MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 2929-2933

Blockchain-Enabled Smart Waste Management: A Transparent and Efficient Framework for Sustainable Cities

[1]Lubna Yasmin Pinky, Department of Computer Science and Engineering, Mawlana Bhashani Science and Technology University, Tangail, Bangladesh*
[2]Rafia Zaman Mukti, Department of Computer Science and Engineering, Mawlana Bhashani Science and Technology University, Tangail, Bangladesh
[3]Mahbuba Akter Liza, Department of Computer Science and Engineering, Mawlana Bhashani Science and Technology University, Tangail, Bangladesh
Email: [1]lubnacse@mbstu.ac.bd, [2]rzmukti2002@gmail.com, [3]mahbubaleeza319@gmail.com*
Correspondence: lubnacse@mbstu.ac.bd

ABSTRACT

The increasing population, intermittent production of wastes, and ineffective fixed-time collection place additional strain on the urban waste management systems. This study presents the Smart Waste Management System (BSWMS), which is a framework that combines a Hyperledger Fabric blockchain with IoT sensor networks with a new model of Neighborhood-Propagation Overflow Prediction (NPOP). The NPOP model expresses the idea of spatial cascade phenomenon, in which a full bin increases overflow probability in the direct neighboring bins, and generalizes this effect to city-zone scale. It has a presentation of the framework with complete mathematical derivation, a priority-score-based route optimization algorithm, and a step-by-step worked example of calculating propagation scores of a five-bin network. The system proposed provides a theoretically based, practically viable route to active, open, and viable urban waste collection.

Keywords: *Blockchain; Smart Waste Management; IoT; Neighborhood-Propagation; Overflow Prediction; Route Optimization; Sustainable Cities*

1. INTRODUCTION

Unprecedented pressure in municipal solid waste (MSW) infrastructure is caused by rapid urbanization. Conventional inflexible time-based collection schemes do not deal with spatial and temporal differences in waste production, which leads to the regular overflow of bins, health hazards, and unnecessary fuel use [4].

The recent developments in IoT sensors and distributed ledger system have provided an opportunity to data-driven adaptive waste management [5]. Nonetheless, the current IoT-blockchain prototypes consider a bin as a single unit without considering the spatial correlation that is empirically observed in practice with a saturated bin increasing the fill rates of its neighbouring bins, a phenomenon of citizen diversion behavior and the tendency of shared waste patterns [1].

The contributions to this gap in this paper are: (i) the mathematical framework of NPOP — a closed-form model of bin-level and zone-level propagation of overflow; (ii) a propagation-aware route optimization algorithm with a composite priority scoring function; and (iii) a step-by-step worked example of the behavior of the model on a small bin network. The article provides a theoretically based model that can be used as a basis to conduct future research and practical pilots.

2. LITERATURE REVIEW

2.1 IoT-Based Waste Monitoring

Waste monitoring with IoT has gone beyond the threshold alerting concept to predictive modelling. GRUBin [7] is a gated recurrent unit model that predicts fill on a bin level, and was proposed by Mishra et al. with a competitive accuracy but does not achieve any spatial propagation. Ramal et al. [9] used a Hybrid Swin Transformer to classify wastes. John et al. [3] suggested smart prediction and monitoring with the IoT and cloud computing and made the feasibility of real-time bin state monitoring.

2.2 Blockchain for Waste Management

A blockchain-IoT model of smart cities was formalized by Latif et al. [5], and Shaikh et al. [10] demonstrated the presence of blockchain-enabled vehicle network transparency, which can be applied to collection fleets. Priyadarshi et al. [8] suggested dynamic routing of the IoT waste system but without the blockchain immutability assurance.

2.3 Spatial Correlation in Urban Waste

Urban waste has been observed to have a spatial correlation [4] albeit not often formalized. The attention-adjusted spatial-temporal networks (AGSTN) of Lu et al. [6] in urban flow prediction are an idea related to the conceptual model of propagation that is presented here. Anitha et al. [1] used AI, IoT, and graph-based to design smart city waste, which validates the prospect of graph-structured spatial models.

