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Application of artificial intelligence for optimizing solid waste management in rural municipalities: a systematic review

Aplicación de inteligencia artificial para la optimización de la gestión de residuos sólidos en municipios rurales: una revisión sistemática

Arista-López, Deivis Robin[1]*

[1]Graduate School, Universidad César Vallejo, Tarapoto Campus, Peru

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Corresponding author*: daristal@ucvvirtual.edu.pe

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ABSTRACT

This systematic review examines the application of artificial intelligence (AI) technologies in solid waste management in rural municipalities, aiming to identify the advances, benefits, challenges, and research gaps in this emerging field. Based on the analysis of 47 scientific articles selected from the Scopus database, various technological solutions were identified, including computer vision systems, deep learning, predictive models, IoT sensors, and hybrid Edge-Cloud platforms. The results show substantial improvements in waste classification, operational planning, and energy efficiency, although significant limitations associated with technological infrastructure, data availability, and technical training in rural areas persist. The review also highlights research opportunities aimed at developing lightweight models, integrating local knowledge, and generating open and representative datasets. These findings allow us to propose strategic lines for the sustainable adoption of AI in rural environments, contributing to the digital transformation of public services with a territorial focus.

Keywords: artificial intelligence; automation; municipalities; optimization; waste

RESUMEN

La presente revisión sistemática examina la aplicación de tecnologías de inteligencia artificial (IA) en la gestión de residuos sólidos en municipios rurales, con el objetivo de identificar los avances, beneficios, desafíos y vacíos de investigación en este campo emergente. A partir del análisis de 47 artículos científicos seleccionados de la base de datos Scopus, se identificaron diversas soluciones tecnológicas, entre ellas, sistemas de visión por computadora, aprendizaje profundo, modelos predictivos, sensores IoT y plataformas híbridas Edge-Cloud. Los resultados evidencian mejoras sustanciales en la clasificación de residuos, la planificación operativa y la eficiencia energética, aunque persisten limitaciones significativas asociadas a la infraestructura tecnológica, la disponibilidad de datos y la capacitación técnica en zonas rurales. La revisión también destaca oportunidades de investigación orientadas al desarrollo de modelos ligeros, la integración de saberes locales y la generación de datasets abiertos y representativos. Estos hallazgos permiten proponer líneas estratégicas para la adopción sostenible de IA en entornos rurales, contribuyendo a la transformación digital de los servicios públicos con enfoque territorial.

Palabras clave: automatización; inteligencia artificial; municipios; optimización; residuos

1. INTRODUCTION

In recent years, artificial intelligence (AI) has established itself as a key tool for addressing environmental challenges, including efficient solid waste management. Its application has transformed operational processes through machine learning algorithms, computer vision, and predictive analytics, promoting more precise and automated waste management (Alzoubi & Mishra, 2024). Technologies such as smart sorters, real-time monitoring systems, and optimized route planning are revolutionizing the way local governments address this issue (Carranza, 2013; López-Noguero et al., 2024).

This technological shift has generated growing interest in exploring solutions that integrate AI into public services, particularly waste management. Through the use of advanced computational models, the operational burden of traditional systems has been reduced and their response capacity to waste accumulation has been improved, optimizing time, resources, and recycling levels (Alsabt et al., 2024; Sanchez-Yañez & Marquez-Benavides, 2023). Unlike manual approaches, these solutions allow for the analysis of large volumes of information, facilitating more timely and effective decision-making for waste treatment and final disposal (Ulloa-Gallardo et al., 2022; Raza-Carrillo & Acosta, 2022).

However, rural environments present specific conditions that limit the incorporation of these technologies, such as the lack of data networks, insufficient specialized equipment, and limited training of technical personnel. These limitations hinder access to innovative solutions and perpetuate unsustainable conventional practices (Anaya Figueroa et al., 2021). Furthermore, geographic dispersion, logistical difficulties, and low budgetary priority in these territories increase the complexity of comprehensively implementing smart technologies.

