The application of artificial intelligence in waste management: understanding the potential of data-driven approaches for the circular economy paradigm

Published version:

DOI:10.1108/MD-10-2023-1733

(Article begins on next page)

Title: The application of artificial intelligence in waste management: understanding the potential of data-driven approaches for the circular economy paradigm.

Abstract

Purpose – Our study examines how artificial intelligence can enhance decision-making processes to promote circular economy practices within the utility sector.

Design/methodology/approach - A unique case study of Alia Servizi Ambientali Spa, an Italian multi-utility company using artificial intelligence for waste management, is analyzed using the Gioia method and semi-structured interviews.

Findings - Our study discovers the proactive role of the user in waste management processes, the importance of economic incentives to increase the usefulness of the technology, and the role of AI in waste management transformation processes (e.g., glass waste).

Originality – The present study enhances the circular economy model (transformation, distribution and recovery), uncovering AI's role in waste management. Finally, we inspire managers with algorithms used for data-driven decisions.

Keywords: Artificial Intelligence, Management Decision, Circular Economy, Waste Management, Case Study.

1. Introduction

In the 21st century, two powerful forces are reshaping society and the economy: the green revolution and digital transformation. The green revolution, arising from a pressing need for environmental preservation and sustainable development, is changing sectors such as renewable energy, agriculture, and waste management (Raworth, 2017). Simultaneously, the digital transformation, characterized by rapid technological advances such as AI and cloud computing, is revolutionizing industries and redefining societal interactions (Agrawal *et al.*, 2019).

Beyond contingent factors, several international entities are raising awareness of multiple players toward the need for a paradigm shift that disrupts the traditional "take, produce, and dispose" model (Adams, 2017). Exogenous pushes from the European Union (EU) and the United Nations have placed the Circular Economy (CE) at the heart of the debate in several recent scientific publications (European Commission, 2020; United Nations, 2023). According to Kouhizadeh et al. (2019), CE represents an economic model for reducing resource consumption and eliminating waste by extending the life cycle of products. The theoretical construct appears feasible only through proper waste disposal leading to material recovery, one of the pillars of CE (Prieto-Sandoval *et al.*, 2018).

Several studies have already explored the impacts on the waste management industry toward sustainability through innovative technologies (Abdallah *et al.*, 2020). Artificial Intelligence (AI) is an advanced technology tool used to predict waste generation patterns, optimize waste collection truck routes, locate waste management facilities, and simulate waste conversion processes (Ihsanullah *et al.*, 2022). With the ability to analyze vast amounts of data and predict patterns, AI can improve resource utilization efficiency, reducing the environmental footprint (Marseglia *et al.*, 2015). For instance, machine learning algorithms can optimize recycling sorting processes by recognizing and classifying waste types more accurately and efficiently than traditional methods (Lu and Chen, 2022). However, new AI-based computing capabilities improve service and provide more users with unknown variables and decision-making processes (Secinaro *et al.*, 2021). In this context, AI can manage data and support managers' decision-making processes, but it can be incorporated into products to facilitate users' needs (Massaro *et al.*, 2017).

Based on these motivations, the present study explores how AI can effectively improve the waste management decision-making process. Specifically, the study considers the assumptions of CE as the target of technology applications within the utility sector.

Although several studies consider the introduction of AI for waste management, their focus is on applying AI to waste management without considering the unique characteristics and attributes of waste management systems (Abdallah *et al.*, 2020). Specifically, neural networks have been explored for predicting waste generation (Golbaz *et al.*, 2019), waste classification (Singh and Satija, 2018), energy recovery (Hannan et al., 2016), and biogas generation (Yetilmezsoy *et al.*, 2011). Other studies consider supervised machine learning algorithms for predicting bin fill levels (D'Morison *et al.*, 2013). To the best of our knowledge, no study considers the perspective of the multi-utilities company and the impact AI has in pushing toward managerial decisions to foster CE. Therefore, the present research analyzes a unique case study of international interest to understand the dynamics related to the application of AI in managerial decisions in the waste management sector (Massaro *et al.*, 2019). Specifically, the authors aim to answer the following research question:

RQ: "How does AI in waste management influence decision-making and promote circular economy principles?

In addressing the RQ, we adopt a qualitative case study analysis using semi-structured interviews inspired by the Gioia et al. (2013) method with operators and managers of the company Alia Servizi Ambientali Spa. Our research presents conceptual and practical implications related to CE, emphasizing the pivotal role of the user in waste disposal processes and suggesting to practitioners the potential of incorporating AI as an enabler of a new decision-making process. Additionally, the paper provides practical implications for AI and new ways of managing decision-making processes, setting aside the technical dimensions of introducing AI into operations but focusing on decision-makers' contributions. Specifically, the revolutionary system under investigation allows for a pay-as-you-throw computation model based on big data to reveal the quality and quantity of waste disposal. The paper proceeds as follows. Section 2 provides the literature review. Section 3 defines the methodology. Section 4 presents the findings. Section 5 discusses the previous results and Section 6 concludes the paper.