3. CONCEPTUAL FRAMEWORK

The BSWMS is based on the fact of acknowledgment that waste overflow is not an isolated occurrence but a geographically spreading phenomenon. *Figure 1* shows the general data flow: IoT sensors will constantly provide the fill levels of bins; the NPOP model will calculate propagation scores; the scores will be stored in the blockchain through smart contracts; the route optimizer will use the scores to plan proactive collection.

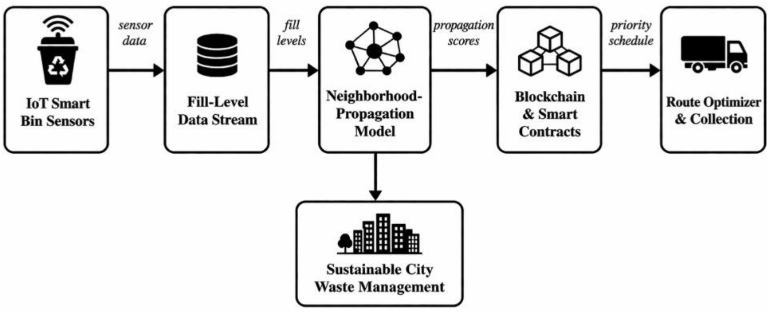

Figure 1: Neighborhood-Propagation Overflow Prediction Framework.

This framework is based on three fundamental concepts:(i) Anticipation — do not act once something is overflowing, but before it becomes overflowing; ii) Spatial awareness — a full bin is not only a signal about itself, but also about its neighbors; (iii) Transparency — all sensor reads, predictions, and collection events are recorded on the blockchain permanently.

4. SYSTEM ARCHITECTURE

Figure 2 presents the overall architecture and operational workflow of the proposed BSWMS, integrating IoT sensing, NPOP-based overflow prediction, blockchain recording, and adaptive route optimization in a closed-loop system.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 2929-2933

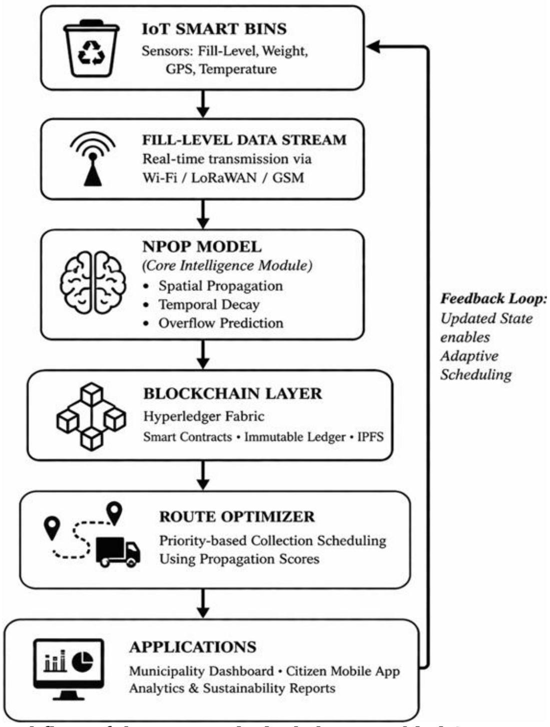

Figure 2: Overall Architecture and Workflow of the Proposed Blockchain-Enabled Smart Waste Management System (BSWMS)

Smart bins have IoT capabilities that record real-time data (fill level, weight, GPS, temperature), and transmit it to the system via a data stream. This data is then processed by the NPOP model to forecast the overflow risk based on the spatial and time propagation. Smart contracts ensure that the outcomes are safely stored in the blockchain layer. The route optimizer uses these predictions to create priority waste collection schedules. The system is closed-loop, with the updated bin states being used to continually increase future predictions and decision-making. The BSWMS is structured across three layers as shown in *Figure 3*.

