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DEVELOPMENT OF IOT-ENABLED SMART TECHNOLOGY FOR SUSTAINABLE MUNICIPAL SOLID WASTE MANAGEMENT IN BISHNUPUR MUNICIPALITY, BANKURA DISTRICT

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Abstract

Municipal solid waste management in small and semi-urban municipalities is increasingly challenged by population growth, changing consumption patterns, and uneven collection demand. This study develops an Internet of Things (IoT)-enabled framework for improving municipal solid waste collection and monitoring in Bishnupur Municipality, Bankura District, West Bengal, India. The framework integrates smart-bin sensing, GPS/GSM communication, Geographic Information System (GIS)-based route planning, cloud data management, and AI-assisted waste forecasting. Field observations, municipal records, household or establishment surveys, waste sampling, and spatial mapping were used to examine waste-generation patterns and collection conditions. The characterized waste stream contained 52% biodegradable material, 18% plastic, 11% paper, 6% glass, 4% metal, and 9% other materials. Supplied projection data indicate an increase in municipal waste generation from 28.59 tonnes per day in 2021 to 33.29 tonnes per day in 2026. The reported comparison between conventional and technology-supported collection indicates improvements in collection efficiency and segregation, together with reductions in fuel use, operating cost, and overflow incidents. These results should be interpreted in relation to the projection dataset, monitoring conditions, sampling design, and other operational changes that may have influenced performance. The study provides a practical framework for more responsive and resource-efficient waste management in small municipalities.

Field surveys, municipal records, waste sampling, and spatial mapping were used to

examine waste-generation patterns and the existing collection infrastructure. The waste-characterization results showed that biodegradable waste was the dominant fraction, accounting for 52% of the sampled waste, followed by plastics (18%) and paper (11%). Projection data indicated that municipal waste generation increased from 28.59 tonnes per day in 2021 to 33.29 tonnes per day in 2026, representing an estimated increase of approximately 16.4%. The proposed monitoring and route-planning approach was associated with an increase in collection efficiency from 58% to 89% and an improvement in segregation efficiency from 18% to 67%. Fuel consumption declined from 92 to 65 L day−1, while daily operating costs decreased from INR 24,500 to INR 16,000. The number of reported overflow incidents also fell from 34 to 9 per month.

These findings suggest that integrating real-time monitoring with demand-based collection and GIS-supported route planning may improve the operational performance of small municipal waste-management systems. However, the reported reductions should be interpreted in relation to the monitoring period, sampling design, baseline conditions, and the contribution of public awareness and segregation activities. The proposed framework offers a practical basis for developing more responsive, resource-efficient, and scalable MSW services in small municipalities.

Keywords: Municipal solid waste; Internet of Things; GIS; artificial intelligence; route optimization; waste segregation.

I. Introduction and Background

Municipal solid waste (MSW) management is now a major environmental and public-health concern in India. Rapid urban growth, changing consumption habits, commercial activity, and tourism are all increasing the amount and variety of waste generated. Many municipalities still struggle with source segregation, adequate treatment capacity, reliable data, and dependable collection infrastructure. When waste is not handled properly, it can contribute to air pollution, greenhouse-gas emissions, leachate, soil and groundwater contamination, odour, litter, and health risks. Fixed collection schedules can also send vehicles to locations that do not yet require service, increasing unnecessary travel, fuel use, operating costs, and the likelihood of overflowing bins [I–IX].

Bishnupur Municipality in Bankura District, West Bengal, offers a useful setting for examining these issues because its wards include residential, commercial, institutional, market, public, and tourism-related areas. The waste profile is therefore unlikely to be uniform. Residential areas may generate more biodegradable material, while markets and commercial locations can produce larger quantities of food waste, plastic packaging, paper, and other recyclables. Tourist locations may also experience short-term increases during weekends, holidays, festivals, and periods of high visitor activity. These differences make a ward-sensitive collection strategy more appropriate than a single routine for the entire municipality [II–IX].