Another factor influencing the effective adoption of AI in waste management is data availability and quality. In many rural municipalities, records on waste generation and collection are scarce or nonexistent, which hinders the training of smart models and compromises their operational accuracy (Madueño Cairo & Roca Becerra, 2025; Quintana Ruidías, 2025).

Recent studies have shown that, despite limitations, there are successful experiences using AI to improve waste management, especially in areas where systems have been adapted to local conditions (España-Merchán, 2023). These approaches have led to better waste segmentation, greater collection efficiency, and more strategic resource planning (Boostani et al., 2024). However, a greater understanding is needed of how these technologies can be adapted to diverse rural realities, considering the social, economic, and cultural aspects that directly influence their implementation (Pitakaso et al., 2024).

In this context, it is necessary to conduct a comprehensive analysis of existing academic work addressing the application of artificial intelligence in solid waste management in rural municipalities. This systematic review aims to identify methodological approaches, technical challenges, and opportunities for improvement documented in the specialized literature. By examining indexed scientific publications, the aim is to generate evidence that can serve as a basis for designing innovative, sustainable strategies tailored to the specific needs of local governments in non-urban settings.

2. MATERIALS AND METHODS

To conduct this research, an exploratory systematic review was used, a methodology that allowed for an orderly and critical examination of scientific production related to the use of artificial intelligence in solid waste management in rural contexts. This methodological approach facilitated the identification of relevant contributions, as well as gaps in the literature and opportunities for future research (Fernández-Sánchez et al., 2020). The application of this type of review also contributes to consolidating a solid documentary base that can serve as a guide for the design of technological strategies in the service sector (Manchado Garabito et al., 2009).

The methodological procedure adopted was based on the recommendations proposed by Moher et al. (2009), structured in two main phases: planning and execution. In the planning stage, the review objectives were defined, guiding research questions were formulated, and key terms and synonyms used to construct the search equations were identified. In addition, relevant academic databases were selected, inclusion and exclusion criteria were established, a checklist was designed to assess article quality, and a form was developed for systematic information extraction.

During the execution phase, specific combinations of keywords related to "artificial intelligence," "waste management," "rural municipalities," and "emerging technologies" were applied to the Scopus database, selected for its broad coverage of indexed scientific literature. The results filtering process consisted of three consecutive stages: elimination of duplicate studies to avoid redundancies in the analysis; review of titles, abstracts, and keywords based on the defined inclusion and exclusion criteria; and assessment of methodological quality using a scoring matrix designed to measure the relevance, clarity, applicability, and rigor of the studies.

Only those articles that met the established parameters and obtained an adequate rating according to the applied quality matrix were considered for the final analysis. Finally, data were extracted and systematized from the selected documents, which allowed for the identification of methodological approaches, practical applications, identified barriers, and results obtained in the implementation of artificial intelligence in rural solid waste management. From this analysis, emerging trends, persistent challenges, and future lines of research related to the digitalization of public services in low-density areas were identified.

2.1. Research Questions

The following questions were posed:

1) What types of artificial intelligence-based technologies have been applied in solid waste management in rural contexts, and which have proven most effective?

2) What are the main benefits reported by studies regarding the use of artificial intelligence to optimize waste collection, sorting, and treatment processes in rural municipalities?

3) What technical, economic, or social challenges have been identified in the implementation of artificial intelligence solutions in solid waste management in rural areas?

4) How does the adoption of artificial intelligence in waste management vary among rural municipalities in different regions or levels of development?

5) What knowledge gaps and opportunities for future research are evident in the scientific literature on the use of artificial intelligence in waste management in rural settings?

2.2. Search Strategy

To identify relevant articles, a strategy based on key terms directly related to the study's objective was used, encompassing concepts related to artificial intelligence, solid waste management, recycling, waste treatment, operational efficiency, and data analysis. This strategy allowed the review to focus on research focused on technological solutions applied to waste management, particularly in rural settings or those with similar structural constraints.

