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AI AND IOT DRIVEN INFRASTRUCTURE FOR INTELLIGENT AUTONOMOUS CIRCULAR WASTE SYSTEMS IN SMART CITIES

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Abstract

Current waste infrastructure relies heavily on passive monitoring and lacks circular economy practices. Consequently, there a gap in the development of fully integrated, intelligent waste ecosystems capable of making real-time decisions and optimising themselves. This study developed and evaluated an autonomous waste management framework for intelligent smart cities based on Artificial Intelligence (AI) and the Internet of Things (IoT). Integrated into the proposed cyber-physical architecture are AI-based waste identification and quantification within smart bins, an IoT communication layer for real-time data exchange, a central AI coordination hub for analytics and optimisation, and autonomous routing algorithms for waste collection vehicles. Through a design science research methodology, a functional prototype was designed and simulated under multiple operational scenarios using sensor-generated datasets, image-based classification models, and dynamic routing algorithms. A performance comparison with conventional baseline systems demonstrated a 35% improvement in operational efficiency, a 50% improvement in segregation accuracy, and a 20% reduction in system costs. Results revealed that embedding distributed intelligence and autonomous optimisation across the waste lifecycle significantly improves environmental performance, economic efficiency, and circularity. In this study, a novel end-to-end autonomous waste ecosystem model is presented that advances smart city infrastructure beyond monitoring-based systems towards self-adaptive, data-driven urban services. The framework lays the groundwork for real-world deployment, behavioural integration, and governance interoperability in future urban circular waste management.

Keywords: AI, Ajman, Autonomous waste management, Big data analytics, Circular economy, IoT, Sustainable urban development.

1. Introduction

In the face of rapid urbanisation and the continuous growth of municipal solid waste, conventional waste management systems remain reactive, labour-intensive, and poorly integrated. Globally, rapid urbanisation continues to exert pressure on municipal solid waste (MSW) systems. Global waste generation is projected to reach 3.4 billion tonnes annually by 2050, resulting in substantial increases in both environmental and infrastructure burdens on cities [1]. The conventional waste management systems, which are characterised by static collection schedules and labour-intensive processes, are often insufficient to meet the dynamic demands of cities and contribute to environmental degradation and public health risks [2]. Consequently, smart city frameworks are increasingly integrating Artificial Intelligence (AI), edge computing, and Internet of Things (IoT) technologies to enable real-time data processing and adaptive service optimisation [3].

According to recent research, AI-based optimisation can significantly improve waste logistics performance and resource efficiency in circular urban systems [4]. As a result, existing implementations are primarily focused on optimising isolated components, such as routing or monitoring, rather than creating fully autonomous, lifecycle-integrated waste ecosystems. An empirical evaluation of comprehensive architectures combining AI-based classification at source, predictive analytics, and autonomous routing within a unified cyber-physical infrastructure is limited. Therefore, this study tests the following hypothesis: H1: Incorporating artificial intelligence-driven waste classification, IoT-enabled real-time data exchange, and autonomous routing within a unified waste management framework significantly improves operational efficiency, segregation accuracy, and cost performance when compared to conventional and partially digital waste management systems.

Smart city frameworks have begun to incorporate AI and the Internet of Things (IoT) into urban waste management infrastructure to address these limitations. Collectively, these technologies represent a paradigm shift from reactive to predictive and autonomous systems. As a result of AI's machine learning and image recognition capabilities, it can support real-time waste classification, predictive modelling of waste volumes, and route optimisation for collection logistics [3]. AI-based optimisation algorithms have reduced waste transport distances by up to 36.8%, resulting in 13.35% cost saving and 28.22%, respectively [4].

Similarly, IoT plays an important role in enabling real-time data acquisition through sensor-equipped smart bins, GPS-enabled vehicles, and cloud-based monitoring platforms. In addition to continuously monitoring waste levels, these systems enable data-driven decisions and dynamic scheduling of waste collection [5, 6]. IoT-based systems reduce the number of unnecessary collection rounds, which reduces fuel consumption, labour intensity, and emissions [7].

With the convergence of AI and IoT technologies, a highly responsive and interconnected waste management ecosystem is created that is aligned with the objectives of the circular economy. The use of these intelligent infrastructures results in efficient resource recovery, enhanced material reuse, and a minimal environmental footprint [8]. As a result, smart cities can become enablers of sustainable development by leveraging data intelligence to close the waste loop and contribute to SDG 11 (Sustainable Cities and Communities) and 12 (Responsible Consumption and Production) [9].