This study proposes an integrated Internet of Things (IoT)-enabled framework for improving waste collection and monitoring in Bishnupur Municipality. The proposed system brings together smart-bin sensing, GPS and GSM communication, Geographic Information System (GIS)-based route planning, cloud data management, and AI-assisted waste prediction. The underlying idea is straightforward: collection

decisions should be guided by the actual condition of bins and local demand rather than relying only on fixed schedules [X–XIX].

II. Literature Review and Research Gap

Sustainable MSW management extends well beyond simply collecting and disposing of waste. It includes generation, source segregation, transport, treatment, recycling, resource recovery, and safe final disposal. Previous studies have repeatedly highlighted source segregation as a key step because mixing organic waste with recyclables reduces material quality and increases the quantity sent for disposal. A substantial biodegradable fraction can support composting or anaerobic digestion, while properly separated recyclables can be directed to material-recovery systems. At the same time, public participation, worker training, awareness, monitoring, and cooperation among stakeholders remain important for long-term success [I–IX, XII, XIII].

IoT-based monitoring can make waste collection more responsive. Smart bins fitted with fill-level sensors, microcontrollers, communication modules, and cloud platforms can provide information on bin status and help authorities decide when collection is needed. GPS and GIS can then be used to map bins, roads, vehicles, collection points, and treatment or disposal facilities, creating a basis for more efficient route planning. AI and machine-learning approaches can further support waste forecasting, classification, route selection, and performance assessment [X, XI, XIV–XIX].

These technologies are not without practical limitations. Sensors can be affected by dust, moisture, irregular waste surfaces, physical damage, battery constraints, calibration errors, and inadequate maintenance. Communication networks may also be unreliable, and AI models need sufficient local data before their predictions can be trusted. Installation, connectivity, software, maintenance, replacement, staff training, and data management all add to the cost of a smart system. For this reason, solutions designed for large cities cannot simply be transferred to smaller municipalities without considering local resources and operating conditions [XI, XVI–XIX].
The main gap addressed by this study is the limited availability of affordable and locally adaptable smart-waste solutions for smaller municipalities in developing regions. The proposed framework combines waste characterization, ward-level projections, smart-bin monitoring, GIS-supported routing, cloud-based information management, and AI-assisted forecasting in a single approach designed for Bishnupur Municipality. The intention is not to introduce technology for its own sake, but to connect field information with practical collection and planning decisions [X–XIX].

III. Objectives of the Study

The study aims to develop and evaluate an integrated IoT–GIS–AI framework for MSW management in Bishnupur Municipality. The framework is intended to connect information collected in the field with day-to-day decisions on collection, transportation, treatment, and planning.

1. Assessing existing waste storage, collection, transportation, segregation, treatment, recycling, and disposal practices.
2. Identifying operational problems such as overflowing bins, irregular collection, inadequate infrastructure, vehicle limitations, and shortage of trained personnel.
3. Quantifying and characterizing waste generation at the ward level.
4. Examining relationships between waste generation, population, households, land use, commercial activity, and tourism.
5. Developing an IoT-based smart-bin monitoring system.
6. Integrating GPS and GIS for spatial mapping and route optimization.
7. Developing AI-assisted waste-generation forecasting.
8. Evaluating collection efficiency, fuel consumption, overflow frequency, segregation efficiency, route distance, operating costs, and potential CO_2 emissions.
9. Assessing the roles of public awareness and stakeholder participation.
10. Developing a practical, affordable, scalable, and locally maintainable model for small municipalities.

IV. Methodology

The research followed a field-based, data-driven approach. It brought together field observations, household and municipal information, waste characterization, ward-level population and waste projections, GPS/GIS mapping, smart-bin monitoring, route analysis, and a comparison of conventional and technology-supported collection practices. The work was carried out in five broad stages: assessment of the existing system; compilation of ward-level data; waste quantification and characterization; development of the IoT–GIS–AI framework; and evaluation of operational, economic, and environmental indicators [X–XIX].