2. Literature review

2.1 Circular economy

The present section aims to define the concept of CE to build a theoretical framework to understand the integration of AI in utilities. The current interpretation of CE considers an economic model to reduce resource consumption and eliminate waste, enabling product life extension (Kouhizadeh *et al.*, 2019). The main novelty of the new economic paradigm lies in creating nonlinear production and consumption because the traditional "take, make, and dispose" model no longer appears sustainable (Upadhyay *et al.*, 2021). In this regard, CE relates to reusing products, parts, and materials within the economy for as long as possible to minimize the generation of non-recoverable waste (Haleem *et al.*, 2021). Along these lines, circular systems view waste as potential inputs to another process (European Commission, 2019).

From another perspective, the CE construct represents an economic system to replace the notion of product end-of-life, emphasizing the use of renewable energy, recycling, and material recovery, minimizing the environmental impact of the production system (Marrucci *et al.*, 2021). Thus, end consumers of products play a crucial role in waste disposal (Borrello *et al.*, 2017). However, activating a CE system daily requires interaction with sensitivity-based moral complexity and partially contradictory ethical practices (Lehtokunnas *et al.*, 2020).

The CE literature emphasizes the possibility of reducing resource inputs and reusing waste to achieve a higher quality of life through increased resource efficiency to understand the role of utility companies within the innovative economic paradigm (Perey *et al.*, 2018). This is also possible by using new innovative technologies that allow waste management companies to analyse big data using algorithms (Paes *et al.*, 2019).

However, garbage has no unambiguous definition. According to Drackner (2005), a residue from a production or consumption process discarded by individuals and considered unusable is considered garbage. Other authors link the concept of garbage and waste to cultural development, arguing that the degree of change and economic development affect what society discards (Douglas, 1996). Therefore, the new paradigm builds on five significant and continuous steps. First, industries transform resources from the environment into products and services (Park *et al.*, 2010). Next, the products of this transformation go to stores and consumers (Prieto-Sandoval *et al.*, 2018). The cycle does not end with waste disposal but closes with the recovery and enrichment of used materials (Stahel, 2016). The present study fits into the last phase by considering management decision challenges as crucial for the transaction to the CE model, including through technology (Paes *et al.*, 2019).

2.2 The link between CE and AI for waste management

Recent advancements in digital technology are significantly changing the landscape of management decision, particularly in the CE and waste management sectors. This transformation is largely propelled by the integration of AI, as highlighted in the research by Ma *et al.* (2020). AI is not only creating new avenues for value but also notably improving collective well-being, as Bag and Pretorius (2020) have emphasized. The effectiveness of AI in these areas, however, hinges on the reliability of the information flow, a critical issue pointed out by Bianchini *et al.* (2019).

Within the context of CE, AI's role in enabling big data analytics has been identified as a key factor. This technology is pivotal in enhancing supply chain management, resource management, and quality control, which are vital for understanding sustainability dynamics (Modgil *et al.*, 2021). AI-based platforms are instrumental in efficiently collecting, analyzing, and disseminating critical information about circular systems (Makarova *et al.*, 2018). Furthermore, AI's ability to detect hidden patterns aids in managerial decision-making, enabling the design of effective environmental cost control and decision support systems for supplier selection based on circularity criteria, a concept further explored by Tang and Liao (2021).

However, the widespread implementation of AI in CE faces several barriers. Ingemarsdotter et al. (2020) identifies challenges including the absence of structured data management processes, complexities in developing IoT-enabled products, and the substantial costs involved in adopting big data technology. Additionally, as Chauhan et al. (2022) point out, the lack of comprehensive regulatory frameworks, limited environmental education, and low market demand create further obstacles. Politically, there's a need for increased governmental support to overcome hurdles in big data application implementation and to address critical issues like data privacy, security, and the need for standardization and interoperability in data formats (Zhang *et al.*, 2019). Ensuring the quality and equitable access to data across different regions and sectors is essential (Mourtzis *et al.*, 2022), and these factors represent major barriers to developing effective CE policies and solutions (Umeda *et al.*, 2020). Addressing these challenges necessitates a revision of existing regulations and a well-informed discussion about the benefits and risks associated with the use of big data in CE, emphasizing the need for collaborative engagement between public and private sectors (Owojori and Okoro, 2022).

In the field of waste management, the application of AI has been extensive. It is being used for forecasting waste generation patterns, optimizing waste collection routes, determining the locations for waste management facilities, and simulating waste conversion processes (Ihsanullah *et al.*, 2022). Applications have included using artificial neural network models for predicting waste generation (Golbaz *et al.*, 2019), classifying waste (Singh and Satija, 2018), recovering energy (Hannan *et al.*, 2016), monitoring bin levels (Rajamanikam and Solihin, 2019), and generating biogas (Yetilmezsoy *et al.*, 2011). These networks, which consist of interconnected layers (Duda and Hart, 2006), along with support vector machines, a method for data analysis (Dixon and Candade, 2008), have been effective for predicting dumpster fill levels (D'Morison *et al.*, 2013) and classifying waste (Singh and Satija, 2018). Decision trees have also been used in waste classification (Cha *et al.*, 2017) and compression (Lu, 2019), applying rule classification techniques to unknown data (Kotsiantis, 2013). Nevertheless, according to Abdallah *et al.* (2020), it's important to consider the unique characteristics and properties of waste management systems when applying AI technologies.