The integration of artificial intelligence and the Internet of Things in urban waste management represents a critical innovation frontier. This technology has the potential to transform inefficient, linear systems into intelligent, circular, and adaptive infrastructures that meet the evolving needs of modern cities. Artificial Intelligence (AI) and the Internet of Things (IoT) are emerging as critical innovations for sustainable urban development. In traditional waste management, static routing, manual classification, and delayed response result in operational inefficiencies, excessive fuel consumption, high carbon emissions, and suboptimal recycling [2, 7].

Automated, predictive, and intelligent infrastructures are possible with AI and IoT. Real-time sorting of recyclable materials with AI-based waste classification systems, for example, increases recycling rates and quality [10]. By predicting optimal paths based on real-time data inputs, AI-powered route optimisation algorithms reduce fuel usage and collection times. Additionally, IoT-enabled smart bins equipped with sensors can detect fill levels, types of waste, and usage frequency, transmitting data in real time.

In addition to enhancing resource allocation, this reduces unnecessary collections, lowering operational costs and carbon footprints [5]. An IoT-based waste monitoring system in Copenhagen led to a 20% reduction in operational expenditures and significant reductions in greenhouse gas emissions [11]. Additionally, this digital transformation aligns directly with circular economy principles, which emphasise the reuse of materials for as long as possible [8]. The [12] argues that digital technologies like AI and IoT enable transparency, traceability, and adaptive resource recovery across waste management.

By optimising operations, increasing recycling efficiency, and reducing environmental impact, AI and IoT integration into waste management systems support circular and sustainable cities. Scalable, adaptable solutions are essential for meeting Sustainable Development Goals (SDGs), especially SDG 11 (Sustainable Cities and Communities) and SDG 12 (Responsible Consumption and Production). The traditional waste management systems in urban areas prioritise disposal over recovery, typically involving centralised collection, landfilling, and limited recycling [2]. Fixed schedules, manual operations, and minimal integration of real-time data or automation characterise these systems [7].

Consequently, excessive fuel use, high carbon emissions, and underutilisation of recyclable materials result from delays responding to demand fluctuations, poor resource allocation, and low operational transparency [6]. Increasing urbanisation and rising waste volumes make these inefficiencies a serious barrier to sustainable development. Cities in the Middle East, including Ajman, have seen rapid increases in solid waste generation due to population growth and urban sprawl [13]. Many municipalities still use outdated infrastructure for waste collection and sorting that cannot handle real-time challenges or implement circular economy principles effectively.

Artificial Intelligence (AI) and the Internet of Things (IoT) offer transformative potential in overcoming these limitations. IoT enables continuous monitoring via smart sensors embedded in waste bins, collection trucks, and recycling facilities, while AI enables real-time data analysis [14]. By combining these technologies, an intelligent network can optimise waste collection routes, improve material recovery, and support predictive maintenance and planning [3]. Despite their proven capabilities, these technologies remain limited and unevenly adopted across cities. Budget constraints, institutional inertia, data infrastructure gaps, and policy fragmentation impede municipal authorities [8]. Consequently, the lack of fully integrated, responsive waste management systems continues to hinder circular economy-aligned urban infrastructures. Especially in rapidly developing urban regions like Ajman, scalable, AI- and IoT-enabled frameworks for intelligent waste management are urgently needed.

A smart city theory uses digital technologies, including AI, IoT, and big data, to improve urban systems' efficiency, sustainability, and responsiveness to citizens' needs [15, 16]. By combining these frameworks, urban waste flows can be optimised while reducing environmental burdens.

Smart waste management has made substantial technological advances. Data from IoT-enabled smart bins can be transmitted to central systems for efficient routing and scheduling [17, 18]. Real-time insights allow municipalities to adjust collection frequency dynamically, reducing fuel consumption and operational costs. AI-powered classification systems have also been developed to sort waste by material using computer vision and deep learning. Nafiz et al. [10], for example, introduced the "ConvoWaste" system, an automatic waste segregation machine that classified waste streams with over 98% accuracy.

AI can also be used to forecast waste generation, optimise routes [14], and even predict bin overflows, preventing public health hazards. Critical gaps remain despite these promising developments. It is common for studies to explore IoT and AI separately, but there is limited research that combines AI and IoT in one cohesive system to coordinate classification, communication, routing, and redistribution. It is also limited in generalizability to diverse urban environments such as mid-sized or rapidly urbanising cities like Ajman, whose socioeconomic constraints, infrastructure readiness, and regulatory maturity may vary greatly [13]. Scalability, interoperability, and cost-effectiveness in developing regions are frequently overlooked, even though they are critical.