Both primary and secondary information were considered. Primary information came from field visits, direct observations, household and establishment surveys, discussions with municipal personnel, waste-sampling activities, GPS mapping, and selected smart-bin monitoring. These activities focused on storage conditions, source segregation, collection frequency, vehicle movement, overflow, and practical difficulties encountered during collection. Secondary information was obtained from municipal records, population and household data, collection records, vehicle records, government documents, annual reports, and the MSW projection dataset [I, II, XI].

The dataset covered 19 wards for the period 2021–2026 and included household numbers, population, and estimated MSW generation in tonnes per day. Before analysis, the data were checked for missing values, inconsistent units, duplicate entries, and arithmetic errors. Projected or estimated figures were kept separate from independently verified field measurements so that the two types of information were not treated as equivalent.

The proposed smart-bin unit combines an ultrasonic fill-level sensor, microcontroller, communication module, GPS, power supply, data storage, and a monitoring interface. The sensor provides an estimate of how full a bin is, while the communication system makes that information available for collection planning. GPS and GIS are used to

map collection points, roads, vehicles, treatment facilities, and disposal locations. Together, these components are intended to reduce unnecessary travel and allow collection priorities to be adjusted according to actual need [X, XI, XIV–XIX].

The AI-assisted component uses population, household numbers, historical waste generation, and other relevant ward characteristics as possible predictors. Its purpose is to estimate future waste generation and support decisions about vehicle capacity, workforce deployment, and collection scheduling. The prediction model should be evaluated with suitable statistical measures, and where the available dataset is small, its outputs should be treated as exploratory rather than as fully validated predictions [X, XVI, XVII].

IV.i. Research Design

The research design was field-based and data-driven, with the aim of examining MSW generation and evaluating an IoT-enabled management framework for Bishnupur Municipality. Field observations were combined with municipal and household information, waste characterization, ward-level projections, GPS/GIS mapping, smart-bin monitoring, route analysis, and comparison of conventional and technology-supported collection. This combination was chosen because waste-management performance depends on several linked factors, including waste quantity and composition, road networks, collection infrastructure, vehicle capacity, community behaviour, and operational planning [I–XIII].

The work was arranged in five stages: assessment of the existing waste-management system; collection and compilation of ward-level information; characterization and quantification of MSW; design of the IoT–GIS–AI framework; and evaluation of operational, economic, and environmental indicators. The approach was kept practical for a small municipality where budgets, technical staff, communication infrastructure, and maintenance capacity may be limited [X–XIX].

IV.ii. Study Area

The study was carried out in Bishnupur Municipality, Bankura District, West Bengal, India. The municipality includes residential neighbourhoods, commercial and institutional premises, markets, roads, public spaces, and tourism-related locations. These different land-use patterns were considered because they can influence both the amount and composition of waste generated.

For analysis, the municipality was considered ward by ward. Ward boundaries, major roads, storage points, collection locations, transfer points, and disposal or treatment facilities were represented in a GIS environment. This made it possible to compare population, households, estimated waste generation, collection requirements, and route conditions across the municipality. GIS-based planning is particularly useful for collection systems because it can incorporate road networks, collection points, vehicle limitations, and travel distances [X–XIII, XVIII, XIX].

IV.iii. Data Sources and Collection

Primary data were collected through field visits, direct observation, household or establishment surveys, discussions with municipal staff, waste sampling, GPS mapping, and monitoring of selected bins. The field assessment recorded storage

conditions, source segregation, collection frequency, vehicle movement, overflow conditions, and difficulties reported or observed during collection [II, XI].

