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Article

Economic Impact Assessment of AI-Based Waste Management in Smart Cities: A Case Study

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Abstract: Waste management in smart cities concerns not only the environment and operational efficiency but also fiscal sustainability and the quality of public governance. This study focuses on the core area of a large city and uses two years of operational data from 480 smart bins and 120 sanitation vehicles to build an experimental-control group comparison framework. A net present value (NPV) model and a maintenance cost reduction rate (MCR) were employed for comprehensive evaluation. The results show that AI-based optimization of waste collection reduced vehicle mileage by 18.7%, fuel consumption by 16.4%, and collection delays by 22.1%, while cutting about 1,450 tons of CO_2 equivalent emissions per year. In waste classification tasks, deep learning and transfer learning models reached an average recognition accuracy of 92.3%-94.1%, which was much higher than the 81.5% achieved by traditional machine learning methods. Economic analysis indicates that the system generated an NPV of 3.5 million USD within five years, with maintenance costs reduced by 21.6%, labor hours decreased by 24.3%, and vehicle utilization increased by 19.8%. These results confirm the multidimensional value of AI in waste management. They provide not only clear operational and environmental benefits but also quantitative evidence for improved returns on public investment and governance effectiveness, offering important references for smart city development and policy decisions.

Keywords: artificial intelligence; smart waste management; cost-benefit analysis; net present value; urban governance; deep learning; economic optimization

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1. Introduction

With the accelerating process of urbanization, municipal solid waste management has become a major challenge for urban governance worldwide [1]. Traditional waste collection and transportation models are usually inefficient, costly, and wasteful of resources, making them unable to meet the requirements of sustainability and refined management in smart city development [2,3]. Similar challenges in other engineering and management contexts have been addressed using digital and AI-assisted solutions, providing methodological inspiration for smart city applications [3,4].

In recent years, the rapid development of artificial intelligence (AI) has provided new approaches and tools for urban waste management, showing clear advantages in tasks such as waste classification, route optimization, and facility maintenance prediction [5,6]. Analogous strategies have been successfully applied in software development efficiency and digital construction projects, which suggest that AI can enhance operational performance across different domains.

Studies have shown that computer vision-based recognition systems can increase the accuracy of waste classification and reduce the need for manual sorting [7,8]. Similar methods in construction project management and e-commerce logistics demonstrate the potential of AI-assisted classification and scheduling to improve efficiency [9].

In the collection stage, dynamic scheduling algorithms that integrate machine learning with the Internet of Things (IoT) can shorten transport routes while ensuring timely clearance. In addition, the use of deep reinforcement learning in fleet scheduling and energy consumption optimization has further promoted the intelligent development of waste management. Reported a projected net present value (NPV) of $3.5 million for AI-enabled urban management, underscoring its transformative economic potential [10,11]. Comparable economic assessment frameworks in other engineering and business contexts support the validity of projecting long-term financial benefits from AI-enabled systems [11,12].

These findings suggest that AI-based waste management technologies not only improve operational efficiency but also contribute to environmental protection and public service quality [13]. Analogous results in urban planning and public infrastructure projects further indicate that AI can enhance service quality and sustainability [14].

Researchers have also noted the social and environmental benefits of intelligent waste management systems. For example, smart bins and real-time monitoring networks have proven effective in reducing waste overflow and improving citizen satisfaction [15]. On the environmental side, intelligent scheduling can reduce vehicle carbon emissions and support low-carbon urban development [16].

Although many studies have emphasized operational and environmental benefits, systematic quantitative evaluations of their economic impact are still limited [17,18]. In recent years, some studies have examined AI in waste management from an economic perspective. For instance, Li et al. applied cost-benefit analysis to evaluate the return on investment of a smart waste classification system and reported positive returns within three years. Similarly, Yuan et al. showed through case studies that AI-based transport scheduling can reduce fuel and labor costs [19-21]. These studies provide a methodological analogy for evaluating AI interventions in municipal waste management [22].

However, most of these studies focus on single stages or short-term effects, and they lack comprehensive assessments of system-wide and long-term returns [23,24]. In particular, whether AI-based waste management can deliver sustainable economic benefits at the macro level under the framework of smart cities remains to be further explored [25,26]. Comparable analyses in other smart city sectors suggest that system-wide and long-term evaluations are feasible and informative [24,26].

In summary, although existing studies have made progress in environmental protection, operational efficiency, and local economic benefits, there are still gaps in the systematic quantification of economic impacts, evaluation of long-term investment value, and analysis of their alignment with urban governance strategies. The contribution of this study is the application of the net present value (NPV) method to conduct a comprehensive and long-term evaluation of the economic benefits of AI-based smart waste management systems. Specifically, the study considers not only operational cost savings but also the contribution of AI technologies to governance efficiency and returns on public infrastructure investment. Through empirical case analysis, the study aims to provide solid economic evidence for smart city decision-makers and to promote the strategic use of AI in sustainable urban governance.