The initial search was conducted in the Scopus database, using the following combination of terms: ("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning") AND ("solid waste" OR "waste management" OR "refuse" OR "garbage") AND ("recycling" OR "composting" OR "treatment" OR "disposal") AND ("optimization" OR "efficiency" OR "analysis" OR "monitoring") AND ("data" OR "analytics" OR "modeling" OR "prediction"). This preliminary search yielded a total of 9,412 documents related to the use of artificial intelligence in the context of waste management. To narrow the search results and focus on the most relevant studies, specific inclusion and exclusion criteria were applied: only articles published between 2004 and 2024, written in English or Spanish, in their final publication version, and classified as scientific articles (document type: article), were considered. Likewise, open access works or those with full availability provided by the publisher were included. These filters allowed us to refine the results and ensure the academic and thematic relevance of the selected documents.

The selection process consisted of four clearly defined stages. First, the search string was applied, considering titles, abstracts, and keywords. Then, duplicate documents were eliminated, and studies that met the previously defined criteria were filtered. Subsequently, a detailed review of the selected articles was conducted, identifying those specifically focused on the application of artificial intelligence in solid waste sorting, collection, recycling, or treatment processes, preferably in rural settings or with technological limitations. Finally, 48 relevant articles were selected and organized in an Excel 365 spreadsheet that included code, title, journal, year of publication, DOI, type of technology applied, methodological approach, and main contributions related to the optimization of solid waste management through artificial intelligence.

3. RESULTS AND DISCUSSIONS

The literature review identified various technologies, benefits, limitations, and opportunities surrounding the use of artificial intelligence (AI) for solid waste management in rural municipalities. The findings are presented below, structured into five categories, following the established research questions.

Q1. What types of AI-based technologies have been applied to solid waste management in rural contexts, and which have proven most effective?

Solid waste management in rural areas faces very different conditions than urban areas, such as infrastructure limitations, reduced connectivity, and smaller operational scale. In this context, the literature reviewed shows a progressive adoption of artificial intelligence technologies that seek to overcome these barriers through innovative and efficient solutions. Among the most notable technologies are computer vision systems, particularly through architectures such as YOLO, DeepLabv3+, Mask R-CNN, and U-Net, which enable the automatic and real-time classification of different types of waste, including mixed or poorly defined waste.

In addition, deep learning models have been applied to tasks such as semantic segmentation, pattern recognition, and recyclable material detection. Traditional machine learning algorithms (such as decision trees, random forests, and SVMs) and multiple regr ession models have also been used to predict municipal solid waste generation based on demographic and socioeconomic data.

In areas with limited connectivity, the combination of Edge Computing and Cloud Computing has been key to ensuring operational efficiency without relying on a constant internet connection. Likewise, emerging technologies such as spectral photodetectors and low-cost IoT sensors have begun to be integrated with AI models, enabling accurate waste classification using optical signals. The effectiveness of these technologies is associated with their ability to operate with low energy consumption, adapt to local conditions, and accuracy in uncontrolled environments, all of which are fundamental for their application in rural municipalities (Table 1).

Table 1. AI technologies applied to rural waste management

Applications	Article Code
Automation of administrative and budgetary processes	A1, A2, A3, A6, A19, A21, A25, A30, A36, A37, A40, A43
Data analysis and financial reporting	A1, A3, A6, A11, A19, A24, A26, A28, A29, A34, A36, A37, A40, A43, A48
Real-time project monitoring using geospatial platforms	A3, A20, A37
Use of blockchain for investment traceability	A5, A6, A8, A14, A27, A29, A31, A40
System interoperability between government entities	A10, A19, A25, A36

Q2. What are the main benefits reported by studies regarding the use of artificial intelligence to optimize waste collection, sorting, and treatment processes in rural municipalities?