Secondary information came from municipal records, ward-level population data, household information, collection registers, vehicle records, annual reports, government documents, and the supplied MSW projection dataset. The spreadsheet contains ward-wise values for 19 wards from 2021 to 2026, including year, household number, population, and estimated MSW generation in tonnes per day. The dataset was reviewed for missing entries, inconsistent units, duplicate values, and arithmetic errors.

The spreadsheet figures were treated as projected or estimated values unless they had independent field confirmation. This distinction is important because a projection should not be presented as though it were a direct experimental measurement. Accordingly, projected values and field observations were considered separately in the analysis.

IV.iv. Waste Characterization

Waste characterization was carried out by separating representative samples into biodegradable waste, plastic, paper, glass, metal, and other materials. Sampling locations were selected to reflect the main activities within the municipality, including residential, commercial, institutional, and tourism-related areas where possible. Samples were handled with appropriate protective measures, weighed, manually separated into categories, and recorded [XIV–XVII].

The mass percentage of each waste category was calculated using

$$\mathrm{Pj} = \frac{W_j}{W_T} \times 100 \tag{1}$$

where P_j is the percentage of waste category j,
W_j is the mass of waste category j,
W_T is the total mass of the analysed sample.

The percentages of all waste categories were checked using

$$\sum_{j=1}^{j=m} P_j = 100 \tag{2}$$

where ‘m’ is the total number of waste categories.

The waste-characterization results used in the manuscript show biodegradable waste at 52%, plastic at 18%, paper at 11%, glass at 6%, metals at 4%, and other materials at 9%. The six fractions together account for 100% of the sampled waste. These proportions were then used to estimate the daily mass of individual waste fractions at different total generation levels, which can help in planning composting, anaerobic digestion, recycling, material recovery, and final-disposal capacity [XIV–XVII].
The daily mass of a particular waste fraction was calculated as

$$W_j = \frac{P_j}{100} \times W_T \tag{3}$$

For example, when total projected MSW generation reaches 33.29 tonnes per day, the estimated biodegradable fraction is

$$W_{bio} = \frac{52}{100} \times 33.29 = 17.31\ tones\ per\ day \quad (4)$$

The corresponding estimated plastic fraction is

$$W_{plastic} = \frac{18}{100} \times 33.29 = 5.99\ tones\ per\ day \quad (5)$$

These calculations provide a practical basis for estimating the quantity of individual waste streams and for planning composting, anaerobic digestion, recycling, material recovery, and final disposal facilities [XIV–XVII].

IV.v. Ward-wise waste-generation analysis

Ward-wise waste generation was examined using the supplied projection dataset. For each year, the total municipal waste generation was obtained by summing the estimated waste generation of all wards. This provides a simple way to examine how the municipal waste load changes over time and how requirements may differ among wards.

$$W_T = \sum_{i=1}^{n} W_i \quad (6)$$

where W_T is total municipal MSW generation in tonnes per day, W_i is MSW generation in Ward I, n is the number of wards.

The calculated municipal totals were 28.59 TPD in 2021, 30.11 TPD in 2022, 30.94 TPD in 2023, 31.66 TPD in 2024, 32.31 TPD in 2025, and 33.29 TPD in 2026. The resulting increase from 2021 to 2026 was 16.44%. These figures are based on the supplied projections and should therefore be interpreted as estimated waste-generation trends rather than direct measurements.

$$\%\ increase = \frac{W_{2026} - W_{2021}}{W_{2021}} \times 100 = \frac{33.29 - 28.59}{28.59} \times 100 = 16.44\% \quad (7)$$

where G_p is per-capita generation in kg person-1 day-1, W_i is ward-level waste generation in tonnes per day, P_i is ward population.

For example, Ward 3 had a projected population of 9,013 and projected waste generation of 3.75 TPD in 2026

$$G_p = \frac{1000 \times 3.75}{9013} = 0.416 Kg\ per\ person\ per\ day \quad (8)$$

The per-capita estimate was used only to compare wards with one another. It was not treated as a replacement for direct household-level measurements.

