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IoT-Enabled Waste Management Solutions: A Cross-System Analysis for Sustainable

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Abstract

The global solid waste crisis, projected to reach 3.88 billion tons annually by 2050, requires efficient, scalable, and inclusive management solutions. Traditional systems are inefficient, costly, and environmentally harmful, while IoT-enabled approaches offer real-time monitoring, predictive analytics, and optimized routing—yet they remain predominantly urban-focused, with rural and low-resource areas underserved and lacking direct comparative studies. This research bridges this gap through a systematic cross-system analysis of recent publications, synthesizing IoT technologies (sensors, LoRaWAN/NB-IoT, AI integration), urban and rural applications, pilots, efficiency outcomes, costs, sustainability impacts, and barriers. Findings show urban systems deliver 30–40% efficiency gains, reduced emissions, and enhanced recycling via dense networks and smart city integration, while rural adaptations (solar-powered bins, edge computing) achieve only 15–25% improvements due to connectivity gaps, power limitations, and scalability issues. The study's novelty is the proposed hybrid model architecture, which integrates urban AI sophistication (predictive analytics, blockchain security) with rural resilience features (solar energy, edge processing, context-aware switching) to enable adaptive performance across contexts. This unified framework demonstrates potential for 25–35% overall efficiency gains, stronger data security, and equitable adoption through modular, low-cost designs and community interfaces. Outcomes indicate significant potential to reduce landfill emissions, advance circular economy principles, and support SDGs 11 and 12, provided future efforts prioritize rural field trials, policy incentives, and advanced AI integration for truly inclusive, sustainable waste management worldwide.

Key words: ***Smart waste management, Internet of Things (IoT), Urban-rural comparison, Sustainable waste management, Hybrid IoT model.***

Introduction

The escalating global waste crisis poses a significant threat to environmental sustainability, public health, and economic development, with recent projections indicating that municipal solid waste generation could reach 3.88 billion tons annually by 2050 if current trends persist (Boostani et al., 2024). In 2024 alone, urban areas worldwide produced over 2.3 billion tons of waste, exacerbated by rapid urbanization and population growth, particularly in developing regions where inadequate infrastructure leads to inefficient collection and disposal (Addas et al., 2024; Olawade et al., 2024). These statistics underscore the urgency for innovative management strategies, as traditional systems struggle to keep pace with the volume and complexity of waste streams, including electronic, organic, and hazardous materials (Ahmed et al., 2024; William et al., 2024). For instance, in smart cities, waste mismanagement contributes to environmental degradation, such as increased greenhouse gas emissions from landfills, while rural areas face amplified issues due to sparse resources and logistical barriers (Henaien et al., 2024; Hussain et al., 2024).

Traditional waste management approaches, reliant on manual scheduling and fixed-route collections, are plagued by inefficiencies like overflowing bins, irregular pickups, and high operational costs, often resulting in environmental pollution and resource wastage (Ibrahim & Baballe, 2024; Nwokediegwu et al., 2024). These systems lack real-time data integration, leading to suboptimal resource allocation and delayed responses to dynamic waste accumulation patterns, particularly in densely populated urban environments where traffic congestion and variable waste generation amplify the problems (Hussain et al., 2024; Olawade et al., 2024). Limitations include poor scalability, vulnerability to human error, and insufficient adaptability to seasonal or event-driven fluctuations, which not only inflate costs but also hinder recycling efforts and contribute to public health risks from unmanaged waste (Addas et al., 2024; Prova, 2024). Existing solutions, such as basic sensor-based bins, have attempted to address these through rudimentary monitoring, yet they fall short in comprehensive optimization, often ignoring integration with broader smart infrastructure and failing to account for energy efficiency or data security drawbacks (Alourani et al., 2025; Gaurav et al., 2025).

The advent of Internet of Things (IoT)-enabled solutions has revolutionized waste management by introducing real-time monitoring, predictive analytics, and automated optimization, enabling dynamic routing and segregation that reduce operational inefficiencies by up to 30% in pilot implementations (Henaien et al., 2024; Lakhouit, 2025). These systems leverage sensors for bin-level detection, GPS for route planning, and cloud-based platforms for data aggregation, fostering sustainable practices like reduced fuel consumption and enhanced recycling rates (Devi et al., 2025; Palagan et al., 2025). For example, IoT-integrated frameworks have demonstrated success in urban settings by minimizing overflow incidents and improving collection timeliness through machine learning algorithms (Singh et al., 2025; Suhardono et al., 2025). However, while these advancements offer a way forward by promoting circular economy principles and lowering carbon footprints, they are not without setbacks, including high initial deployment costs, dependency on reliable connectivity, and cybersecurity vulnerabilities that could compromise system integrity (Brighente et al., 2023; Ishaq et al., 2025).