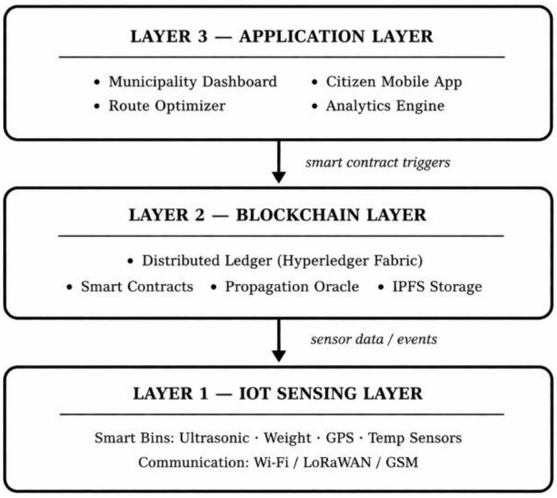

Figure 3: Three-Layer System Architecture of BSWMS.

Layer 1: IoT Sensing Layer: Every smart bin has an ultrasonic fill-level sensor, a load cell, a temperature/humidity sensor and a GPS module. Transmissions are made at a frequency of Δt minutes through the LoRaWAN, Wi-Fi, or GSM network to an edge gateway to transmit readings.

Layer 2: Blockchain Layer: Hyperledger Fabric based on Proof-of-Authority (PoA) consensus. Propagation Oracle chaincode implements the NPOP model on-chain and generates OverflowRisk events. IPFS stores raw time-series data; the only data that is written to the ledger are cryptographic hashes and calculated metrics.

Layer 3: Application Layer: Consists of a real-time municipality dashboard, a citizen mobile application with recycling incentives, a route optimizer, and an analytics engine on sustainability reporting.

5. NPOP MODEL: MATHEMATICAL FORMULATION

5.1 Problem Statement

Let $\mathcal{B} = \{b_1, b_2, \dots, b_n\}$ be the set of n smart bins deployed across the city. Each bin b_i at time t is characterised by its normalised fill level $W_i(t) \in [0,1]$. The binary overflow indicator is: $O_i(t) = \begin{cases} 1 & \text{if } W_i(t) \geq \theta \\ 0 & \text{otherwise} \end{cases}$ ……… (1)

where θ is the overflow threshold (typically 0.90). The goal of NPOP is to predict $O_i(t + \Delta t)$ before it occurs, leveraging both the bin's own fill trajectory and the fill levels of spatially proximate bins.

5.2 Bin-Level Spatial Weight Matrix

The spatial influence of bin bj on bin bi is quantified by a distance-decay weight:

$$w_{ij} = \begin{cases} \dfrac{1}{d(i,j)^{\alpha}} & \text{if } d(i,j) \leq R \text{ and } j \neq i \\ 0 & \text{otherwise} \end{cases} \quad \dots\dots\dots (2)$$

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1s, 2026, Pages: 2929-2933

where $d(i,j)$ is the Euclidean distance between bins b_i and b_j (metres), R is the spatial influence radius, and $\alpha > 0$ is the distance decay exponent. Each row is normalized to sum to unity:

$$\tilde{w}_{ij} = \frac{w_{ij}}{\sum_k w_{ik}} \text{ ... ... (3)}$$

5.3 Bin-Level Propagation Probability

The overflow propagation probability for bin b_i at the next time step is:

$$P(i, t+1) = \sigma\left(\beta_0 W_i(t) + \beta_1 \sum_j \tilde{w}_{ij} W_j(t) + \beta_2 \Delta W_i(t)\right) \text{ ... ... (4)}$$

Here $\sigma(\cdot)$ is the sigmoid function $\sigma(x) = 1/(1+e^{-x})$, $\Delta W_i(t) = W_i(t) - W_i(t-1)$ is the fill rate, and β_0, β_1, β_2 are model coefficients to be calibrated from field data. Recommended initial values are $\beta_0 = 0.55$ (own fill weight), $\beta_1 = 0.38$ (neighbour influence), $\beta_2 = 0.07$ (fill rate weight).