IV.vi. Table Placement and Data Presentation

Table 1. Composition of municipal solid waste in Bishnupur Municipality

Waste category	Percentage (%)
Biodegradable waste	52
Plastic	18
Paper	11
Glass	6
Metal	4
Other materials	9
Total	100

IV.vii. IoT-enabled smart-bin system

The proposed smart-bin system consists of an ultrasonic fill-level sensor, microcontroller, GSM or another suitable communication module, GPS unit, power supply, data-storage platform, and monitoring interface. The ultrasonic sensor measures the empty distance between the sensor and the waste surface. From this distance, the percentage fill level of the bin can be estimated. A collection alert can then be generated when the level reaches a selected threshold, such as 80%, although the threshold should be adjusted for bin capacity, waste density, collection frequency, safety, and local operating conditions [X, XI, XIV–XIX].

$$F = \frac{H-h}{H} \times 100 \tag{9}$$

where F is bin fill level in percentage,
H is the total internal height of the bin,
h is the distance from the sensor to the waste surface.

If the bin height is 100 cm and the measured empty distance is 20 cm:

$$F = \frac{100-20}{100} \times 100 = 80 \tag{10}$$

A collection alert may be generated when the fill level reaches a predefined threshold, such as 80%. In practice, the threshold should be selected according to bin capacity, waste density, collection frequency, safety requirements, and local operating conditions [XI, XV, XIX].

Sensor accuracy should be checked by comparing the readings with manually measured fill levels. The mean absolute error can be used as a simple measure of the difference between the two sets of observations [XI, XV].

$$MAE = \frac{1}{N}\sum_{k=1}^{N}\left|F_k - \widehat{F_k}\right| \tag{11}$$

where F_k is the manually measured fill level,
$\hat{F}_k$ is sensor-estimated fill level,
N is the number of observations.

Averaging or filtering the sensor readings is advisable because dust, moisture, irregular waste surfaces, and movement of the waste can introduce fluctuations into ultrasonic measurements [XI, XV].

IV.viii. GPS and GIS-based route optimization

GPS mapping was used to record collection-point locations and the movement of collection vehicles. The GIS database included ward boundaries, road links, bin locations, collection points, transfer stations, treatment facilities, disposal locations, and vehicle depots. Route planning was based on practical road-network distance rather than straight-line distance. The optimized route was selected while considering travel distance together with vehicle capacity, road accessibility, collection priorities, working hours, and the destination facility [X–XIII, XVIII, XIX].

For a route connecting n collection points, total distance was calculated as:

$$D = \sum_{i=0}^{n-1} d_{i,i+1} \tag{12}$$

where d {i,i+1} is the road-network distance between two consecutive points.

The optimized route was selected by minimizing total travel distance while considering vehicle capacity, road accessibility, collection priorities, working hours, and the location of the disposal or treatment facility:

$$D_{min} = min\left(\sum_{i=0}^{n-1} d_{i,i+1}\right) \tag{13}$$

The percentage reduction in distance was calculated as:

$$\%\ distance\ reduction = \frac{D_c - D_s}{D_c} \times 100 \tag{14}$$

GIS-supported route planning can reduce unnecessary travel and improve collection decisions when road-network and operational constraints are included. For a small municipality, this approach is particularly useful because collection resources can be directed toward locations where the need is greatest [X–XIII, XVIII, XIX].

IV.ix. AI-assisted waste prediction

The AI-assisted prediction component was treated as a decision-support tool rather than as a stand-alone replacement for municipal judgement. Population, household number, historical waste generation, and ward-level characteristics were considered as possible explanatory variables. A simple regression form can be used as an initial model, with its performance assessed through measures such as MAE, RMSE, and RZ [X, XVI, XVII].

$$\widehat{W} = a + b_1 P + b_2 H + b_3 C + \varepsilon \tag{15}$$

where $\hat{W}$ is predicted waste generation, P is population,
H is the number of households,
C is a commercial or activity-related indicator,
a is commercial,
b_1,b_2,b_3 are model coefficients, ε is the error term.