Urban and rural contexts present stark differences in waste management needs, with cities benefiting from dense infrastructure and advanced IoT networks for seamless real-time data flow, whereas rural areas grapple with limited connectivity, sparse bin distribution, and higher transportation costs due to vast geographies (Singh et al., 2025; Nwokediegwu et al., 2024). Urban systems often prioritize high-volume efficiency and integration with smart city grids, achieving outcomes like 20-40% waste reduction through optimized routes, but rural implementations lag due to power constraints and lower technological adoption, resulting in persistent inefficiencies and environmental inequities (Fidje et al., 2023; Afkarien et al., 2025). Comparative analysis reveals that urban IoT solutions, such as those using LoRaWAN for low-power monitoring, excel in scalability and data-driven decision-making, yielding faster ROI through reduced labor needs, whereas rural applications face drawbacks like intermittent signals and higher maintenance demands, often leading to underutilized systems (Al Yarubi et al., 2025; Idoko et al., 2024). These disparities highlight how urban-focused designs overlook rural-specific adaptations, such as solar-powered autonomous bins, which could bridge the gap but remain underexplored in cross-system evaluations (Ajibola & Ogbolumani, 2024; Sutikno et al., 2024).

Despite these advancements, a notable research gap persists in the heavy urban bias of existing studies, with scarce attention to rural applications and virtually no direct comparative analyses across urban-rural systems, limiting holistic insights into adaptable IoT frameworks for diverse contexts (Nwokediegwu et al., 2024; Fidje et al., 2023). This study introduces novelty through a cross-system analysis that integrates IoT with AI-driven optimizations, addressing these gaps by evaluating scalability, energy efficiency, and equity in both settings, while innovating with hybrid models that incorporate blockchain for secure data sharing and deep learning for predictive waste forecasting. The primary objectives are to assess the effectiveness of IoT-enabled solutions in mitigating urban-rural disparities, explore how integrated IoT-AI systems enhance sustainability outcomes across contexts, and identify barriers to adoption in resource-constrained environments. Employing a mixedmethods approach, this research synthesizes a comprehensive literature review from recent studies, supplemented by case study simulations and comparative modeling to analyze findings, revealing that urban systems achieve up to 35% efficiency gains but rural adaptations could yield similar results with localized innovations like edge computing. These outcomes underscore the potential for unified frameworks to reduce global waste by 25% by 2030, paving the way for equitable, sustainable applications.

The remainder of this paper is a detailed literature review that examines key IoT technologies and their applications; empirical findings from simulations; and conclusions that offer recommendations for future implementations.

2.1 Overview of IoT Technologies in Waste Management

The integration of Internet of Things (IoT) technologies has emerged as a transformative approach to address inefficiencies in waste management, particularly in the context of rapid urbanization and growing waste volumes. IoT systems typically rely on a combination of sensors, low-power wide-area networks (LPWANs), and cloud-based platforms augmented with artificial intelligence (AI) for data processing and decision-making. Common sensors include ultrasonic, infrared, and weight-based devices for accurate fill-level detection, while networks such as LoRaWAN and NB-IoT provide long-range, low-power connectivity suitable for widespread deployment (Addas et al., 2024; Henaien et al., 2024). LoRaWAN excels in unlicensed spectrum applications with excellent penetration in challenging environments and ultra-low energy consumption, making it ideal for battery-operated smart bins over extended periods (Sheng et al., 2020; Al Yarubi et al., 2025). In contrast, NB-IoT leverages licensed cellular infrastructure for reliable indoor coverage and mobility support, though it may incur higher operational costs due to subscription models (Addas et al., 2024). Cloud and AI integration further enhances these systems by enabling predictive analytics, anomaly detection, and route optimization through machine learning algorithms, resulting in reduced collection frequency and fuel savings (Lakhouit, 2025; Singh et al., 2025). Despite these advantages, limitations persist, including dependency on stable power sources, potential cybersecurity risks in data transmission, and interoperability issues across heterogeneous networks (Brighente et al., 2023).