3. Methodology

3.1 Case study identification

The need to measure the quality and quantity of waste produced belongs to administrations in every region of the world. As a result of the Environmental Code (Italian Government, 1997), the Italian government began a community awareness process regarding separate waste management. Specifically, the law established guidelines for waste management, including waste disposal, recovery, and recycling, to promote sustainable waste treatment. Subsequently, the legislature emphasized producer responsibility through the Consolidated Environmental Act (CEA) (Italian Government, 2006). The main consequence resulted in the empowerment of the producer to participate in the management and treatment of the subsequent waste, mainly for special and dangerous wastes.

Furthermore, national targets for waste recycling and recovery are set to promote recycling and reduce the amount of waste going to landfills. To encourage separate waste collection, CEA introduced the "door-to-door" system as one of the main tools to promote separate waste collection. Under this system, different materials (such as paper, plastic, glass, organic, etc.) are collected separately directly by citizens, who must specially sort the waste according to the directions given by local governments. Unlike the ordinary collector, the system fosters a more sustainable approach to waste management by encouraging greater responsibility from citizens and local governments in managing the waste they produce. Figure 1 shows the area of central Italy served by Alia Spa, covering 58 Tuscan municipalities with 1,532,299 inhabitants. The multi-utility company has revenues of € 377,767,153 million in 2022, up more than 9 percent from the previous period. This figure confirms the growth trend during the last fiscal period, where the increase in turnover was more than 12 percent. Overall, the company generates revenue of about € 250 per inhabitant. The multi-utility company's broad coverage and significant customer base make it an ideal case for study, offering a comprehensive view of waste management challenges and practices in a diverse and extensive urban setting.

PLEASE PLACE FIGURE 1 HERE

Despite attempts to incentivize better quality collection, the charging system has been based on household size. However, as of January 2023, a fee-based tariff has been introduced. The system is founded on the effective measurement of waste produced by users. It aims to promote more responsible waste management by citizens by rewarding users who make more effort to separate waste. The system aims to provide more equitable bills, with households or businesses of the same type potentially receiving different bills based on their waste disposal behavior: the more committed one is to separate waste collection, the greater the chance of receiving the expected rewards. In this regard, the case study investigates the pioneering approach of Alia, a leading utility company in central Italy. The research explores the new tariff system developed by Alia with the help of the Tuscany region based on accurate, real-time data derived from users' waste disposal behavior. Along these lines, the Point-based Compensatory Tariff (PBCT) is developed by integrating advanced technologies such as AI applied to Big Data. The case study of Alia becomes particularly relevant for its potential to be applied in similar contexts globally, thereby highlighting the generalizability of the findings under similar conditions.

The primary purpose of this groundbreaking tariff is to incentivize and increase the proper disposal of sorted waste while pushing the performance of the CE to new heights. The system balances environmental sustainability and economic feasibility by accurately assessing individual waste disposal habits. The approach departs from the traditional pay-as-you-throw (PAYT) model, as payment per individual disposal makes users prone to throw waste outside designated containers, resulting in litter and environmental hazards. Alia's innovative approach focuses on rewarding responsible behavior rather than punishing waste generation, making the case study of international interest valuable for understanding how AI integration can support decision-making. The company's focus on rewarding responsible behavior rather than punishing waste generation provides valuable insights into sustainable waste management practices that can be adopted internationally.

3.2 Research design

The current section outlines a qualitative approach to investigate how technological implementation can impact stakeholders in the utility sector, building upon principles outlined in the literature review. This method, which facilitates a deeper understanding of various factors and enriches existing knowledge (Lanzalonga *et al.*, 2023), is structured into four key stages to ensure the reliability of the results, as outlined by Cascante et al. (2022). Initially, the research design and objectives are defined (Eisenhardt, 1989), followed by the adoption of a transparent and rigorous methodology for the validation of case studies (Massaro *et al.*, 2019). In this context, the research focuses on Alia's Point-Based Compensatory Tariff (PBCT), previously mentioned, involving through interviews various professionals with decision-making or operational roles to explore the support of artificial intelligence in managerial decisions. The research process employs the snowball sampling technique, allowing access to information through a network of contacts (Noy, 2008), and selection strategies aimed at identifying non-obvious cases through auxiliary and informal channels (Hendriks *et al.*, 1992).

In the third phase, primary data are collected through semi-structured interviews with technology development managers (Secinaro *et al.*, 2021). Finally, data analysis occurs through an iterative reasoning cycle based on an inductive research approach, specifically the Gioia method (Gioia *et al.*, 2013). This method emphasizes the importance of discovering new concepts in the organizational context and building a more authentic and meaningful understanding of organizational dynamics. Through a systematic and iterative approach, researchers explore the socially constructed reality of organization members, going beyond mere standardized measurement of phenomena. The technique helps explain the phenomena of interest and make relevant connections between information flows and theory (Figure 2).

PLEASE PLACE FIGURE 2 HERE

3.3 Interviews data

Applying the technique of information triangulation, the authors used a variety of sources to implement the holistic case study (Flick, 1998). Precisely, exploring the phenomenon followed a stream of consultation of whole materials, disclosable documents, and semi-structured interviews with business practitioners involved in managerial decisions. The interviews lasted 847 minutes, and five process experts proceeded with coding, transcribing, and refining the texts. The interview texts were coded through ATLAS.TI version 9 software provides transparency and reliability to the authors (Hwang, 2008). Information was collected over five months, and Tables 1 and 2 summarize the data from the semi-structured interviews and respondents. Some interviews were conducted by the author in groups of 3 or more people, a factor that positively affected the variety of responses offered (Balasubramanian *et al.*, 2021).