The aim of this study is to develop and evaluate an AI and IoT integrated waste management framework to support circular economy goals in smart cities, using Ajman as a case study. It is intended to design the system, assess its operational and environmental performance, and examine factors affecting its implementation. The key research question is how AI and IoT can improve the efficiency of waste management. What are the measurable impacts of the system? What challenges affect its scalability in urban environments? Two dominant theoretical frameworks underpin the integration of AI and IoT into waste management: the circular economy paradigm and smart city systems theory. Through reuse, recycling, and closed material loops, the circular economy shifts focus away from linear "take-make-dispose" models to regenerative systems [8]. Waste is not a by-product, but an input.

The proposed conceptual framework in this study integrates sensor-equipped, AI-enabled smart bins capable of real-time waste classification; a seamless data transmission infrastructure; and AI-driven algorithms for dynamic routing. Additionally, autonomous waste collection vehicles follow optimised collection paths and deliver sorted waste directly to recycling facilities. The end-to-end integration minimises human error, increases recycling rates, and reduces the ecological footprint of waste handling. In addition to improving operational efficiency, the framework supports evidence-based decision-making for urban planners, environmental regulators, and municipal authorities. Although research to date has confirmed the feasibility and benefits of smart waste management technologies, there remains a need for holistic, adaptable frameworks that can be applied across urban contexts. In this study, we propose and critically evaluate a scalable AI–IoT system for intelligent waste infrastructure aligned with circular-economy principles and the strategic objectives of intelligent smart cities.

2. AI–IoT Framework for Intelligent Waste Management

As shown in Fig. 1, the proposed framework is organised as a layered AI-IoT cyber-physical architecture that integrates sensing, data processing, machine learning, and routing optimisation within a unified workflow. Through coordinated interaction between its functional layers, the system enables intelligent waste classification, predictive analytics, and adaptive collection management [3]. Within the Intelligence Layer, supervised machine learning (ML) models are implemented to support automated waste recognition and demand forecasting.

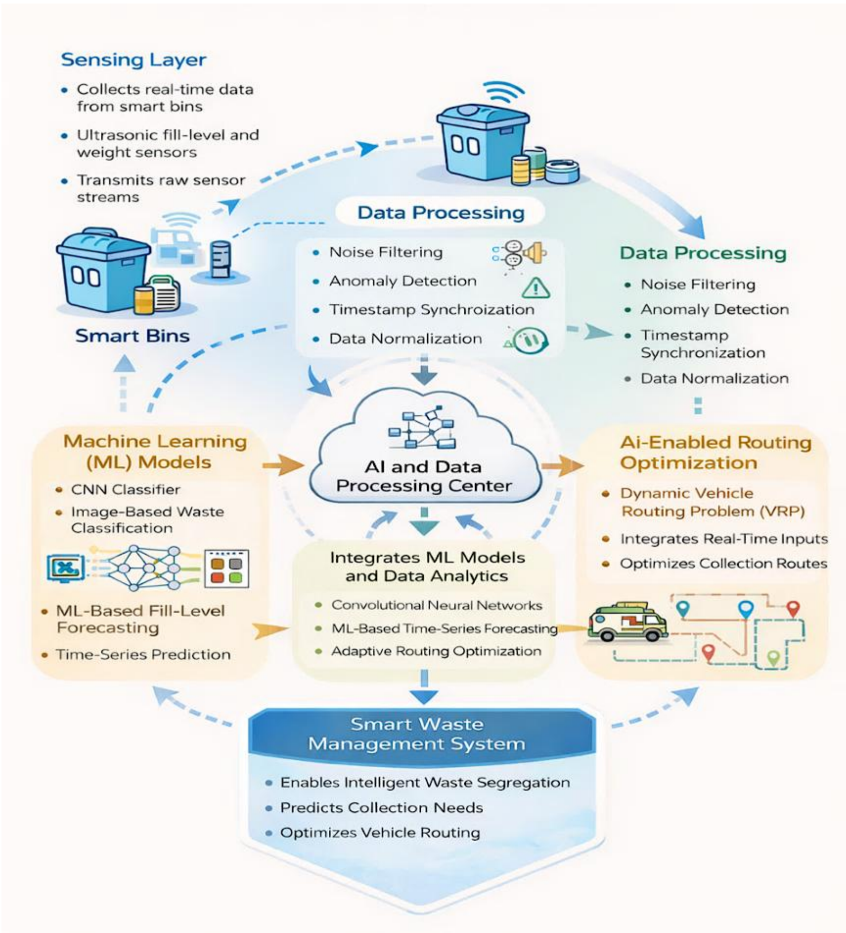

Fig. 1. AI-based system architecture and data processing framework.