Model performance should be assessed using the mean absolute error

$$MAE = \frac{1}{n}\sum_{k=1}^{N}\left|W_i - \widehat{W_l}\right| \tag{16}$$

and the root mean square error

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{N}(W_i - \widehat{W_l})^2} \tag{17}$$

The coefficient of determination may also be reported:

$$R^2 = 1 - \frac{\sum_{k=1}^{N}(W_i - \widehat{W_l})^2}{\sum_{k=1}^{N}(W_i - \overline{W_l})^2} \tag{18}$$

Where enough observations are available, the model should be trained and tested on separate datasets. If the available data are limited, the resulting predictions should be presented as exploratory estimates rather than as evidence of a fully validated AI system. This precaution is important when applying data-driven methods to small municipalities with relatively limited historical records [XVI, XVII].

IV.x. Performance Evaluation

The conventional and IoT-enabled approaches were compared using collection efficiency, fuel consumption, overflow incidents, segregation efficiency, and operating cost. These indicators were selected because they provide a practical picture of operational performance and resource use.

$$\%\ fuel\ reduction = \frac{F_c - F_s}{F_c} \times 100 \tag{19}$$

Using 92 L day-1 for the conventional system and 65 L day-1 for the smart system

$$\%\ fuel\ reduction = \frac{92-65}{92} \times 100 = 29.35\% \tag{20}$$

Overflow reduction was calculated as:

$$\%\ overlow\ reduction = \frac{O_c - O_s}{O_c} \times 100 \tag{21}$$

Using 34 and 9 incidents per month

$$\%\ overlow\ reduction = \frac{34-9}{34} \times 100 = 73.53\% \tag{22}$$

The reduction in operating cost was calculated as:

$$\%\ cost\ reduction = \frac{C_c - C_s}{C_c} \times 100 \tag{23}$$

Using INR 24,500 and INR 16,000 per day

$$\%\ cost\ reduction = \frac{24500-16000}{24500} \times 100 = 34.69\% \tag{24}$$

Collection-efficiency improvement was reported both as an absolute difference and as a relative improvement

$$\Delta E = E_s - E_c \tag{25}$$

$$\%\, relative\ improvement = \frac{E_s - E_c}{E_c} \times 100 \tag{26}$$

For collection efficiency values of 89% and 58%, the absolute improvement was 31 percentage points, while the relative improvement was approximately 53.4%.

Carbon-dioxide emissions were estimated from fuel use as:

$$M_{co_2} = F \times EF \tag{27}$$

Carbon-dioxide emissions were estimated from fuel consumption using a fuel-specific emission factor. The fuel type and the selected emission factor should be stated clearly and supported by an official or peer-reviewed source before an emission-reduction figure is presented as a firm result. When the same fuel and emission factor are used for both systems, the percentage change in estimated emissions follows the percentage change in fuel consumption.

V. Major Results and Discussion

The analysis indicates a clear rise in municipal waste generation, with total MSW increasing from
28.59 tonnes per day in 2021 to 33.29 tonnes per day in 2026. This represents an estimated increase of about 16.4%. The trend points to a growing need for collection capacity, suitable storage, adequate treatment facilities, and better transport planning. The ward-level figures also vary considerably: in 2026, Ward 3 had the highest projected generation at 3.75 TPD, followed by Ward 19 at 2.89 TPD and Ward 18 at 2.38 TPD, while Ward 13 had the lowest at 0.89 TPD. Such variation supports a ward-specific approach rather than applying an identical collection plan everywhere [I–IX].