PLEASE PLACE TABLE 1 HERE

PLEASE PLACE TABLE 2 HERE

Several components ensure the triangulation of sources throughout the entire process of case study analysis. The present research follows a protocol for source triangulation that permits the phenomenon to be observed from multiple perspectives (Flick, 1998). The process involves gathering information from other sources or through different methods and comparing and corroborating these different lines of evidence. In management decisions, data triangulation might include interviews with various internal and external stakeholders, analysis of internal documents, and observational data collected in the field. By comparing information obtained through these different channels, researchers can identify common patterns and differences, providing a more complete and multifaceted understanding of the phenomenon under study. Data triangulation enriches the researcher's understanding, helps mitigate bias, and increases confidence in the study's conclusions, making the results more robust and credible. As in traditional qualitative research, identifying sources with this method enables the combination of data from different sources at different periods, different locations, or from other individuals while balancing the subjective influences of individuals (Flick, 2004). In addition to interviews with company practitioners, the present research utilizes recent literature on the topic and internal project documents to substantiate the veracity of information and to combine only methodologies within a single research approach (Blaikie, 1991). The authors used the white paper to investigate examples consistent with each partner's reference domains regarding CE and AI features (Secinaro *et al.*, 2021). This approach allowed for a comprehensive analysis of the intersection between CE principles and AI technologies, providing a global understanding of the subject. By examining real-life cases that align with each partner's expertise, the authors could draw meaningful insights and identify common patterns in implementing CE practices in conjunction with AI advancements. All interviews were conducted in a virtual room utilizing Cisco Webex software, and the resulting minutes were subsequently analyzed as described below.

4. Results

4.1 A new landscape for circular economy

The different international and national pressures to implement a beneficial CE model have made companies in the utility sector critical players in an unavoidable change (European Commission, 2019; Italian Government, 1997). The anonymity of the disposal process has made monitoring difficult over the years. Consequently, technological evolutions have supported the user's identification during waste disposal and allowed the entire tariff payment system to be rethought in a tailor-made approach.

"The government has focused on educational information to improve the quality of waste disposal. However, basing the payment through a PBCT *system accelerates user awareness and establishes a model rewarding good behavior."*

(A-3 interviews, Scientific strategist and consultant)

Moreover, the system can only be implemented by introducing waste containers that consider filling curve levels a game-changer in the waste management sector. Based on sensors, the technology allows more support for the CE process, with waste management as its crucial point. Therefore, the innovation makes managing differences in the volumetric amount of waste possible.

"Seasonal fluctuations in waste generation have been a longstanding challenge, often resulting in inefficient waste collection and transportation. However, Alia's data-driven approach tackles this issue head-on, allowing decision-makers to analyze historical patterns and strategically plan waste collection and transportation activities, minimizing wastage of resources and energy."

(A-6 interviews, Senior level professional with experience in AI application)

Along with quantitative measurement, the innovative approach includes user recognition via a smartphone application or ID code. In this vein, it is possible to monitor the correct delivery of waste to the bins dedicated to different materials. Tracking user behavior allows for a change in the payment paradigm and enables the establishment of a data-driven approach. It follows that managerial decisions will be based on the number of deliveries recognized by a sensor that measures the volume of waste and the different container openings.

"The success of Alia's forward-thinking approach has the potential to serve as a role model for waste management systems worldwide. By embracing data-driven strategies, cities and regions can tailor their waste management practices suiting specific needs, leading to better resource allocation, increased environmental protection, and improved overall quality of life for residents."

(A-1 interviews, IT Manager)

Beyond the immediate benefits of encouraging responsible waste disposal and recovery of material, implementing this innovative system based on the new payment paradigm opens the door to other positive outcomes. By accurately measuring the filling levels of waste containers, data becomes available to transform decision-making processes for managerial choices within multi-service companies. Figure 3 describes the six-step process developed by Alia to achieve the PBCT. Step 1 involves the user, who needs to be recognized through a digital ID code such as a smart card or phone application in the wasting disposition operation. Subsequently, in phase 2, the user unlocks access to the required garbage collector to follow the municipal separate waste collection policies. In step 3, the waste is delivered, and the volumetric amount added to the bin is measured. The collectors are equipped with sensors that measure the amount of waste and allow the data collection to be not anonymized but pointed at the user. In phase 4, AI-based technological systems allow monitoring and quantitative prediction of the level of bin refilling and qualitative verification of the consistent opening of each bin based on user behavior. On the one hand, in phase 5, it will be possible to streamline the route of the garbage collector, which will be able to collect the waste when the garbage collector has reached the maximum capacity. On the other hand, validating the user's valuable waste disposal behavior allows unique patterns to be calculated for each user and creates a tailored tariff based on the quality and quantity of waste. The last one represents step 6.

PLEASE PLACE FIGURE 2 HERE

4.2 The pivotal role of the user in enhancing environmental and technological awareness.

This section explores points 1, 2, and 3 (Figure 2), focusing on the user's role. Several community services have been digitized to increase safety in processes and strengthen the CE process (Pagoropoulos *et al.*, 2017). Although different systems have been implemented to increase citizens' awareness of recycling disposal, the regulations introduced to educate users have yet to be effective. The stimulus presented by the pioneering system of the present case study makes it possible to relate the quality of the deliveries to the fee payment. In this way, the user can improve their behavior and habits to gain an advantage in the price paid for the service.