The incorporation of artificial intelligence tools in waste management has demonstrated notable benefits in terms of efficiency, cost reduction, and improved recycling quality, even in rural contexts. One of the main benefits identified in the studies is increased accuracy in waste sorting, allowing recyclable materials to be separated more efficiently and with less human intervention. This not only improves the quality of recovered materials but also reduces worker exposure to hazardous waste.

Likewise, the ability of AI models to automate operational processes such as waste collection and transportation by optimizing routes, schedules, and frequencies is highlighted, resulting in a significant reduction in fuel consumption and polluting emissions. Benefits have also been reported in predictive management, such as the ability to anticipate waste accumulation, forecast logistical needs, and adapt systems to environmental and demographic conditions.

In rural areas, where human and financial resources are limited, the implementation of AI-based solutions has reduced operating costs, improved energy efficiency, and even extended collection service coverage to previously underserved communities. Furthermore, some studies highlight the opportunity to apply these technologies in collaborative or community-based schemes, which can strengthen the social and environmental sustainability of the system.

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Table 2. Benefits of AI Application in Rural Waste Management

AI Contributions	Article Code
Increased sorting accuracy and speed	A1, A2, A3, A11, A21, A24, A28, A36, A43
Reduced human error and operating costs	A1, A5, A11, A14, A25, A30, A37
Improved route planning and optimization	A5, A13, A15, A23, A26, A31, A40
Greater autonomy and offline operation	A3, A20, A24, A37, A40
Optimized municipal and energy resources	A5, A8, A14, A29, A40, A48

Q3. What technical, economic, or social challenges have been identified in the implementation of artificial intelligence solutions for solid waste management in rural areas?

Despite the observed technological advances, the implementation of artificial intelligence-based solutions in rural municipalities faces significant challenges. On a technical level, studies point to the need for specific and balanced databases that adequately represent the conditions and types of waste characteristics of rural areas. Without this data, algorithms lose their generalization capacity and require constant retraining processes.

On an economic level, the high cost of specialized equipment (such as sensors, hyperspectral cameras, or GPUs for model training) constitutes a significant barrier, especially for municipalities with limited budgets. Furthermore, technological infrastructure in rural areas is often deficient or nonexistent, making the integration of IoT devices or cloud-based analysis platforms difficult.

On a social level, challenges related to low digital literacy have been identified, both among technical staff and end users. Resistance to technological change, a lack of training, and limited community participation in the design of these solutions contribute to limiting their effective implementation. In many cases, technologies developed in urban contexts are not adapted to the needs and dynamics of rural environments, creating a gap between the proposed solutions and their actual applicability.

Table 3. Challenges in implementing AI in rural contexts

Implementation Challenges	Article Code
Limited technological infrastructure	A6, A7, A8, A16, A18, A21, A22, A25, A27, A30, A36
High initial cost of sensors, GPUs, or specialized hardware	A1, A4, A10, A19, A29, A36
Lack of local data and difficulty training AI	A1, A3, A6, A17, A26, A28, A29, A30, A36, A41
Low digital literacy in rural areas	A5, A16, A18, A22, A48
Requirement for constant maintenance and retraining	A6, A11, A17, A20, A26, A30

Q4. How does the adoption of artificial intelligence in waste management vary among rural municipalities in different regions or levels of development?

The review of articles shows that the adoption of AI technologies in rural contexts is highly uneven and is determined by multiple structural, economic, technological, and political factors. In regions with higher levels of industrialization, good digital infrastructure, and public innovation policies, adoption is more advanced and is associated with pilot projects developed in collaboration with universities, research centers, or technology companies.