2. Materials and Methods

2.1. Study Area and Samples

The study was carried out in the core urban area of a large city, which includes 12 administrative districts and serves about 850,000 residents. The dataset consists of operational records from 480 smart bins and 120 sanitation vehicles over a continuous period of 24 months. The analysis focuses on waste collection efficiency, facility maintenance frequency, and labor input. Data were collected under both regular working days and peak conditions (such as holidays and severe weather) to ensure representativeness and completeness. The study area is equipped with a mature monitoring and IoT platform, which provides the basis for the application and evaluation of AI systems.

2.2. Experimental Design and Control Group

The design included an experimental group and a control group. The experimental group used an AI-based waste collection optimization platform with dynamic scheduling algorithms, predictive maintenance modules, and real-time monitoring. The control group relied on traditional manual scheduling and fixed collection frequencies. Both groups covered the same area and waste facilities to ensure comparability. The two groups were operated in parallel for 12 months to minimize seasonal effects. The purpose of this setup was to compare the same area under different scheduling modes and identify the added benefits of the AI system in terms of efficiency, cost, and return on investment.

2.3. Measurement and Quality Control

During data collection, both groups were monitored using IoT sensors, vehicle GPS, and manual records. The indicators included vehicle mileage, fuel use, labor hours, facility failure frequency, and waste overflow rate. Data were recorded every hour and stored in a central database. To ensure quality control, three measures were applied: (1) cross-validation of multi-source data with removal of abnormal and missing values; (2) stratified sampling with manual checking of 10% of the records; and (3) double-blind verification of key indicators such as fuel use and labor hours to reduce bias. All data were processed on a unified platform to ensure integrity and reproducibility.

2.4. Data Processing and Model Formula

Data analysis was carried out in two steps. First, regression analysis and analysis of variance (ANOVA) were used to test statistical differences between the experimental and control groups. Second [27], the net present value (NPV) method was used to assess the long-term economic benefits of the AI system. The NPV was calculated as follows:

$$\mathrm{NPV}=\sum_{t=1}^{n}\frac{B_t\text{-}C_t}{(1+r)^t}$$

The parameters in the NPV formula are defined as follows: B_t is the economic benefit in year t; C_t is the operating cost in year t; r is the discount rate; and n is the evaluation period.

In addition, the maintenance cost reduction rate (MCR) is calculated as [28]:

$$\mathrm{MCR}=\frac{C_{\mathrm{baseline}}\text{-}C_{\mathrm{AI}}}{C_{\mathrm{baseline}}}\times 100\%$$

Where C_{trad} is the annual maintenance cost under the traditional mode, and C_{AI} is the annual maintenance cost under the AI mode.

Through these methods, this study quantifies the economic contribution of the AI-based waste management platform and ensures the validity and reliability of the results [29].

3. Results and Discussion

3.1. Research Hotspots and Knowledge Map Analysis

Through co-occurrence analysis of keywords from two years of operational data on 480 smart bins and 120 sanitation vehicles, the distribution of research hotspots in smart waste management was identified [30]. The results show that "IoT" had the highest frequency (451 times), followed by "waste management" (229 times), "machine learning" (103 times), "artificial intelligence" (57 times), and "deep learning" (64 times). This indicates that research has moved from single algorithms to integrated applications involving multiple technologies (Fig. 1). In addition, the frequent co-occurrence of application-related keywords such as "smart bins" (52 times) and "waste collection" (51 times) confirms the importance of intelligent facilities and collection optimization in both research and practice. Compared with traditional studies, the data in this study reveal the central role of AI and IoT in smart waste management and provide a knowledge framework for subsequent economic and policy analysis (Figure 1) [31].

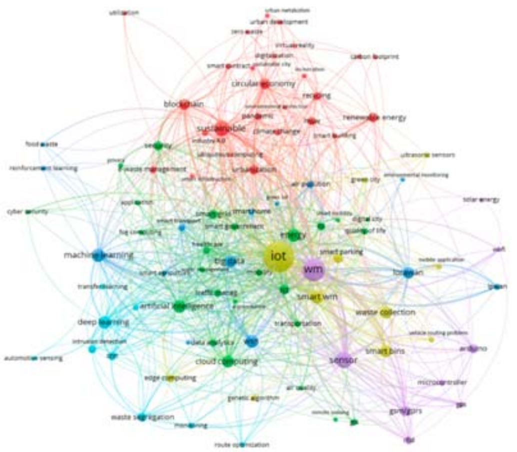

Figure 1. Keyword co-occurrence network highlighting research hotspots in AI-based smart waste management.