Therefore, the PBCT necessitates precisely measuring each user's waste disposal. This is a significant shift from the previous system based on estimated waste production. The new approach requires an accurate record of the amount and type of waste each user disposes of, which is then used to calculate their waste management fee. This shift represents a considerable technological and operational challenge. The need for precise measurement has driven the development and deployment of new technologies and systems.

"The technologies must accurately record waste disposal data for each user, which must then be processed and used to calculate individual fees. This is a complex task that requires significant resources and expertise."

(A-7 interviews, Senior data analyst involved in the CE program)

Integration of technological innovation is crucial to applying the new paradigm successfully. The user plays a central role and needs to understand new processes to improve perceived usability and usefulness. The need to record delivery means that users will digitize the waste disposal habit. This system enhances the level of attention required and extends the confidence that the waste can be reused.

4.3 AI integration to data-driven management decision in the utility sector

The present section aims to focus on steps 4, 5, and 6 of the process to understand how AI in waste management can support management decisions in a data-driven system (Figure 3). AI is widely used to predict waste generation patterns, optimize waste collection truck routes, locate waste management facilities, and simulate waste conversion processes (Ihsanullah *et al.*, 2022).

"For street collection, the measurement process appears complex. To overcome this challenge, Alia has had to patent various supporting technologies. Specifically, a "brain" and a volume sensor."
(B-3 interviews, Academic consultant expert in AI)

The "brain" represents a highly advanced circuit integrated into the waste management infrastructure. An array of essential components is included in this circuit, including a smart alarm system designed to swiftly respond to critical events such as fires, impacts, or overturning of waste containers. The system ensures enhanced safety and security in waste management operations by promptly detecting and alerting relevant authorities. Furthermore, the "brain" also features a sophisticated telemetry system that continuously monitors crucial parameters related to the waste containers' functionality. This includes real-time data on battery temperature and charge levels, enabling proactive maintenance and optimal performance of the waste management equipment. The telemetry system's ability to provide valuable insights allows for efficient resource allocation and cost-effective management of waste disposal facilities.

"Leveraging cutting-edge technology, this comprehensive system improves not only operational efficiency but also encourages responsible waste disposal behavior and contributes to creating cleaner, more sustainable communities."
(A-2 interviews, Internal CE Expert)

Informed literature interviews highlight two primary paradigm shifts for the sector, as illustrated in points 5 and 6 of Figure 3. Specifically, the new system allows for reductions in carbon footprint from transportation consistent with EU targets. These targets, as outlined by the European Parliament, include a commitment to reduce greenhouse gas emissions by at least 55% by 2030, compared to 1990 levels, as part of the European Green Deal, aiming for climate neutrality by 2050 (European Parliament, 2022). The EU’s Sustainable and Smart Mobility Strategy plays a vital role here, aiming to cut transport-related CO2 emissions by 90% by 2050, which involves a shift towards zero-emission vehicles, development of alternative fuel infrastructures, and enhancement of public transport efficiency. The EU has also introduced stricter regulations for new vehicle emissions, encouraging the transition to electric vehicles, and is investing in sustainable infrastructure, like electric vehicle charging stations and low-impact public transport systems. Financial incentives are being provided to both companies and consumers for adopting sustainable practices, including subsidies and tax breaks for electric vehicle purchases. This comprehensive approach aligns with the wider EU climate goals established under the European Green Deal, emphasizing the importance of circular economy initiatives, international and local collaborations to ensure a consistent implementation of these policies across member states.

Since the collection phase is triggered only at a predetermined filling level, managerial decisions that design operators' routes will benefit from AI.

"With knowledge about filling levels and efficient mapping of disposal stations, waste operators can optimize collection routes, minimizing unnecessary trips and significantly reducing the carbon footprint associated with waste management."

(A-9 interviews, CE professional employed in the recycling process)

Thus, this reveals a twofold advantage. On the one hand, the AI-based system pursues achieving emission reduction targets. On the other hand, it improves the quality of the environment for communities and enables increased cleanliness around roadside garbage collection centers. Analysis of data collected on an AI basis can allow the innovation of the present case study.

"Data collected based on user information makes it possible to analyze users' delivery habits and record the volumetric amount of garbage."

(B-1 interviews, Independent expert consultant in utility management)

A data-driven system allows customization of rates employing a usage counter by establishing a system rewarding good user habits. The already explained PBCT roots in the analysis through AI of Big Data allow for forecasting user behavior in the disposal to the street collector.

4.4 Decisions underlying waste management – The glass recovery process

The system described above integrates with what are the waste recycling needs according to the EU (European Commission, 2019). From a product life cycle extension perspective, the user's ability to manage waste responsibly is critical in the chain of transformation, distribution, use, recovery, and take (Sadraei *et al.*, 2023).

"The simplest example I can give you is glass waste management. Glass represents a processable material almost entirely. In particular, glass is higher quality and simplifies raw material recovery."

(A-5 interviews, Professional with experience in the CE program)

According to Prieto-Sandoval et al. (2018), the results show users' responsibility is crucial in achieving the material repurposing result.

"Glass is a material that any citizen can recycle without any inconvenience regarding management. For example, compared to plastic, it does not need to be composed of certain technical characteristics to be recycled. In addition, compared with organic waste, it allows for easier management by not producing inconveniences related to fermentation of the waste."