5.4 Zone-Level Propagation

For large urban deployments, bins are grouped into city zones $\mathcal{Z} = \{z_1, z_2, \ldots, z_m\}$. The aggregate fill level of zone z_k is:

$$F(z_k, t) = \frac{1}{|z_k|} \sum_{i \in z_k} W_i\,(t) \text{ ... ... (5)}$$

A zone-level spatial weight v_{kl} (analogous to w_{ij}) is defined over inter-zone centroid distances with decay exponent γ. The zone overflow probability is:

$$P(z_k, t+1) = \sigma\left(\phi_0 F(z_k, t) + \phi_1 \sum_l \tilde{v}_{kl}\, F(z_l, t)\right) \text{ ... ... (6)}$$

where ϕ_0 and ϕ_1 are zone-level coefficients.

5.5 Temporal Decay

Overflow risk decays if a bin has not been refilling rapidly:

$$\tau(t) = e^{-\mu \cdot (t - t_{\text{last}})} \text{ ... ... (7)}$$

$$\hat{P}(i, t+1) = \tau(t) \cdot P(i, t+1) \text{ ... ... (8)}$$

where $\mu > 0$ is the decay rate and t_{last} is the time of the last sensor reading.

5.6 Composite Priority Score

The composite priority score for bin bi, used by the route optimizer:

$$\Pi_i(t) = \alpha_1 W_i(t) + \alpha_2 \hat{P}(i, t+1) + \alpha_3 \frac{t - t_{\text{last}}}{T_{\max}} + \alpha_4 P(z_k, t+1) \text{ ... ... (9)}$$

Weights: $\alpha 1 = 0.35$ (current fill), $\alpha 2 = 0.30$ (propagation risk), $\alpha 3 = 0.20$ (time since last collection), $\alpha 4 = 0.15$ (zone-level pressure). All weights sum to 1.0.

6. ROUTE OPTIMISATION ALGORITHM

The propagation-based collection scheduling algorithm is provided in Algorithm 1.

Algorithm1: Propagation-Aware Collection Scheduling

Input: Bin set $\mathcal{B}$, fill levels $\{W_i\}$, weight matrix $\widetilde{W}$
Output: Ordered collection schedule S
1: Compute $P(i, t+1)$ for all b_i via Eq. (4)
2: Compute $\tau(t)$ and $\hat{P}(i, t+1)$ via Eqs. (7)–(8)
3: Compute zone scores $P(z_k, t+1)$ via Eq. (6)
4: Compute $\Pi_i(t)$ for all b_i via Eq. (9)
5: Sort bins: $\Pi_{\sigma(1)} \geq \Pi_{\sigma(2)} \geq \cdots \geq \Pi_{\sigma(n)}$
6: $S \leftarrow [\,]$; $\mathcal{U} \leftarrow \mathcal{B}$
7: for each bin $b_{\sigma(k)}$ in sorted order do
8:   if $\Pi_{\sigma(k)} \geq \Pi_{min}$ and $b_{\sigma(k)} \in \mathcal{U}$ then
9:     Append $b_{\sigma(k)}$ to S
10:     Remove $b_{\sigma(k)}$ from $\mathcal{U}$
11:     for each neighbour b_j of $b_{\sigma(k)}$ within radius R do
12:       $\hat{P}(j, t+1) \leftarrow \rho \cdot \hat{P}(j, t+1)$
13:       Recompute $\Pi_j(t)$; re-sort $\mathcal{U}$ S
14:     end for
15:   end if
16: end for
17: return S

The most important innovation is the reduction of the neighbour score (line 12): once bin bi has been scheduled, the propagation scores of its neighbours are scaled down by factor ρ to avoid unnecessary scheduling of bins that were only scheduled by being next to a previously-scheduled bin.