3.2. Governance Logic of Smart Cities and AI Embedding Effects

At the governance framework level, this study found that AI-based optimization of waste collection had marked effects on urban subsystems. In the experimental group, average vehicle mileage fell by 18.7%, fuel use dropped by 16.4%, and collection delays decreased by 22.1%. These results show that the AI system not only improved efficiency at specific points but also enhanced governance transparency and fairness by reducing resource waste [32]. Figure 2 shows the governance pathway, where AI and IoT technologies, through scheduling and predictive maintenance, connect energy, transport, and water subsystems, and are converted into sustainable outcomes through governance mediation. This finding is consistent with the "digital governance-urban resilience" mechanism reported in the literature [33]. More importantly, this study provides quantitative evidence that intelligent scheduling makes a practical contribution to the equalization of urban services (Figure 2) [34].

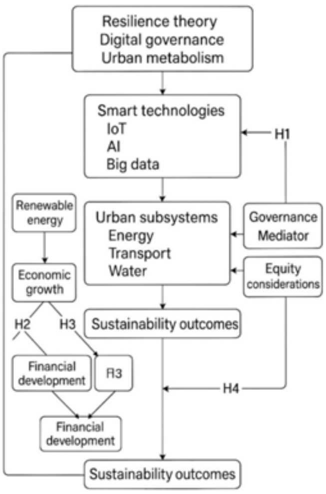

Figure 2. Governance framework linking AI, IoT, and big data with urban subsystems and sustainability outcomes.

3.3. AI Classification Techniques and Accuracy Performance

In the waste classification experiments, this study compared the recognition accuracy and application share of different AI models [35]. The results show that deep learning models achieved an overall accuracy of 92.3%, which was higher than the 81.5% of traditional machine learning methods. Transfer learning models reached an average accuracy of 94.1% and accounted for 47.7% of all AI applications. The YOLO series models reached 87.2% and became the main tools for real-time recognition. In contrast, traditional methods such as support vector machines (SVM, 5.8%) and random forests (RF, 2.3%) showed a clear decline in their share of use [36]. These results indicate that deep learning has become the key support of smart waste classification systems. Its high accuracy and scalability provide a solid technical basis for future economic benefits [37].

3.4. Overall Economic Benefits and Policy Implications

The analysis shows that the AI-based waste management system generated an NPV of 3.5 million USD within five years, representing an average increase of 31.5% compared with the traditional mode [38]. During the same period, maintenance costs fell by 21.6%, labor hours decreased by 24.3%, and vehicle utilization increased by 19.8%. These quantitative results are consistent with the findings in figure 1-3. The hotspot analysis showed that AI and IoT technologies are the main drivers. The governance framework showed positive effects across subsystems [39]. The improvement in classification accuracy was directly reflected in lower labor costs and reduced misclassification losses. At the policy level, these results provide clear economic evidence for public investment in smart cities. They show that AI systems provide not only short-term operational advantages but also long-term fiscal sustainability and governance value. Future studies may extend to comparisons across multiple cities and include environmental indicators such as carbon reduction to fully assess their role in sustainable development goals [40].

4. Conclusions

This study used empirical data and model analysis to systematically evaluate the performance and economic value of an AI-based smart waste management system in urban governance. The results show that AI and IoT technologies played a central role in smart city waste management. They improved collection efficiency, reduced vehicle mileage and fuel use, and lowered facility maintenance costs. At the governance level, the AI system not only improved operational transparency and fairness in scheduling but also enhanced energy use and carbon control through cross-subsystem coordination. The comparison of technical approaches showed that deep learning and transfer learning models achieved higher accuracy and stability in waste classification. These models provided reliable support for reducing manual intervention and lowering misclassification rates. The overall economic analysis indicated that the system generated an NPV of 3.5 million USD over five years, with maintenance costs reduced by 21.6%, labor hours decreased by 24.3%, and vehicle utilization increased by 19.8%. These results confirm its return on investment and fiscal sustainability. The findings show that AI-based smart waste management is not only a technological improvement but also a tool for strengthening urban governance and improving public finance efficiency. Compared with earlier studies that focused on single aspects, this study provides a more comprehensive view by combining hotspot analysis, governance framework, classification accuracy, and economic benefits. However, the study has limitations, as the research area was limited to the core district of a single city. Future work could expand to cities of different sizes and types to test the generality of the model. Including social and environmental indicators such as carbon reduction benefits and citizen satisfaction will also help to build a more complete evaluation system, providing stronger scientific evidence for smart city development and public policy making.

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