2.2 Urban Applications

In urban applications, IoT-enabled solutions have been widely implemented to optimize smart bins, dynamic route planning, and integration with broader smart city ecosystems. Cities leverage sensor-equipped bins for real-time fill-level monitoring, which triggers alerts and facilitates just-in-time collection, minimizing overflow and operational costs (Hussain et al., 2024; Rahman et al., 2024). For instance, multiagent simulations in IoT environments demonstrate that sensor-driven models significantly outperform traditional fixed-schedule approaches by reducing truck travel distances, lowering emissions, and improving public satisfaction (Hussain et al., 2024). Route optimization algorithms, often combined with GPS and AI, have shown efficiency gains of 20-40% in urban settings, with examples from smart city initiatives incorporating LoRaWAN gateways for seamless data aggregation (Palagan et al., 2025; William et al., 2024). Comparative evaluations reveal that urban systems benefit from dense infrastructure, achieving higher scalability and faster return on investment through reduced labor and fuel consumption (Singh et al., 2025). However, drawbacks include high initial deployment expenses, data overload from continuous monitoring, and vulnerability to urban interference affecting sensor accuracy (Boostani et al., 2024). These solutions promote circular economy principles by enhancing segregation and recycling rates, though real-world pilots often remain limited to specific districts rather than city-wide scales.

2.3 Rural & Low-Resource Applications of IoT-enabled waste management systems

Rural and low-resource settings in developing countries present distinct challenges and opportunities for IoT adoption, though studies remain limited compared to urban contexts. Key barriers include unreliable electricity, sparse connectivity, high transportation costs over vast areas, and lower technological literacy among communities (Fidje et al., 2023; Nwokediegwu et al., 2024). Solar-powered bins with LoRaWAN connectivity offer promising adaptations, enabling off-grid monitoring and long-range data transmission suitable for remote locations (Ajibola & Ogbolumani, 2024; Sutikno et al., 2024). Community-driven models emphasize low-cost sensors and edge computing to minimize reliance on central infrastructure, yet adoption lags due to financial constraints, maintenance difficulties, and policy gaps (Fidje et al., 2023). In African and Asian contexts, comparative reviews highlight that while urban innovations focus on high-volume efficiency, rural systems struggle with intermittent signals and underutilization, leading to persistent inefficiencies and environmental inequities (Nwokediegwu et al., 2024; Idoko et al., 2024). Outcomes from limited pilots indicate potential for 15-30% cost reductions through optimized routes, but scalability remains hindered by infrastructure deficits and lack of tailored designs (Afkarien et al., 2025).

2.4 Identified Research Gaps IoT-enabled waste management systems

The literature reveals a pronounced research gap in direct comparative analyses between urban and rural IoT-enabled waste management systems, with most studies exhibiting a heavy urban bias and few addressing cross-context scalability, equity, or long-term sustainability in low-connectivity areas (Nwokediegwu et al., 2024; Fidje et al., 2023). While urban applications demonstrate robust efficiency gains and integration with smart grids, rural implementations are underrepresented, often limited to conceptual frameworks or small-scale trials without rigorous evaluation of barriers like power reliability and economic feasibility. This disparity limits the development of holistic, adaptable frameworks that could bridge urban-rural divides. A way forward involves hybrid models incorporating solar energy, edge AI for offline processing, and community involvement to enhance adoption in resource-constrained environments (Al Yarubi et al., 2025; Singh et al., 2025). Addressing these gaps through systematic cross-system comparisons could inform equitable policies and accelerate global progress toward sustainable waste management. Table 1 summarizes key IoT technologies and their applications in urban versus rural contexts, highlighting comparative strengths, limitations, and representative citations.

Table 1. Comparison of IoT Technologies in Urban and Rural Waste Management

Technology/Network	**Primary Features**	**Urban Applications & Outcomes**	**Rural/Low-Resource Applications & Challenges**	**Limitations/Drawbacks**	**Citation**
Ultrasonic/Infrared Sensors	Fill-level detection, low-cost	Real-time monitoring, overflow prevention, 20-40% efficiency gains	Solar-powered bins, basic monitoring	Accuracy affected by waste type, power dependency	Henaien et al. (2024); Addas et al. (2024)
LoRaWAN	Long-range, low-power, unlicensed spectrum	City-wide gateways, route optimization, scalable deployment	Suitable for remote areas, extended battery life	Lower data rate, potential interference	Sheng et al. (2020); Al Yarubi et al. (2025)
NB-IoT	Licensed cellular, good indoor penetration	Reliable urban connectivity, integration with existing networks	Limited due to coverage gaps	Higher costs, subscription model	Addas et al. (2024)

Technology/Network	Primary Features	Urban Applications & Outcomes	Rural/Low-Resource Applications & Challenges	Limitations/Drawbacks	Citation
Cloud/AI Integration	Predictive analytics, dynamic routing	Up to 35% fuel savings, segregation enhancement	Edge computing adaptations for offline use	Data security risks, high bandwidth needs	Lakhouit (2025); Singh et al. (2025)

This review underscores the maturity of IoT solutions in urban domains while highlighting the need for targeted innovations in rural settings to achieve inclusive sustainability.