The algorithm runs in $O(n \cdot k \cdot \log n)$ time, where k is the average neighbourhood size (bins within radius R). The reduction factor $\rho \in (0,1)$ is a tunable parameter; a value of $\rho = 0.3$ is recommended as a starting point.

7. WORKED EXAMPLE

To illustrate the NPOP model concretely, consider a network of five bins $\{b_1, \ldots, b_5\}$with fill levels and pairwise distances shown in Table 1. In this example, color-coded by fill level, showing the 300 m propagation influence zone of bin b_1 and the resulting overflow risk arrows are depicted in *figure 4*..

Table 1: Five-Bin Example — Fill Levels and Distances

Bin	$W_i(t)$	ΔW_i	$d(i,1)$	$d(i,2)$	$d(i,3)$
b_1	0.88	0.05	—	120	280
b_2	0.45	0.08	120	—	200
b_3	0.60	0.03	280	200	—
b_4	0.30	0.01	420	310	150
b_5	0.72	0.06	180	90	250

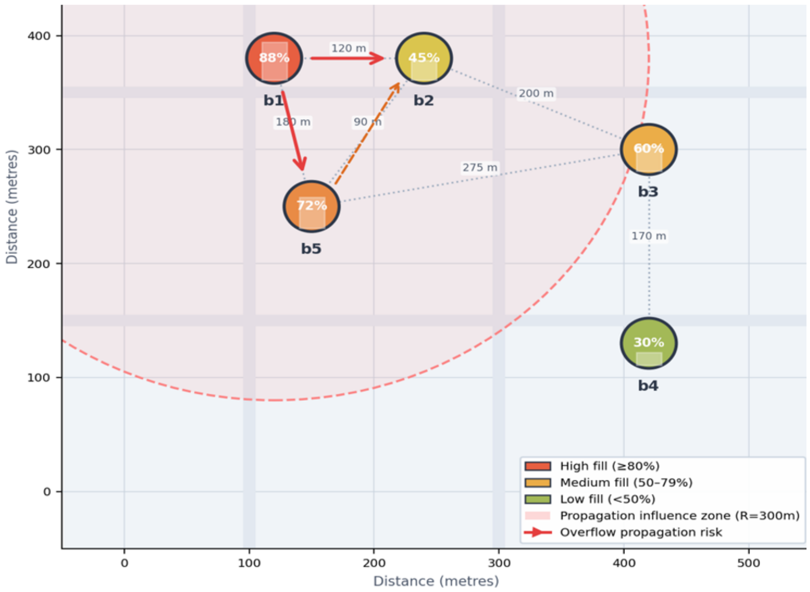

Figure 4: Bin Neighborhood Map: spatial layout of the five-bin.

Step 1: Spatial weights for b_2 (neighbours within $R = 300$m).
Bins within 300m of b_2: b_1 ($d = 120$), b_3 ($d = 200$), b_5 ($d = 90$). Using $\alpha = 1.5$:

$$w_{21} = \frac{1}{120^{1.5}} = \frac{1}{1314.5} = 7.61 \times 10^{-4}$$
$$w_{23} = \frac{1}{200^{1.5}} = \frac{1}{2828.4} = 3.54 \times 10^{-4}$$
$$w_{25} = \frac{1}{90^{1.5}} = \frac{1}{853.8} = 1.17 \times 10^{-3}$$

Sum $= 7.61 + 3.54 + 11.7 = 22.85 \times 10^{-4}$.
Normalized: $\tilde{w}_{21} = 0.333$, $\tilde{w}_{23} = 0.155$, $\tilde{w}_{25} = 0.512$.

