z

Saraiva, A. B., Clímaco, J. N., Valle, R. D. A. B. D., & Mahler, C. (2021). Multi-criteria analysis and consequential lifecycle assessment of solid waste management: An integrated approach. *International Journal of Decision Support System Technology*, *13*(3), 1–17. https://doi.org/10.4018/IJDSST.2021070101

Sharanya, S., Sathyabama, K., Rishikesavan, H., & Saffrin Banu, M. (2025). Edge-Driven Smart Waste Bin Network for Decentralized Urban Waste Management. *Proceedings of 2025 International Conference on Signal Processing, Computation, Electronics, Power and Telecommunication, IConSCEPT 2025*. https://doi.org/10.1109/IConSCEPT66142.2025.11437363

Shbool, M. A., Al-Bazi, A., Jebril, L. S., Nasrallah, N. M., Al-Amad, S. A., & Al-Souliman, B. O. (2026). Promoting sustainability in Urban waste management in Amman for a circular economy. *Journal of Material Cycles and Waste Management*, *28*(1), 176–198. https://doi.org/10.1007/s10163-025-02405-2

Song, W., Zhao, N., & Ouyang, X. (2026). Municipal Solid Waste Target Detection Algorithm Based on Improved YOLOv11n. *IAENG International Journal of Computer Science*, *53*(5), 1985–1997.

Swan, K. H., Towprayoon, S., & Phongphiphat, A. (2026). Development of a city-level sustainability and resilience index for municipal solid waste management: Methodological framework and application to Bangkok. *Environmental and Sustainability Indicators*, *31*, 101274. https://doi.org/10.1016/j.indic.2026.101274

Tang, J., Wang, T., Tian, H., & Yu, W. (2025). AI- and Security-Empowered End–Edge–Cloud Modular Platform in Complex Industrial Processes: A Case Study on Municipal Solid Waste Incineration. *Sensors*, *25*(22), 6973. https://doi.org/10.3390/s25226973

Teng, J., Guo, S., Wu, W., Yu, J., & Chen, Y. (2026). MSWNet: A Deep Learning Fusion Framework for Municipal Solid Waste Detection From Optical and SAR Images. *Transactions in GIS*, *30*(6), e70376. https://doi.org/10.1111/tgis.70376

Vatsala, G. A., Fathimunnisa, Mudassir, M. S., Vasudeva, G., Jyothi, P., & Rudresha, D. C. (2025). SmartBinX: A Cost-Effective Hybrid AI and SensorBased Autonomous Waste Sorting System for

Public Spaces. *Proceedings of the 2025 International Conference on Computational Innovations and Sustainable Technologies, ICCIST 2025*. https://doi.org/10.1109/ICCIST67338.2025.11438295

Vohra, R., & Mishra, P. (2026). Sustainable mapping identification of municipal solid waste disposal zones using RS-GIS-basedMCDA techniques: a case study in Darjeeling, West Bengal. *Environmental Monitoring and Assessment*, *198*(3), 265. https://doi.org/10.1007/s10661-026-15089-4

Wei, L., Lao, Y., Zhao, Z., Lao, Y., & Qiu, J. (2026). Research on behavioral action control technology for the sorting module of intelligent waste sorting robots in complex waste streams. *Proceedings of SPIE - The International Society for Optical Engineering*, *14139*, 1413908. https://doi.org/10.1117/12.3109047

Wu, C., & Yang, Y. (2026). Dual-stream context aggregation network for waste sorting. *Discover Artificial Intelligence*, *6*(1), 906. https://doi.org/10.1007/s44163-026-01529-0

Xia, H., Tang, J., Pan, X., Yu, W., & Qiao, J. (2024). Multimodal Data-Driven Interpretable Deep Modeling Approach of Dioxins Generation for Municipal Solid Waste Incineration Processes. *IEEE Transactions on Instrumentation and Measurement*, *73*, 1–18. https://doi.org/10.1109/TIM.2024.3476561

Yu, Y., Wang, L., & Peng, Y. (2025). Deep Learning Based Integrated Removable Smart Waste Sorting Device. *Proceedings of International Conference on Artificial Life and Robotics*, 309–312.

Yu, Y., Zou, S., & Yin, K. (2020). A novel detection fusion network for solid waste sorting. *International Journal of Advanced Robotic Systems*, *17*(5). https://doi.org/10.1177/1729881420941779

Zhang, Z. (2026). Multi-Model Fusion and Data Augmentation for Optimization of Waste Sorting Recognition. *2026 11th International Conference on Electronic Technology and Information Science, ICETIS 2026*, 523–527. https://doi.org/10.1109/ICETIS70504.2026.11633384

About Author(s)

Adelin Adelin is a doctoral student in the Computer Science Doctoral Program, Faculty of Information Technology, Budi Luhur University, Jakarta, Indonesia, and a lecturer at Institut Teknologi dan Bisnis Palcomtech, Palembang, Indonesia. Her research interests include information systems, decision support systems, data analytics, software usability, and multimodal urban waste analytics. SINTA ID: 6021269. ORCID iD: 0009-0007-7578-7599.

Prof. Ir. Wendi Usino, M.Sc., M.M., Ph.D. is a Professor of Computer Science in the Faculty of Information Technology, Budi Luhur University, Jakarta, Indonesia. His research interests include information systems, data management, smart environments, mobile and networking systems, and artificial intelligence applications. SINTA ID: 5991673. ORCID iD: 0009-0009-6583-0818.

Prof. Dr. Arief Wibowo, S.Kom., M.Kom. is a Professor of Intelligent Systems for Crisis and Disaster Management in the Faculty of Information Technology, Budi Luhur University, Jakarta, Indonesia. His research interests include intelligent systems for crisis and disaster management, artificial intelligence, machine learning, data mining, predictive analytics, and decision support systems. Scopus ID: 57195675462. SINTA ID: 259862. ORCID iD: 0000-0001-8544-5145.