(A-8 interviews, Sustainable development specialist)

Therefore, the glass recovery and transformation process, when stimulated through techniques related to AI, can be summarized as follows in the five stages of the framework (Figure 4).

PLEASE PLACE FIGURE 4 HERE

(i) Glass containers are commonly used in households and the hospitality industry. Waste management systems typically consider two primary collection methods: bins (bell-shaped containers) and door-to-door collection services.

"The door-to-door collection service enables higher quality separation of waste. However, compared to bell-shaped container systems, it can be strenuous for users who need to collect the waste themselves. The door-to-door waste management does not incorporate an automated waste loading system onto the truck."

(B-5 interview, Expert scientific coordinator of utility companies)

(ii) Glass materials collected through recycling are sent to processing centers where they are separated from foreign materials such as crystals, ceramics, or other waste. Various phases involve selection using specific optical and electronic machines and manual sorting.

(iii) In glass furnaces, the glass scrap is melted at around 1500°C, and the resulting glass is fed into forming machines where, using special molds, it takes the shape of a new container. The bottle or other container is properly cooled and moves to the cold zone of the glassworks, where it undergoes rigorous in-line checks via sophisticated electronic machines. The new container can then be delivered to bottling companies.

(iv) At the bottling plant, the glass container is packaged and resold to food companies, filled with various products, and sent to the retail network.
(v) Bottles and other containers are given a new lease on life and return to supermarket shelves to contain wine, oil, liqueurs, beverages, and all liquid foods. This restarts the cycle, initiating an accurate circular economy process.

"Technology can support the entire process to drive efficient glass waste collection. However, the primary responsibility for the success of this circular process lies with consumers who use the products. A rewarding system enables higher-quality collection, even for less environmentally sensitive but more attentive to financial savings."

Taken and adapted from internal documents

5. Discussion

The unique case study allows us to feed the debate on CE and AI applications for waste management. Table 3 summarises the main results obtained and their conceptual and practical implications.

PLEASE PLACE TABLE 3 HERE

5.1 AI fostering CE transformation and distribution model

According to Kouhizadeh et al. (2019), a generally accepted interpretation of the CE considers an economic model for reducing resource consumption and avoiding waste, enabling transformation and product life extension. Some research finds manufacturing companies to play a crucial role because of the daily waste generated (Perey *et al.*, 2018; Peters *et al.*, 2007). On the other hand, other scholars have spotlighted the critical part of the end user (Borrello *et al.*, 2017). Although the importance of companies in the process needs to be considered inevitably, our unique case study using AI contributes to understanding the role of the citizen as pivotal in the process of waste disposal to achieve successful quality recycling. Therefore, economic incentives represent the solution to overcome the reluctance to change behavior that different regulations have attempted to address through unsuccessful educational programs. Additionally, data-driven strategies promote increasing waste quality in the transformation processes thanks to reduced operational steps required (Prieto-Sandoval et al., 2018).

A second implication comes from observing the process of glass collection and processing. The case study suggests us that artificial intelligence can be used to increase the accuracy of glass collection and recycling. This increases the processing efficiency and subsequent distribution of recycled glass, creating value for the waste management company (Prieto-Sandoval et al., 2018).

5.2 AI enables data analysis for new decision-making processes: the case of dumpster collection

According to Abdallah et al. (2020), several studies on waste management and technology have already explored the potential of AI in improving processes and predicting dumpster fill levels. However, research has been conducted from a technical standpoint, demonstrating the potential to understand waste generation (Abbasi et al., 2014) and waste classification (Singh & Satija, 2018). Therefore, the present study offers a broader and less technical perspective, integrating managerial decision perspectives into the ongoing debate.

Furthermore, the case study reported in the research allows for the convergence of waste management and the CE concept through AI's potential. In this sense, the PBCT system proposed by Alia SpA involves an AI-driven process based on data analysis (Modgil et al., 2021), capable of engaging users not by focusing on awareness but on financial savings. Therefore, the study conceptualizes a CE process based on AI that supports decision-making based on data analysis.

Finally, the study implies the transfer of decision-making power guided by AI in the context of CE by integrating it through various tools such as neural networks (Singh & Satija, 2018) or decision trees (Kotsiantis, 2013) to provide waste generation models, optimize waste collection truck routes, locate waste management facilities, and simulate waste conversion processes (Ali et al., 2019; Ihsanullah et al., 2022). In this regard, the study allows for the integration of AI's potential with managerial decisions stemming from technological potential to overcome barriers already highlighted in the waste management literature, such as the absence of structured data management processes, challenges in developing IoT-enabled products, and costs associated with adopting big data technology.

6. Conclusion

Implementing a CE model can use AI to meet international pressures (European Commission, 2019; United Nations, 2015). Although several studies have investigated the technical potential of AI applications in the waste management industry (Singh & Satija, 2018; Hannan et al., 2016), the present research explored the enabling features for management decisions. Using the CE perspective, the study analyzed a single case study based on semi-structured interviews, applying Gioia et al. (2013). The multi-utility service company Alia Spa represents a case study of international interest due to multiple AI applications allowing service efficiency and facilitating managerial decisions. Specifically, the research spotlighted the integrated waste collection process with AI, highlighting two primary benefits. First, the ability to design optimal routes for waste collection through sensors providing information on the level of bin filling. Second, the ability to recognize the user to have a PBCT can disrupt the traditional paradigm and encourage the user to pursue a CE model.