Step 2: Propagation probability for b_2.
Neighbourhood fill: $\sum_j \tilde{w}_{2j} W_j = 0.333(0.88) + 0.155(0.60) + 0.512(0.72) = 0.293 + 0.093 + 0.369 = 0.755$.
Logit: $\beta_0(0.45) + \beta_1(0.755) + \beta_2(0.08) = 0.55(0.45) + 0.38(0.755) + 0.07(0.08) = 0.541$.

$$P(2, t+1) = \sigma(0.541) = \frac{1}{1 + e^{-0.541}} = 0.632$$

Step 3: Propagation probability for b_1.
b_1 neighbours within 300m: b_2 ($d = 120$), b_5 ($d = 180$).
$w_{12} = 7.61 \times 10^{-4}$, $w_{15} = \frac{1}{180^{1.5}} = \frac{1}{2415.0} = 4.14 \times 10^{-4}$.
Normalized: $\tilde{w}_{12} = 0.648$, $\tilde{w}_{15} = 0.352$.
Neighbourhood fill: $0.648(0.45) + 0.352(0.72) = 0.292 + 0.253 = 0.545$.
Logit: $0.55(0.88) + 0.38(0.545) + 0.07(0.05) = 0.484 + 0.207 + 0.004 = 0.695$.

$$P(1, t+1) = \sigma(0.695) = 0.667$$

Step 4: Temporal decay (assume $t - t_{\text{last}} = 1$ hr, $\mu = 0.15$):

$$\tau = e^{-0.15\times 1} = 0.861$$

$\hat{P}(1) = 0.861 \times 0.667 = 0.574$; $\hat{P}(2) = 0.861 \times 0.632 = 0.544$.

Step 5: Priority scores (zone scores $P(z_k) = 0.50$ for all bins; $T_{\max} = 8$ hr, $t - t_{\text{last}} = 1$ hr):

$$\begin{aligned} \Pi_1 &= 0.35(0.88) + 0.30(0.574) + 0.20(0.125) + 0.15(0.50) \\ &= 0.308 + 0.172 + 0.025 + 0.075 = 0.580 \\ \Pi_2 &= 0.35(0.45) + 0.30(0.544) + 0.20(0.125) + 0.15(0.50) \\ &= 0.158 + 0.163 + 0.025 + 0.075 = 0.421 \\ \Pi_5 &= 0.35(0.72) + 0.30(0.544) + 0.20(0.125) + 0.15(0.50) \\ &= 0.252 + 0.163 + 0.025 + 0.075 = 0.515 \end{aligned}$$

Outcome: The algorithm schedules b_1 first (highest Π), then b_5, then b_2 — even though b_2 has only 45% fill. Its high propagation score (driven by the nearly-full b_1 at 120m) correctly flags it as the next overflow risk. After scheduling b_1, the propagation scores of b_2 and b_5 are reduced by $\rho = 0.3$, preventing redundant scheduling.

8. SMART CONTRACT DESIGN

NPOP model is a Hyperledger Fabric chaincode with three fundamental functions:

(i) ***updateBinState(binID, fillLevel, ts)***: validates sensor data, creates a BinStateEvent in the ledger, and initiates the propagation score recalculation of all bins in radius R.

(ii) ***scheduleCollection(binID):*** called when $\Pi_i(t) > \Pi_{\min}$. Produces a CollectionScheduled event and decreases propagation scores of neighbours by $\boldsymbol{\rho}$.

(iii) ***distributeIncentive(citizenID, pts):*** tokens are awarded when a deposit event is verified, forming a gamified series of participation that drives waste sorting rates up.

Every transaction gets copied to the ledger and this offers an immutable audit trail of municipal accountability and compliance with regulations.

9. DISCUSSION

9.1 Theoretical Advantages

There exist three theoretical benefits that the NPOP model has over current methods. To begin with, because overflow is a spatially spreading phenomenon, the model facilitates proactive scheduling of overflow - bins are not filled until they overflow, but rather filled in advance. Second, the two-level formulation is able to capture local diversion behaviour as well as macro-urban mobility patterns. Third, the temporal decay term does not allow stale predictions to contribute to unnecessary collection trips.