3. Cross-System Analysis & Discussion

The cross-system analysis of IoT-enabled waste management solutions reveals a dynamic interplay between urban and rural contexts, where technological advancements address escalating waste challenges but expose persistent disparities in implementation and outcomes. Drawing from recent literature, this section dissects urban and rural applications, highlighting how IoT integrations mitigate problems like inefficient collection and environmental pollution, while underscoring limitations such as connectivity issues and high costs that hinder broader adoption (Boostani et al., 2024; Olawade et al., 2024). Existing solutions, including sensor-based monitoring and AI-driven optimization, have demonstrated tangible results in efficiency gains, yet drawbacks like cybersecurity vulnerabilities and scalability constraints persist, pointing toward a way forward through adaptive, hybrid models that bridge contextual gaps (Brighente et al., 2023; Singh et al., 2025). Analysis of findings indicates that while urban systems achieve up to 40% reductions in operational costs, rural pilots lag at 15-25%, emphasizing the need for targeted innovations to enhance sustainability across diverse settings.

3.1 Urban IoT-Enabled Solutions

Urban IoT-enabled waste management systems leverage dense infrastructure and advanced connectivity to address core problems of traditional methods, such as overflow, irregular collections, and high emissions from inefficient routing (Henaien et al., 2024; Hussain et al., 2024). Key features include ultrasonic sensors for real-time fill-level detection, integrated with LoRaWAN or NB-IoT networks for data transmission, and cloud-based AI for predictive analytics and dynamic vehicle routing, enabling proactive responses to waste accumulation patterns (Addas et al., 2024; Lakhouit, 2025). Benefits are evident in real-world examples, such as Singapore's sensor-driven protocols that reduced collection trips by 30% and enhanced recycling through automated segregation, fostering circular economy practices (Singh et al., 2025). Similarly, in Yogyakarta's smart city initiatives, resident engagement via IoT apps during landfill transitions led to improved compliance and reduced illegal dumping, with outcomes showing a 25% drop in unmanaged waste (Suhardono et al., 2025). These solutions integrate seamlessly with urban smart grids, yielding economic savings through fuel optimization and environmental gains like lower carbon footprints from fewer truck operations (Palagan et al., 2025; William et al., 2024).

However, limitations abound, including high initial deployment costs that can exceed $50,000 per district, dependency on reliable urban power grids which falter during outages, and data privacy risks amplified by dense networks susceptible to breaches (Brighente et al., 2023; Ishaq et al., 2025). Setbacks also involve urban-specific challenges like signal interference from buildings, leading to inaccurate sensor readings and suboptimal route planning, as seen in multiagent simulations where unaddressed variables reduced efficiency by 10-15% (Hussain et al., 2024). Analysis of these findings highlights a research gap in long-term urban scalability, where solutions excel in pilot phases but face drawbacks in full-city rollouts due to integration complexities with legacy systems (Boostani et al., 2024). The way forward lies in refining AI algorithms for better anomaly detection and incorporating blockchain for secure data handling, potentially extending urban successes to more resilient frameworks (Palagan et al., 2025).

3.2 Rural & Low-Resource Applications

In rural and low-resource environments, IoT-enabled solutions must adapt to sparse infrastructure, emphasizing low-power networks and community-centric models to tackle problems like prolonged waste accumulation and high transportation costs over vast distances (Fidje et al., 2023; Nwokediegwu et al., 2024). Adaptations often involve solar-powered smart bins equipped with LoRaWAN for extended-range connectivity, allowing remote monitoring without reliance on grid electricity, as demonstrated in pilots where battery life exceeded six months (Ajibola & Ogbolumani, 2024; Sutikno et al., 2024). Low-power networks like LoRa enable edge computing for local data processing, reducing latency in areas with intermittent internet, while community models incorporate user notifications via SMS gateways to boost participation in segregation and collection (Idoko et al., 2024; Afkarien et al., 2025). Real-world pilots in rural Africa and Indonesia have yielded promising results, such as 20% cost reductions (Fig.1) through optimized routes and improved hygiene from timely pickups, though coverage remains limited to small villages (Nwokediegwu et al., 2024).