Biodegradable material formed the largest part of the characterized waste stream at 52%, followed by plastic at 18% and paper at 11%. This composition points to meaningful opportunities for composting or anaerobic digestion of organic waste and recovery of recyclable materials. However, these benefits depend on effective source segregation. Technology alone cannot guarantee better segregation; awareness, worker training, appropriate containers, supervision, and community participation also matter [I–IX, XII–XVII].

The comparison of the conventional and IoT-enabled approaches shows notable operational gains. Collection efficiency increased from 58% to 89%, an improvement of 31 percentage points, while fuel consumption fell from 92 to 65 litres per day, a reduction of about 29.3%. These changes are consistent with the intended benefits of demand-based collection, real-time monitoring, and GIS-supported route planning, which can reduce unnecessary vehicle movement and improve the use of available resources [X–XIX].

Overflow incidents fell from 34 to 9 per month, corresponding to an approximate reduction of 73.5%. Having timely information about bin conditions can help

municipal staff identify locations that need immediate attention and may reduce litter, odour, complaints, and drainage blockage. At the same time, the size of this reduction should be considered in relation to bin capacity, collection frequency, seasonal conditions, rainfall, public behaviour, and the length of the monitoring period [XI, XV–XIX].

Segregation efficiency increased from 18% to 67%, a gain of 49 percentage points. This indicates greater potential for recycling and resource recovery. For meaningful comparison with other studies, however, the method used to calculate segregation efficiency should be stated explicitly. Daily operating costs also decreased from INR 24,500 to INR 16,000, representing savings of about 34.7%. Lower fuel use, shorter routes, fewer unnecessary trips, and improved deployment of vehicles and workers may all have contributed. A complete economic assessment should also include sensors, communication systems, software, installation, calibration, maintenance, and staff training [X–XIX].

The lower fuel requirement suggests a corresponding possibility of reducing transport-related carbon emissions. If the same fuel type and emission factor are applied to both systems, the estimated emission reduction would be approximately the same as the 29.3% reduction in fuel use. However, the fuel type, emission factor, monitoring period, and calculation procedure should be documented before this is reported as a fully substantiated emissions result.

VII. Data Quality, Ethics, Limitations and Overall Conclusion

Data quality was addressed by checking units, missing values, duplicate observations, and consistency among the tables, figures, equations, and written discussion. Ethical practice included informing field workers and respondents about the purpose of the survey and protecting personal information. The main limitations include the difference between projected and actual waste generation, seasonal and location-related variation in waste composition, sensor errors, equipment failure, traffic and road conditions, vehicle capacity, and changes in collection practices. Improvements in segregation may also have been influenced by awareness programmes, training, supervision, and other operational changes rather than by IoT monitoring alone.

Overall, the study shows that combining IoT-based monitoring, GIS-supported route planning, demand-responsive collection, cloud data management, and AI-assisted forecasting has practical potential for municipal waste management. The results indicate possible improvements in collection efficiency, fuel use, operating costs, overflow control, and source segregation when these tools are used alongside appropriate operational practices [X–20].

A practical starting point would be to introduce the framework in wards with high waste generation or frequent overflow and then expand it gradually across the municipality. The observed improvements should not, however, be attributed entirely to technology because staff involvement, public awareness, supervision, and changes in operating practices may also have played a role. Longer monitoring over different seasons and tourism periods would provide stronger evidence of sustained performance.

In conclusion, the proposed IoT–GIS–Cloud–AI framework offers a promising and locally adaptable route toward more responsive MSW management in Bishnupur Municipality. By linking real-time information about waste conditions with spatial planning and operational decision-making, the system can support more efficient collection, reduce avoidable costs, improve resource recovery, and contribute to cleaner neighbourhoods. Its long-term value will depend on reliable data, appropriate technology, regular maintenance, trained personnel, community participation, and continued performance evaluation. The study therefore provides a practical foundation for developing an affordable, scalable, and resource-efficient waste-management model for small municipalities [X–20].

Conflict of Interest:

There was no relevant conflict of interest regarding this paper.

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