Based on the discussion section, our research points out multiple coceptual implications of CE.

Adopting the CE model of (Prieto-Sandoval et al., 2018), our paper contributes to extending the significance of the "transformation", "distribution", and "recovery" theoretical concepts. First, considering the transformation process, we demonstrate the pivotal role of citizens in waste disposal for recycling success and suggest economic incentives to achieve behavior change. Furthermore, increasing awareness and reducing anonymity through smart cards increase users' responsibility, improving the effectiveness of CE. At the same time, user empowerment through behavioral choices highlights individual contributions to advancing the CE systems. Second, using AI, we discover the extension of the distribution concept thanks to the glass transformation. Third, our findings also in developing the "recovery" concept improving waste identification processes.

Our research also reveals several practical implications. First, AI facilitates enhanced decision-making, leading to efficient and automated waste disposal processes, which can be incentivized through a PBCT computational system. Additionally, AI-driven data collection optimizes waste collection programs, reducing carbon footprints and improving urban environments. Application of the design promotes widespread responsibility in the CE, empowering users and businesses to adopt valuable behaviors. The data abundance obtained from the model supports continuous service performance improvement processes, facilitating managerial decisions and promoting CE principles.

Like any research, ours also has some limitations. Although the case study is of international interest and presents significant challenges, the application may differ based on geographic area regulations. Also, application to the Italian area makes the CE suitable for the context of the present scenario. Other regions could benefit from applying different approaches. Finally, the application of pioneering technologies and the embryonic stage of the AI study could make the case study outdated in the coming years. However, the present study suggests areas for future research. Specifically, differences in regulations in different geographic regions deserve further investigation. There is a need for further investigation, and other researchers may consider stakeholder theory to understand how to overcome challenges arising from multiple process dimensions. Moreover, additional researchers can evaluate the technology acceptance model to understand how users may respond to introducing technological tools to traditional practices.

Acknowledgment

The authors are grateful to Alia Servizi Ambientali Spa for their interviews and enthusiasm toward the research project.

References

Abbasi, M., Abduli, M.A., Omidvar, B. and Baghvand, A. (2014), "Results uncertainty of support vector machine and hybrid of wavelet transform-support vector machine models for solid waste generation forecasting", *Environmental Progress & Sustainable Energy*, Wiley Online Library, Vol. 33 No. 1, pp. 220–228.

Abdallah, M., Talib, M.A., Feroz, S., Nasir, Q., Abdalla, H. and Mahfood, B. (2020), "Artificial intelligence applications in solid waste management: A systematic research review", *Waste Management*, Elsevier, Vol. 109, pp. 231–246.

Adams, C.A. (2017), "Conceptualising the contemporary corporate value creation process", *Accounting, Auditing and Accountability Journal*, Emerald Group Publishing Ltd., Vol. 30 No. 4, pp. 906–931, doi: 10.1108/AAAJ-04-2016-2529.

Agrawal, A., Gans, J. and Goldfarb, A. (2019), *The Economics of Artificial Intelligence: An Agenda*, University of Chicago Press.

Bag, S. and Pretorius, J.H.C. (2020), "Relationships between industry 4.0, sustainable manufacturing and circular economy: proposal of a research framework", *International Journal of Organizational Analysis*, Emerald Publishing Limited, Vol. 30 No. 4, pp. 864–898, doi: 10.1108/IJOA-04-2020-2120.

Balasubramanian, S., Shukla, V., Sethi, J.S., Islam, N. and Saloum, R. (2021), "A readiness assessment framework for Blockchain adoption: A healthcare case study", *Technological Forecasting and Social Change*, Elsevier, Vol. 165, p. 120536, doi: 10.1016/j.techfore.2020.120536.

Bianchini, A., Rossi, J. and Pellegrini, M. (2019), "Overcoming the main barriers of circular economy implementation through a new visualization tool for circular business models", *Sustainability*, MDPI, Vol. 11 No. 23, p. 6614.

Blaikie, N. (1991), "A critique of the use of triangulation in social research", *Quality & Quantity: International Journal of Methodology*, Springer, Vol. 25 No. 2, pp. 115–136.

Borrello, M., Caracciolo, F., Lombardi, A., Pascucci, S. and Cembalo, L. (2017), "Consumers' perspective on circular economy strategy for reducing food waste", *Sustainability*, MDPI, Vol. 9 No. 1, p. 141.

Cascante, M.Q., García, N.A. and Fold, N. (2022), "The role of external forces in the adoption of aquaculture innovations: An ex-ante case study of fish farming in Colombia's southern Amazonian region", *Technological Forecasting and Social Change*, Elsevier, Vol. 174, p. 121185.

Cha, G.-W., Kim, Y.-C., Moon, H.J. and Hong, W.-H. (2017), "New approach for forecasting demolition waste generation using chi-squared automatic interaction detection (CHAID) method", *Journal of Cleaner Production*, Elsevier, Vol. 168, pp. 375–385.

Chauhan, C., Parida, V. and Dhir, A. (2022), "Linking circular economy and digitalisation technologies: A systematic literature review of past achievements and future promises", *Technological Forecasting and Social Change*, Vol. 177, p. 121508, doi: 10.1016/j.techfore.2022.121508.