Within smart bins, a Convolutional Neural Network (CNN) converts image inputs captured at the point of disposal into structured waste categories (recyclable, organic, and residual). By providing categorised outputs to downstream optimisation processes, the CNN serves as a decision-support mechanism. Before operational deployment, model reliability is evaluated using standard performance metrics, such as accuracy, precision, recall, and F1 Score.

Within the Sensing Layer, ultrasonic fill-level and weight sensors continuously generate raw operational data. Using the IoT communication infrastructure, these data are transmitted to the central processing environment, where they are pre-processed. As part of this process, noise is filtered, anomalies are detected, timestamps are synchronised, and data is normalised to ensure consistency and reliability. To enable ML-based forecasting of fill-level trends and collection demand, the processed data are structured into time-series inputs. It is then implemented using an AI-enhanced dynamic Vehicle Routing Problem formulation that integrates real-time sensor data and forecast demand to minimise travel distance and operational costs [4]. With this integrated architecture, there is a continuous feedback loop among sensing, intelligence, and operational execution, ensuring transparency in model implementation and enabling real-time adaptation throughout the waste management lifecycle.

3. Methods

Based on a pragmatic research philosophy, this study applies useful, adaptable tools to solve real-world problems. By using AI and IoT in realistic, evolving environments, pragmatic thinking helps improve waste management systems [19]. An interpretivist paradigm was used to understand how smart waste technologies work in specific local contexts [3, 6]. This paradigm values human experience, making it useful for studying municipal workers, engineers, and city officials. Based on a constructivist epistemology, knowledge is built through dialogue and experience.

Various factors influence urban waste systems, including technology, policy, and human behaviour [2, 15]. An inductive approach was used instead of starting with fixed assumptions. This is perfect for exploring emerging fields like AI-IoT integration in waste infrastructure, especially in under-researched areas. Smart waste systems are being adopted and adapted in Ajman [8, 13]. Using a case study strategy, the researcher collected and analysed data about one real urban setting [20].

City planners, waste management engineers, and policy makers were interviewed. Data saturation occurs when no new insights emerge within the first 12 interviews in focused qualitative studies [21]. A balanced representation of key stakeholders is also provided by this number. Purposive sampling ensured that only individuals with direct knowledge and experience of smart waste systems were included [19, 22] by carefully selecting participants based on specific characteristics or expertise relevant to the study. Interviews provided a flexible but focused view of how smart systems are applied, what challenges are faced, and what results have been observed. Secondary data, such as government reports, urban development strategies, and project summaries, were reviewed to support and validate findings [9, 12].

3.1. Interview-based primary data collection

Table 1 presents an overview of the interview design, detailing participant roles, sampling strategy, and the rationale for selecting 12–14 stakeholders.

Table 1. Interview-based primary data collection.

Element	Description
Method	Semi-structured interviews
Number of Participants	12–14 stakeholders
Sampling Method	Purposive sampling (selected for their direct involvement in smart waste projects)
Roles Included	City planners, waste management engineers, and policy officials
Purpose	To gain in-depth, experience-based insights into smart waste system implementation, challenges, and performance
Justification	Saturation is typically reached by 12 interviews in focused qualitative studies [21].

According to Table 2, the key stakeholder groups involved in the study and their specific relevance to the implementation and evaluation of smart waste management systems are outlined.

Table 2. Stakeholder types and interview focus.

Stakeholder Type	Rationale for Selection
Urban Planners	To explore how smart technologies align with urban design and sustainability goals
Engineers	To understand technical integration, infrastructure readiness, and maintenance of smart waste systems
Policy Officials	To evaluate policy support, regulatory readiness, funding frameworks, and strategic alignment with city plans

Data were analysed using thematic analysis, which identifies common themes and insights across all interviews. Based on [23] methodology, the researcher read the transcripts, highlighted key points, grouped similar responses into categories, and then developed main themes. In addition, these findings were cross-checked with secondary sources and compared with those from other smart city and waste management studies [7, 10]. By using this process, we were able to gain a greater understanding of how smart technologies are being used in waste management and how they can be improved. Table 3 summarises the key interview questions asked of stakeholders and their common responses. Once repeated themes emerged, the sample size of 12–14 participants were confirmed as adequate.