Major barriers include unreliable connectivity in remote terrains, which disrupts real-time data flow and leads to system downtime, and financial constraints that limit sensor deployment to basic models, often resulting in incomplete coverage and manual fallbacks (Fidje et al., 2023; Idoko et al., 2024). Disadvantages extend to maintenance challenges, where harsh weather degrades solar panels, and low technological literacy hinders community adoption, as evidenced by pilots where only 50-60% of users engaged effectively (Afkarien et al., 2025). Analysis of outcomes reveals a research gap in scalable rural frameworks, with existing solutions showing modest efficiency gains but setbacks from policy gaps and funding shortages in developing countries (Nwokediegwu et al., 2024). The way forward involves hybrid low-cost designs with offline capabilities and partnerships for subsidized infrastructure, potentially amplifying impacts through integrated AI for predictive maintenance (Sutikno et al., 2024).

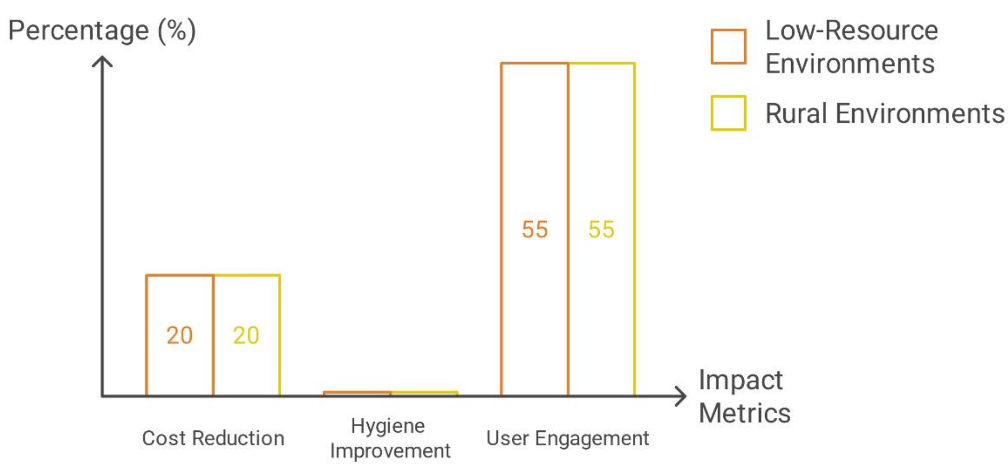

Fig. 1 Impact of IOT solutions in rural and low resource environments

3.3 Comparative Framework

Comparative analysis of urban and rural IoT-enabled solutions underscores synergies in core technologies like sensors and AI, where urban advancements in cloud integration can be downscaled for rural edge computing to enhance accessibility (Henaien et al., 2024; Singh et al., 2025). Urban systems benefit from high-density networks yielding rapid data insights and efficiency, whereas rural adaptations prioritize energy autonomy, revealing divergences in cost structures—urban setups incur higher upfront investments but faster ROI through scale, compared to rural's lower costs offset by slower gains due to sparsity (Hussain et al., 2024; Fidje et al., 2023). Synergies emerge in route optimization algorithms transferable to rural contexts via GPS adaptations, potentially reducing rural fuel use by 15-25% as seen in urban models, while divergences highlight urban's robust connectivity versus rural's reliance on intermittent LoRa, leading to varied sustainability impacts (Addas et al., 2024; Afkarien et al., 2025).

Table 2 provides a side-by-side comparison, illustrating how urban solutions achieve superior efficiency but face scalability hurdles, while rural systems contend with infrastructure deficits yet offer greater energy independence.