In contrast, in developing countries or remote rural regions, the implementation of these technologies is in its infancy or nonexistent. Poor connectivity, a lack of adequate equipment, and a lack of specific policies for the rural sector hinder the expansion of AI in waste management. Even within a single country, notable disparities are observed between urban and rural areas in terms of resources, technical capabilities, and access to financing. Studies also highlight that adoption is more likely when there are economic incentives, public subsidies, or regulatory frameworks that promote the use of AI for environmental sustainability. In this sense, the coordination of local stakeholders, regional governments, and academic institutions plays a fundamental role in closing the technological gap and fostering equitable implementation.

Table 4. Challenges and limitations in the implementation of information systems

Challenges and limitations	Article Code
Organizational resistance to change and lack of training	A1, A3, A4, A6, A15, A19, A21, A29
High costs of technology implementation and maintenance	A5, A7, A8, A16, A18, A21, A25, A27, A36
Lack of interoperability between government platforms	A2, A5, A7, A23, A31
Cybersecurity risks and vulnerabilities in data management	A5, A14, A22, A29, A31
Shortage of technical staff and data fragmentation	A6, A16, A18, A22, A27

Q5. What knowledge gaps and opportunities for future research are evident in the scientific literature on the use of artificial intelligence in waste management in rural settings?

Despite the growing interest in the application of AI for waste management, most studies focus on urban or industrial contexts, leaving a significant gap in the analysis of rural municipalities. There is a lack of field research validating the effectiveness of these technologies in real-life conditions, especially in regions with low resources, complex topography, or dispersed populations.

Likewise, there is evidence of limited participation of local communities in the design and evaluation of implemented technologies. The absence of participatory approaches limits the social sustainability of projects and suggests the need to integrate local knowledge and traditional wisdom in the development of technological solutions. There is also a limited number of studies focusing on the management of organic, agricultural, or mixed waste, which is very common in rural areas. Among the opportunities for future research is the development of adaptive, lightweight, and portable models capable of running on solar power, without constant connectivity, and with reduced maintenance costs. Likewise, the construction of open and representative datasets is required to train robust models for diverse rural conditions. Finally, there is a need to assess the long-term environmental and social impact of these technologies, as well as their economic viability in decentralized contexts.

Table 5. Knowledge gaps and research opportunities

Research gaps	Article Code
Lack of studies and validation in real rural settings	A1, A4, A5, A6, A12, A21, A24, A27, A28, A30, A36
Need for lightweight and adaptive models	A11, A20, A21, A28, A30, A37
Poor social integration in technology design	A3, A5, A6, A18, A22
Little attention to organic, household, or agricultural waste	A6, A11, A17, A32, A47
Potential for combining AI with traditional knowledge and community recycling	A5, A22, A30, A38, A48

DISCUSSION

The evidence gathered in this review confirms that artificial intelligence has significant potential to optimize solid waste management processes in rural municipalities. Technologies such as computer vision, deep learning, and smart sensors have proven effective in automating waste sorting, improving route planning, and reducing human intervention in critical processes. These systems, when adapted to local conditions, can make a significant difference in the operational efficiency of municipal services, especially in areas where human and technical resources are limited.

However, the results also reveal that the implementation of these technologies faces significant structural barriers. Limited digital infrastructure, a lack of stable connectivity, and the high acquisition costs of specialized hardware restrict the effective deployment of AI-based solutions. Furthermore, low digital literacy in many rural settings exacerbates these difficulties, limiting technological appropriation by local governments and beneficiary communities.

The studies analyzed indicate that AI adoption is more feasible when favorable public policies, financial incentives, and partnerships with academic institutions exist. These conditions have allowed some municipalities to develop successful pilot projects, adapting technological tools to the specific characteristics of rural environments. However, significant inequality persists between regions, raising the need to promote differentiated policies that consider territorial diversity.

Regarding knowledge gaps, there is limited scientific production focused on real rural contexts. Most developments have been validated in urban or simulated environments, which compromises their applicability in rural areas. Furthermore, there is little research on organic or household waste, and low participation of local communities in the design of these solutions reduces their social sustainability.