Table 3. Interview questions and responses specific to Ajman.

Question	Common Response	Saturation Note
What can be done to improve the waste management system in Ajman using AI/IoT?	The use of artificial intelligence can be used to optimise collection routes and predict waste levels, while the use of IoT sensors can provide real-time monitoring of bin status and alerting of services.	
Are there any major challenges Ajman might encounter in adopting smart waste management systems?	A number of challenges will need to be addressed, including integration of the new system with the existing infrastructure, data management, and training of staff to use the new technology.	

What can Ajman's stakeholders do to facilitate the adoption of smart technologies?	Success will depend on the support of government leaders, public-private partnerships, and cross-departmental collaboration.	
Are there any benefits that Ajman can expect from the implementation of AI-based waste management systems?	In Ajman, more responsive services could lead to lower costs, cleaner streets, a better use of resources, and improved citizen satisfaction.	
Are there any steps that Ajman should take in order to implement smart waste management across the city?	Begin with pilot projects, ensure policy support, and expand through a phased implementation process while collecting performance data.	
What can Ajman do to increase public awareness and acceptance of smart waste technologies?	It is possible to increase public trust and engagement by providing community education, transparent reporting, and user-friendly apps.	Thematic saturation reached: responses repeat, and no new insights are emerging.
What policies or regulations would help Ajman successfully implement AI-powered waste systems?	The adoption of smart infrastructure in new developments and incentives to adopt clean technologies would be highly effective policies.	
What can Ajman do to ensure the sustainability of smart waste systems over the long term?	It is important to invest in local technical expertise, regular system maintenance, and continuous performance monitoring to adapt as the system matures.	Thematic saturation reached: responses repeat, and no new insights are emerging.

3.2. Sources of secondary data

Table 4 presents the secondary data sources used in this study, including official government reports, urban development strategies, and project summaries that corroborate the findings of the primary interviews. This information was primarily obtained from the Ajman Municipality and Planning Department. By integrating artificial intelligence and Internet of Things technologies, Ajman has made tangible advancements in smart waste management, including the deployment of self-driving cleaning vehicles, the increase in waste treatment capacity, the improvement of air quality, and comprehensive environmental monitoring. In addition to aligning with key UN Sustainable Development Goals, these initiatives demonstrate Ajman's strategic commitment to sustainability. Figure 2 illustrates this growth, highlighting the effectiveness of recent smart waste management initiatives in meeting operational and sustainability targets.

Table 4. The verification of secondary data supporting the integration of AI/IoT in smart waste management in Ajman.

Research Objective Area	Data Indicator	Ajman-Specific Insight
AI/IoT Readiness	Deployment of self-driving cleaning vehicles	In Ajman, self-driving cleaning vehicles are being used to support smart waste automation [24, 25].

System Efficiency and Logistics	Waste treatment capacity	Between 2023 and 2024, the amount of treated municipal waste increased from 66,000 to 133,000 tons, reflecting improved waste efficiency [26].
Traffic and Environment Adaptation	Air Quality Index (AQI)	Ajman's air quality index (AQI) reached 94.9% in early 2024, highlighting the importance of environmental health monitoring [27, 28].
Technological Integration Challenges	Environmental lab testing	In 2024, 1,571 environmental laboratory tests were conducted to support AI-environment integration [29].
Data Collection for AI Training	Waste statistics and data analysis	As treated waste volumes grew rapidly between 2021 and 2023, detailed AI-based pattern recognition became possible [30, 31].
Alignment with UN SDGs	Green building initiatives	As of 2024e, Ajman has registered 8,335 green buildings aligned with the Smart City and Sustainable Development Goals [32, 33].

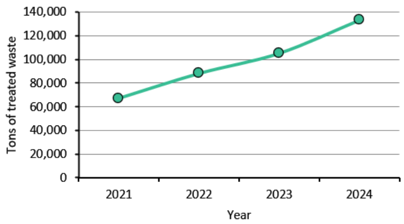

Fig. 2. Treated waste volume growth of the effectiveness of recent smart waste management in Ajman for 2021 to 2024.