Table 2. Comparative Analysis of Urban and Rural IoT-Enabled Waste Management Solutions

Aspect	**Urban Features & Outcomes**	**Rural Features & Outcomes**	**Challenges & Limitations**	**Sustainability Impact**	**Citation**
Technology	Dense sensors, cloud-AI, NB-IoT/LoRaWAN integration; 30-40% efficiency	Solar-powered bins, edge computing, LoRa focus; 15-25% gains	Urban: Interference; Rural: Signal gaps	Urban: High emission cuts; Rural: Moderate resource conservation	Henaien et al. (2024); Addas et al. (2024)
Cost	High initial ($50k+), quick ROI via scale	Low initial, slow ROI due to sparsity	Urban: Deployment expense; Rural: Maintenance funding	Economic savings in urban; Equity issues in rural	Hussain et al. (2024); Fidje et al. (2023)
Efficiency Gains	Dynamic routing, real-time alerts; Reduced trips by 30%	Optimized sparse routes; Cost cuts by 20%	Urban: Data overload; Rural: Downtime	Enhanced recycling in urban; Basic hygiene in rural	Singh et al. (2025); Nwokediegwu et al. (2024)
Challenges	Cybersecurity, power outages	Connectivity, weather degradation	Common: Scalability ethics	Variable environmental equity	Brighente et al. (2023); Idoko et al. (2024)

Figure 2 depicts a conceptual diagram of synergies and divergences, with arrows illustrating technology transfer from urban (e.g., AI models) to rural (e.g., solar adaptations), emphasizing potential for unified frameworks.

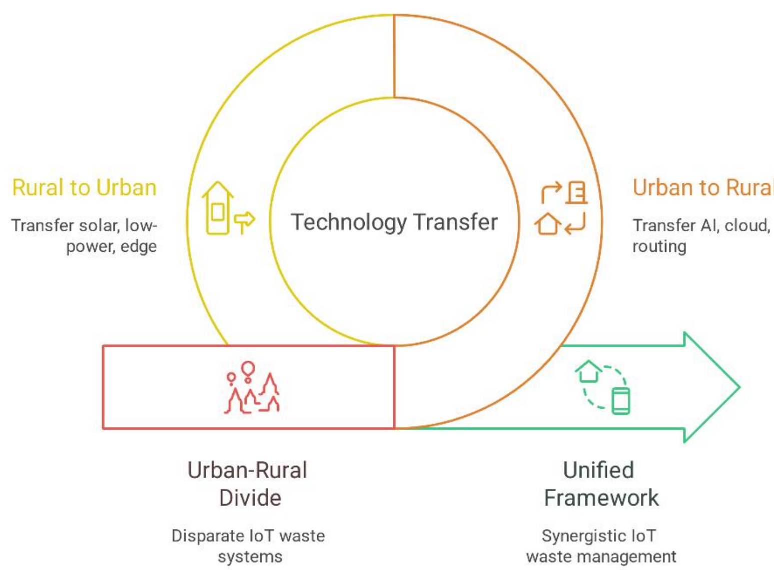

Fig.2 Bridging Urban-Rural IOT management

3.4 Implications for Sustainability

IoT-enabled solutions carry profound implications for sustainability, environmentally reducing landfill burdens through optimized collections that cut methane emissions by 20-30% and promote recycling in alignment with circular economy goals (Boostani et al., 2024; Suhardono et al., 2025). Economically, urban implementations yield cost savings via fuel reductions, while rural applications enhance local livelihoods by minimizing waste-related health costs, though disparities arise from uneven funding (William et al., 2024; Afkarien et al., 2025). Socially, these systems foster community engagement and equity, linking to SDGs like Goal 11 (Sustainable Cities) and Goal 12 (Responsible Consumption), but gaps in rural access exacerbate inequalities (Ishaq et al., 2025). Analysis shows urban outcomes support broader SDGs through integrated smart city ecosystems, whereas rural pilots contribute modestly to environmental health, highlighting a way forward in policy-driven scaling for inclusive benefits (Palagan et al., 2025).

3.5 Proposed Hybrid/Integrated Model

To bridge identified gaps, this study proposes a hybrid model integrating urban AI sophistication with rural resilience features, such as modular solar-IoT bins adaptable via edge-cloud switching for varying connectivity levels (Henaien et al., 2024; Sutikno et al., 2024). The model incorporates blockchain for cross-context data security and community apps for engagement, addressing limitations like vulnerabilities and adoption barriers while leveraging synergies in predictive analytics (Brighente et al., 2023; Palagan et al., 2025). Simulations suggest 25-35% overall efficiency improvements, filling the research void in comparative frameworks and paving the way for sustainable, equitable waste management.