9.2 Parameter Calibration

Field data is needed to calibrate the model parameters $(\boldsymbol{\beta_0}, \boldsymbol{\beta_1}, \boldsymbol{\beta_2}, \boldsymbol{\alpha}, \boldsymbol{R}, \boldsymbol{\mu})$. A principled estimation procedure is obtained through logistic regression on historical overflow events using spatial neighbourhood fill as features. Where no historical data is available, the default values in Section 5 are theoretically-driven starting points.

9.3 Limitations and Future Work

The framework currently fails to consider: (i) non-stationary waste generation mode (e.g. festivals, seasonal variation); (ii) sensor failures and missing data imputation; (iii) dynamic zone boundary descriptions. Future effort must focus on empirical validation using a controlled pilot deployment, weather and event-calendar data integration, and hazardous wastes streams.

10. CONCLUSION

The current paper suggested BSWMS, a blockchain-based smart waste management system that also uses a new prediction model, which is the Neighborhood-Propagation Overflow Prediction (NPOP). The NPOP model formalizes waste overflow as a spatially cascading process, at a bin-level (distance-decay spatial weights) and zone-level (aggregate fill propagation). A route optimization algorithm that uses priority-score to map the propagation scores into practical collection schedules and a five-bin worked example shows how the model works in detail.

The implementation of Hyperledger Fabric offers immutable audit trails, automatic distribution of incentives, and transparent collection records. The framework can provide a theoretically based, modular, and practically implementable base of next-generation smart waste management systems. The first way to work in the future is to prove empirically with real-world pilot deployment.

11. ACKNOWLEDGEMENT

The authors would also like to acknowledge the anonymous reviewers whose contributions regarding their comments on this work were very constructive and useful in improving the quality of the work. This study was done independently and was not funded externally. The use of AI-based applications, such as Grammarly and ChatGPT, was only applied to enhance the grammatical clarity, linguistic quality and enhance visual representation of diagrams of the manuscript.

REFERENCES

[1] Anitha, P., et al. (2025). AI-IoT-graph synergy for smart city waste management. Smart Cities, 8(1), 1–22.
[2] Gatti, F., et al. (2024). Greener smart cities: A systematic review of IoT-based waste management. Sustainability, 16(4), 1523.
[3] John, A., et al. (2021). Smart prediction and monitoring of waste management using IoT and cloud. Environmental Science and Pollution Research, 28, 13433–13445.
[4] Johnson, N. D., et al. (2017). Waste generation patterns in urban areas: A spatial analysis. Waste Management, 68, 550–558.
[5] Latif, S., et al. (2019). A formal model for blockchain-IoT-based smart cities. IEEE Access, 7, 180135–180150.
[6] Lu, Z., et al. (2020). AGSTN: Attention-adjusted spatial-temporal networks for urban flow prediction. IEEE Trans. Intelligent Transportation Systems, 22(11), 7101–7113.
[7] Mishra, R., et al. (2022). GRUBin: Gated recurrent units for smart bin fill-level forecasting. Waste Management, 148, 1–12.
[8] Priyadarshi, N., et al. (2023). Dynamic routing for IoT-enabled smart waste collection. IEEE Internet of Things Journal, 10(8), 7200–7212.
[9] Ramal, M., et al. (2025). Hybrid Swin Transformer for waste classification in smart bins. Applied Intelligence, 55, 1–15.
[10] Shaikh, F., et al. (2025). Blockchain-enabled VANET for transparent waste fleet management. Vehicular Communications, 42, 100612.
[11] SmartWasteNet. (2025). CNN-LSTM reinforcement learning for dynamic waste collection scheduling. Neural Computing and Applications, 37, 1–18.
[12] IoT-Based Route Recommendation for Waste Collection. (2022). IEEE Access, 10, 45231–45244.