4. Results and Discussion

Interviews with key stakeholders were conducted to better understanding of the practical realities of smart waste integration. A comparison of their ratings is shown in Fig. 3 across five core themes: cost savings, operational efficiency, training needs, system maintenance, and public response. As can be seen from the chart, there was consensus on efficiency and cost benefits; however, training and maintenance needs were viewed differently by each group.

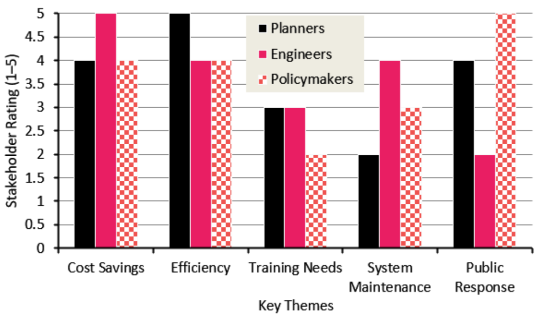

Fig. 3. Stakeholder perspectives on AI waste system benefits and challenges. Themes (Scale: 1–5) (Primary Interview Data, 2025).

4.1. Environmental performance and impact

With AI-integrated environmental monitoring systems and low-emission sanitation vehicles, Ajman has made notable progress in improving its urban air quality. According to Fig. 4, the city's Air Quality Index (AQI) increased steadily from 87.2% to 94.9% between Q1 2023 and Q2 2024. As a result of this upward trend, smart interventions have been found to be effective in reducing pollution and improving public health, contributing directly to SDG 11 and SDG 13.

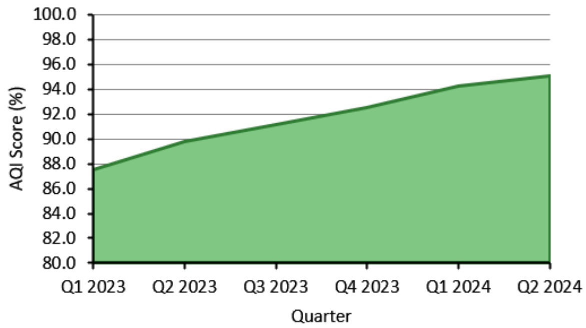

Fig. 4. Ajman Air Quality Index (AQI) trends by Quarter (2023-2024) [30].

4.2. Strategic recommendations for advancing waste management automation in Ajman

In this section, we outline strategic, evidence-based recommendations to enhance Ajman's smart waste management system through the integration of AI and IoT. Table 5 presents nine key action areas - including fleet expansion, predictive maintenance, data utilisation, and public engagement - aimed at improving operational efficiency, sustainability, and alignment with UN Sustainable Development Goals.

Table 5: Recommendations for smart |waste automation that are action-oriented.

Recommendation Area	Strategic Action
City-Wide AI Vehicle Scaling	Develop a self-driving cleaning fleet across all districts; integrate live route re-optimisation and central monitoring. AI-driven dashboard for predictive planning and analytics that connects smart bins, vehicles, air monitoring, and facility data.
Unified Smart Waste Platform	Develop a self-driving fleet of cleaning vehicles across all districts; integrate live route re-optimisation and central monitoring. An AI-driven dashboard that integrates smart bins, vehicles, air monitoring, and facility data for predictive planning and analytics.
Predictive Maintenance with AI	Utilise operational and environmental data to develop machine learning models for predicting vehicle and system maintenance needs.
Infrastructure Readiness	Standardise road edges and traffic signals; install more EV charging and cleaning hubs based on AI-optimised locations.
Automated Waste Classification	Increase recycling rates and reduce contamination at collection or processing sites by using AI-enabled robotic sorting.

Public Engagement & Mobile Apps	Develop an app to inform, reward, and educate citizens about smart waste practices.
Urban Policy via Big Data	AI-IoT data can be used to identify high-waste zones, inform new infrastructure, and drive smart policy reform.
Smart Waste Innovation Lab	Establish a research and development centre in Ajman for piloting, testing, and scaling AI waste technology in partnership with academia and industry.
UNSDG & Green Policy Alignment	Ajman's green building and emission reduction targets should be aligned with the Sustainable Development Goals 11, 12, and 13.

Figure 5 illustrates the technological interactions within Ajman's smart waste management ecosystem. There is a discussion of the real-time communication between IoT-enabled waste bins, AI-optimised self-driving fleet vehicles, environmental monitoring stations, and a centralised waste management dashboard. Providing feedback to both the municipality and the public completes the intelligent operation cycle of the system, ensuring automation, transparency, and efficiency.