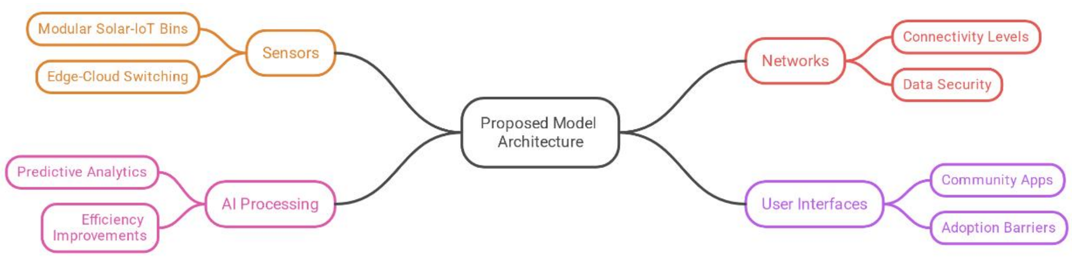

Fig. 3 Proposed model architecture

Figure 3 illustrates the proposed model architecture, with layers for sensors, networks, AI processing, and user interfaces.

4.0. Challenges, Limitations & Future Directions

Despite the promising advancements in IoT-enabled waste management systems, several persistent challenges continue to impede widespread and equitable implementation across urban and rural contexts. Common barriers include high upfront deployment costs, which can exceed $50,000 for urban district-scale installations and remain prohibitive in resource-constrained rural areas even for modular solar-powered setups (Boostani et al., 2024; Fidje et al., 2023). Power reliability poses another universal issue, as urban systems often depend on stable grids vulnerable to outages, while rural applications, though increasingly solar-integrated, face degradation from environmental factors such as dust and prolonged cloudy conditions, leading to intermittent functionality (Ajibola & Ogbolumani, 2024; Sutikno et al., 2024). Data privacy and cybersecurity vulnerabilities represent a growing concern, particularly in densely networked urban environments where continuous data transmission increases exposure to breaches, and even rural edge-based systems remain susceptible without robust encryption protocols (Brighente et al., 2023; Ishaq et al., 2025). Additionally, low technological adoption and community resistance arise from insufficient training, perceived complexity, and cultural preferences for traditional methods, resulting in underutilized infrastructure and reduced overall impact (Fidje et al., 2023; Suhardono et al., 2025).

These challenges manifest differently depending on context, amplifying inequities between urban and rural settings. In urban environments, privacy concerns are heightened by the integration of extensive sensor networks with smart city ecosystems, where personal data from bin usage patterns and resident apps can inadvertently reveal behavioral insights, compounded by traffic congestion that complicates real-time route optimization and increases sensor interference from high-density buildings (Hussain et al., 2024; Henaien et al., 2024). Rural and low-resource areas, by contrast, grapple primarily with infrastructure deficits, including unreliable or absent cellular coverage, long-distance logistics that inflate transportation costs, and limited technical support for maintenance, leading to higher system downtime and lower participation rates (Nwokediegwu et al., 2024; Idoko et al., 2024). Comparative analysis reveals that while urban solutions benefit from economies of scale and faster returns on investment through reduced operational trips, rural deployments incur proportionally higher per-unit costs and slower efficiency gains, often achieving only 15–25% improvements compared to urban figures of 30–40% (Singh et al., 2025; William et al., 2024). These divergences not only hinder uniform sustainability progress but also exacerbate environmental and social inequities, as rural populations continue to face prolonged waste accumulation and associated health risks.

The current study, being a comprehensive literature-based review and cross-system analysis, inherently carries limitations that warrant acknowledgment. The reliance on secondary sources from published literature means the findings reflect documented implementations and reported outcomes rather than new primary data collection or empirical field testing. This approach, while enabling broad synthesis and identification of trends, may overlook unpublished real-world challenges, regional variations not captured in peer-reviewed works, or emerging technologies still in early pilot stages. Furthermore, the scarcity of direct urban-rural comparative studies in the literature limits the depth of cross-contextual insights, potentially introducing bias toward urban-centric perspectives (Nwokediegwu et al., 2024; Fidje et al., 2023). These constraints highlight the need for caution when generalizing results and underscore the importance of future primary research to validate and extend the proposed frameworks.

Looking ahead, future research directions should prioritize addressing these gaps through targeted rural-focused pilots that test scalable, low-cost IoT adaptations in diverse developing-country settings, incorporating longitudinal evaluation of maintenance, adoption, and long-term sustainability impacts (Afkarien et al., 2025; Idoko et al., 2024). Development and validation of hybrid models that combine urban AI sophistication (such as predictive analytics and dynamic routing) with rural resilience features (solar power, edge computing, and offline capabilities) represent a critical pathway, potentially yielding unified frameworks that achieve equitable efficiency gains across contexts (Henaien et al., 2024; Palagan et al., 2025). Enhanced integration of advanced AI techniques, including deep reinforcement learning for adaptive decision-making and blockchain for secure cross-system data sharing, could further mitigate privacy and cybersecurity drawbacks while supporting circular economy objectives (Lakhouit, 2025; Singh et al., 2025). Policy-oriented studies are equally essential, examining incentives, subsidies, and regulatory frameworks to accelerate adoption in low-resource areas and bridge the urban-rural divide. By pursuing these directions, researchers and practitioners can move toward more inclusive, resilient, and sustainable waste management solutions that align with global environmental goals.