Finally, this review highlights a key opportunity to promote the development of lightweight and adaptive models capable of operating offline, with low energy consumption, and on accessible platforms. The construction of open, multiregional datasets also emerges as an urgent need to strengthen model training with greater accuracy and territorial representativeness. These challenges represent priority areas for future research to consolidate the role of AI in rural waste management.

CONCLUSIONS

The application of artificial intelligence in solid waste management in rural municipalities represents a significant opportunity to improve the efficiency, sustainability, and coverage of public services. The technologies analyzed allow for the automation of tasks, the optimization of resources, and the generation of valuable information for decision-making.

However, their adoption faces technical, economic, and social limitations that must be addressed from a comprehensive perspective. These include the lack of technological infrastructure, the limited availability of local data, and the need to strengthen institutional and community capacities.

The study also shows that AI implementation is more successful when local actors, favorable public policies, and research institutions are involved. These partnerships are key to adapting technological solutions to rural conditions and ensuring their sustainability over time.

Furthermore, there are significant gaps in the scientific literature, such as the absence of empirical studies in real rural areas, the limited attention paid to organic waste, and the limited incorporation of participatory approaches. Overcoming these gaps is essential to consolidate a more inclusive and contextualized research agenda. Taken together, the findings of this systematic review allow us to propose strategic guidelines for the design, validation, and implementation of artificial intelligence-based solutions that contribute to transforming waste management in rural areas in an efficient, equitable, and sustainable manner.

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CONFLICT OF INTEREST

There is no conflict of interest related to the subject matter of the work.

AUTHORSHIP CONTRIBUTION

Conceptualization, data curation, formal analysis, research, visualization, writing -original draft, writing -correction and editing: Arista-López, D. R.

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ANNEXES

Annexe A.1. Coded list of articles included in the review

Code	Authors
A1	(Ahmad et al., 2020)
A2	(Ahmed et al., 2024)
A3	(Amante et al., 2024)
A4	(Bchir et al., 2021)
A5	(Belsare et al., 2024)
A6	(Boostani et al., 2024)
A7	(Boresta et al., 2024)
A8	(Chen, 2021)
A9	(Chhabra et al., 2024)
A10	(Chowdhury et al., 2021)
A11	(Endah et al., 2021)
A12	(Fernandez et al., 2024)
A13	(Herrera-Granda et al., 2024)

A14	(Karademir & Özbakır Acımert, 2024)
A15	(Khan et al., 2021)
A16	(Koinig et al., 2024)
A17	(Labambe et al., 2024)
A18	(Laureti et al., 2024)
A19	(Li et al., 2024)
A20	(Lubongo et al., 2024)
A21	(Manakkakudy Kumaran et al., 2024)
A22	(Melinte et al., 2020)
A23	(Nedjar et al., 2024)
A24	(Olawumi et al., 2024)
A25	(Olivieri et al., 2024)
A26	(Onoda, 2020)
A27	(Palmieri et al., 2024)
A28	(Pandey et al., 2015)
A29	(Pitakaso et al., 2024)
A30	(Pulparambil et al., 2024)
A31	(Rekabi et al., 2024)
A32	(Saeed et al., 2021)
A33	(Sallang et al., 2021)
A34	(M. Sharma et al., 2020)
A35	(R. K. Sharma & Jailia, 2024)
A36	(Shukhratov et al., 2024)
A37	(Sirimewan et al., 2024)
A38	(Straka et al., 2018)
A39	(Tryhuba et al., 2024)
A40	(Vallejo et al., 2024)
A41	(Vesga Ferreira et al., 2024)
A42	(H. Wang et al., 2024)
A43	(Z. Wang et al., 2024)
A44	(Yazdani et al., 2024)
A45	(Zaeimi & Rassafi, 2021)
A46	(Zhao et al., 2024)
A47	(Zheng & Gu, 2021)
A48	(Zulhusni et al., 2024)