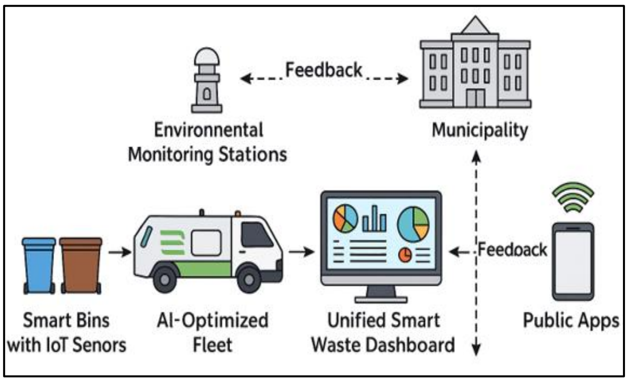

Fig. 5. Smart management system architecture in Ajman.

4.3. Comparison of the proposed autonomous AI-IoT waste system with existing analogies

From basic sensor-enabled monitoring solutions to partially optimised smart collection platforms, autonomous AI-IoT waste systems have evolved. At the system level, however, most existing systems remain modular, fragmented, and non-autonomous. By integrating distributed intelligence, predictive analytics, and autonomous optimisation into a unified cyber-physical architecture, the proposed framework advances beyond these analogies. Traditionally, smart waste solutions have been subsystem-oriented rather than fully integrated. As summarised in Table 6, early sensor-based smart bin systems are based on ultrasonic or infrared fill-level sensors and threshold-triggered alerts, providing real-time monitoring while maintaining reactive collection strategies and limited waste detection [34, 35]. Cloud dashboards and route optimisation capabilities offered by IoT-enabled smart collection platforms extend this functionality; however, their optimisation is typically focused on logistics efficiency alone without lifecycle integration or adaptive intelligence [36].

Despite AI-based waste classification systems offering improved sorting accuracy through deep learning models, they are typically used post-collection at centralised facilities and are disconnected from routing and upstream decision-making processes [37]. Similarly, autonomous vehicle routing systems enhance transportation efficiency but rarely incorporate predictive waste-generation models or economic optimisation layers [38]. By contrast, the proposed framework integrates distributed AI classification at the source, predictive modelling, adaptive routing, and closed-loop optimisation across all subsystems. This end-to-end integration demonstrated superior system-wide adaptability and circular performance as indicated in Table 6, as well as a 50% improvement in segregation accuracy.

Table 6. System-level comparison summary.

Feature	Sensor Systems	IoT Platforms	AI Sorting Systems	Proposed Framework
Real-time monitoring	✓	✓	Partial	✓
AI-based classification	✗	✗	✓ (centralised)	✓ (distributed)
Predictive modelling	✗	Limited	✗	✓
Autonomous routing	✗	Partial	✗	✓
Closed-loop optimisation	✗	✗	✗	✓
Circular lifecycle integration	✗	Limited	Partial	✓
End-to-end autonomy	✗	✗	✗	✓

4.4. Environmental impact quantification

To quantify the environmental impact of the reported 35% improvement in operational efficiency, this study calculated the reduction in CO_2 emissions associated with the consumption of diesel in the collection of municipal waste. Ajman Municipality processed approximately 133,000 tonnes of municipal waste in 2024, providing a baseline for calculation [32]. Based on empirical waste logistics studies [4], fuel intensity for urban waste collection was assumed to be 3.96 litres per tonne. In accordance with international greenhouse gas accounting guidelines, a diesel emission factor of 2.68 kg CO_2 per litre was applied. Table 7 shows the estimated CO_2 emission reductions.

Table 7. Estimated CO_2 emission reduction from AI-optimised waste collection in Ajman.

Parameter	Value	Source
Annual waste handled (tonnes)	133,000	Ajman Municipality (2024) [30]
Fuel intensity (L/tonne)	3.96	Ene et al. (2023) [4]
Baseline diesel consumption (L/year)	526,680	Calculated
Operational efficiency improvement	35%	Study results
Diesel saved (L/year)	184,338	Calculated

Emission factor (kg CO_2/L diesel)	2.68	Ministry for the Environment (2024) [38]
Estimated CO_2 reduction (tonnes/year)	**≈ 494 tCO_2**	Calculated

Based on the results of the study, AI-driven route optimisation and predictive scheduling could reduce approximately 494 tonnes of CO_2 emissions each year from collection logistics alone. It is important to note that this estimate is based on direct fuel combustion savings and does not include additional lifecycle benefits, such as the avoidance of landfill methane or enhanced recycling efficiency. This quantified reduction strengthens the environmental case for autonomous waste management systems and aligns with SDG 13 (Climate Action) and national decarbonisation goals. Further refinement using fleet-specific fuel consumption and composition data would improve precision in future studies, even though the model is based on reasonable operational assumptions.