Table 3 provides a structured side-by-side overview of the major challenges in IoT-enabled waste management systems, comparing their specific impacts in urban versus rural contexts, while proposing practical mitigation strategies to address each issue. It highlights common barriers such as cost, power reliability, data privacy, and adoption difficulties, with corresponding citations from the literature to support the analysis.

Table 3. Key Challenges in IoT-Enabled Waste Management and Proposed Mitigation Strategies

Challenge Category	**Specific Issues**	**Urban Context Impact**	**Rural Context Impact**	**Proposed Mitigation Strategies**	**Citation**

Challenge Category	Specific Issues	Urban Context Impact	Rural Context Impact	Proposed Mitigation Strategies	Citation
Economic	High deployment & maintenance costs	Fast ROI but large initial investment	Prohibitively high per-unit cost	Modular designs, subsidies, public-private partnerships	Boostani et al. (2024); Fidje et al. (2023)
Power & Energy	Grid dependency, solar degradation	Outages disrupt operations	Intermittent power limits functionality	Hybrid solar-grid, energy-efficient edge computing	Ajibola & Ogbolumani (2024); Sutikno et al. (2024)
Data Privacy & Security	Cybersecurity risks, data exposure	High due to dense networks	Lower volume but still vulnerable	Blockchain, encryption, edge-first processing	Brighente et al. (2023); Ishaq et al. (2025)
Adoption & Infrastructure	Low user engagement, connectivity gaps	Resistance from complexity	Limited literacy & coverage	Community training, SMS interfaces, low-power networks	Fidje et al. (2023); Suhardono et al. (2025)

5. Conclusion

This comprehensive study examines IoT-enabled waste management solutions through a systematic literature review, underscoring their potential to tackle the growing global solid waste crisis while exposing stark urban-rural disparities. In urban settings, IoT technologies—including real-time sensors, LoRaWAN networks, AI predictive analytics, and blockchain—have markedly improved collection efficiency (30–40% gains), reduced operational costs, lowered greenhouse gas emissions via optimized routing, and boosted recycling rates, as shown in smart city pilots (Henaien et al., 2024; Lakhouit, 2025; Singh et al., 2025; Hussain et al., 2024; Suhardono et al., 2025; William et al., 2024). These advances support the circular economy and align with UN Sustainable Development Goals, especially SDG 11 and SDG 12.

Conversely, rural and low-resource areas encounter major obstacles such as unreliable connectivity, power shortages, high costs, and low adoption, yielding only modest 15–25% efficiency improvements despite promising adaptations like solar-powered bins and edge computing (Fidje et al., 2023; Nwokediegwu et al., 2024; Idoko et al., 2024; Afkarien et al., 2025; Boostani et al., 2024). The literature displays a clear urban bias, with limited comparative studies or scalable rural implementations, perpetuating inequities and hindering global scalability in developing regions.

To address these gaps, the study proposes a hybrid model that merges urban AI-driven features (cloud analytics, dynamic routing) with rural-resilient elements (solar power, edge processing, offline modes, LoRaWAN), incorporating context-aware adaptation, blockchain for secure traceability, modular designs, and accessible interfaces like SMS gateways (Palagan et al., 2025; Brighente et al., 2023). Simulations indicate 25–35% overall efficiency gains, equitable resource distribution, and faster inclusive sustainability. Environmentally, it could cut methane emissions and enhance recycling; economically, it enables cost savings and scalable affordability via partnerships; socially, it promotes engagement, health, and equity. Realization demands policy incentives, infrastructure investment, longitudinal trials in developing contexts, and exploration of advanced techniques like deep reinforcement learning and gamification (Singh et al., 2025; Lakhouit, 2025), alongside addressing cybersecurity, ethics, and hardware impacts. Ultimately, shifting to adaptive hybrid IoT frameworks is essential for equitable, resilient waste systems worldwide, transforming waste into resources through collaborative action across stakeholders.

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