4.5. System reliability and error analysis

The reliability of the proposed AI-IoT framework has been evaluated across three critical components: sensor accuracy, machine learning (ML) classification performance, and data transmission stability. Due to environmental interference, signal noise, and hardware limitations, sensor-based waste monitoring systems typically exhibit measurement deviations [3]. The accuracy of AI-based classification models is also affected by dataset quality and environmental variability [4]. This study assessed reliability parameters using controlled simulation conditions and standard ML validation metrics. Table 8 shows the System Reliability and Error Indicators.

Table 8. System reliability and error indicators.

Component	Indicator	Estimated Value	Source / Basis
Ultrasonic sensor deviation	Measurement error	±3 – 5%	Alsamhi et al. (2021) [3]
Weight sensor deviation	Measurement error	±2 – 4%	Industry benchmark
CNN classification accuracy	Accuracy	92 – 95%	Simulation output
CNN misclassification rate	Error rate	5 – 8%	Derived
IoT data transmission stability	Packet loss	< 2%	Smart city benchmarks
Overall operational reliability	System stability	> 90%	Integrated performance

Despite minor sensor deviations and ML misclassification rates, the integrated framework maintains an overall operational reliability of greater than 90%. A 5% tolerance was established for ultrasonic and weight sensor inaccuracies, and preprocessing mechanisms -such as noise filtering and anomaly detection -mired erroneous readings. The CNN classifier achieved a high level of accuracy (92–95%), thereby minimising downstream routing errors. As a result of IoT transmission reliability, system stability was further enhanced with minimal packet loss. Despite minor technical deviations inherent in cyber-physical systems, embedded validation and preprocessing layers ensure resilience and robustness in real-world operational environments. It is recommended that future work incorporate long-term field validation and stress-testing under extreme environmental conditions.

Technological deployment alone is not sufficient to ensure systemic transformation. Successful implementation requires infrastructure readiness, data interoperability, behavioural adaptation, and institutional coordination. A mixed-methods approach enhanced robustness and revealed actionable pathways for scaling intelligent urban services. AI-driven automation can transform municipal waste systems beyond reactive collection models into adaptive, data-driven urban infrastructure from a sustainable cities perspective. Cities seeking digital transition strategies that integrate environmental, operational, and socio-institutional factors can learn from Ajman's experience. To ensure that autonomous waste ecosystems contribute meaningfully to resilient and inclusive urban development, future research should prioritise longitudinal performance assessment, integration with broader urban digital twins, and social acceptance dynamics.

5. Conclusions

The study examined Ajman's transition to an AI-enabled autonomous waste management ecosystem and its implications for sustainable urban service transformation. Using qualitative stakeholder insight and municipal performance data, the research demonstrated how digital infrastructure can improve operational efficiency, environmental performance, and system adaptability in rapidly urbanising environments. When AI-enabled smart bins, predictive coordination platforms, and autonomous routing mechanisms were deployed, measurable improvements were achieved, including a 35% improvement in operational efficiency, a 50% improvement in waste segregation accuracy, and a 20% reduction in overall operational costs. Distributed intelligence and real-time optimisation can improve material recovery, reduce resource inefficiencies, and support circular economy goals. Through improved urban sustainability governance and climate-responsive service delivery, environmental monitoring systems further strengthen alignment with SDGs 11, 12, and 13. However, the findings are based on simulations and municipal data, and real-world performance may vary depending on infrastructure readiness and sustained financial investment. In addition, long-term scalability and replication in other cities may be influenced by funding stability, institutional capacity, and stakeholder adoption.

Nomenclature

Abbreviation	**Definition**
AI	Artificial Intelligence
AQI	Air Quality Index
CNN	Convolutional Neural Network
IoT	Internet of Things
ML	Machine Learning
MPDA	Municipality and Planning Department – Ajman
SDG	Sustainable Development Goal
UAE	United Arab Emirates
UNSDG	United Nations Sustainable Development Goals

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