Dixon, B. and Candade, N. (2008), "Multispectral landuse classification using neural networks and support vector machines: one or the other, or both?", *International Journal of Remote Sensing*, Taylor & Francis, Vol. 29 No. 4, pp. 1185–1206.

D'Morison, F., Bittencourt, C. and Ferraz, L. (2013), "Bin level detection based on wall entropy perturbation in electronic waste collection", *Proceedings of the World Congress on Engineering and Computer Science*, Vol. 1.

Douglas, M. (1996), *Thought Styles: Critical Essays on Good Taste*, Sage.

Drackner, M. (2005), “What is waste? To whom?-An anthropological perspective on garbage”, *Waste Management & Research*, Sage Publications Sage CA: Thousand Oaks, CA, Vol. 23 No. 3, pp. 175–181.
Duda, R.O. and Hart, P.E. (2006), *Pattern Classification*, John Wiley & Sons.
Eisenhardt, K.M. (1989), “Building theories from case study research”, *Academy of Management Review*, Vol. 14 No. 4, pp. 532–550.
European Commission. (2019), *Accelerating the Transition to the Circular Economy: Improving Access to Finance for Circular Economy Projects*, Publications Office, LU.
European Commission. (2020), *Categorisation System for the Circular Economy*.
European Parliament. (2022), “Towards carbon neutrality through ambitious transformation of the EU energy system”.
Flick, U. (1998), *The Psychology of the Social*, Cambridge University Press.
Flick, U. (2004), “Triangulation in qualitative research”, *A Companion to Qualitative Research*, Thousand Oaks Sage, Vol. 3, pp. 178–183.
Gioia, D.A., Corley, K.G. and Hamilton, A.L. (2013), “Seeking qualitative rigor in inductive research: Notes on the Gioia methodology”, *Organizational Research Methods*, Sage Publications Sage CA: Los Angeles, CA, Vol. 16 No. 1, pp. 15–31, doi: 10.1177/1094428112452151.
Golbaz, S., Nabizadeh, R. and Sajadi, H.S. (2019), “Comparative study of predicting hospital solid waste generation using multiple linear regression and artificial intelligence”, *Journal of Environmental Health Science and Engineering*, Springer, Vol. 17, pp. 41–51.
Haleem, A., Khan, S., Luthra, S., Varshney, H., Alam, M. and Khan, M.I. (2021), “Supplier evaluation in the context of circular economy: a forward step for resilient business and environment concern”, *Business Strategy and the Environment*, Wiley Online Library, Vol. 30 No. 4, pp. 2119–2146.
Hannan, M.A., Arebey, M., Begum, R.A., Basri, H. and Al Mamun, M.A. (2016), “Content-based image retrieval system for solid waste bin level detection and performance evaluation”, *Waste Management*, Elsevier, Vol. 50, pp. 10–19.
Hendriks, V.M., Blanken, P., Adriaans, N.F.P. and Hartnoll, R. (1992), *Snowball Sampling: A Pilot Study on Cocaine Use*, IVO, Instituut voor Verslavingsonderzoek, Erasmus Universiteit Rotterdam.
Hwang, S. (2008), “Utilizing qualitative data analysis software: A review of Atlas. ti”, *Social Science Computer Review*, Sage Publications Sage CA: Los Angeles, CA, Vol. 26 No. 4, pp. 519–527.
Ihsanullah, I., Alam, G., Jamal, A. and Shaik, F. (2022), “Recent advances in applications of artificial intelligence in solid waste management: A review”, *Chemosphere*, Elsevier, p. 136631.
Ingemarsdotter, E., Jamsin, E. and Balkenende, R. (2020), “Opportunities and challenges in IoT-enabled circular business model implementation–A case study”, *Resources, Conservation and Recycling*, Elsevier, Vol. 162, p. 105047.
Italian Government. (1997), “Legislative Decree February 5, 1997”.
Italian Government. (2006), “Legislative Decree April 3, 2006”.
Kotsiantis, S.B. (2013), “Decision trees: a recent overview”, *Artificial Intelligence Review*, Springer, Vol. 39, pp. 261–283.
Kouhizadeh, M., Sarkis, J. and Zhu, Q. (2019), “At the nexus of blockchain technology, the circular economy, and product deletion”, *Applied Sciences*, MDPI, Vol. 9 No. 8, p. 1712.
Lanzalonga, F., Oppioli, M., Dal Mas, F. and Secinaro, S. (2023), “Drones in Venice: Exploring business model applications for disruptive mobility and stakeholders’ value proposition”, *Journal of Cleaner Production*, Elsevier, p. 138764.
Lehtokunnas, T., Mattila, M., Närvänen, E. and Mesiranta, N. (2020), “Towards a circular economy in food consumption: Food waste reduction practices as ethical work”, *Journal of Consumer Culture*, SAGE Publications Ltd, doi: 10.1177/1469540520926252.
Lu, W. (2019), “Big data analytics to identify illegal construction waste dumping: A Hong Kong study”, *Resources, Conservation and Recycling*, Elsevier, Vol. 141, pp. 264–272.
Lu, W. and Chen, J. (2022), “Computer vision for solid waste sorting: A critical review of academic

research", *Waste Management*, Elsevier, Vol. 142, pp. 29–43.
Ma, S., Zhang, Y., Liu, Y., Yang, H., Lv, J. and Ren, S. (2020), "Data-driven sustainable intelligent manufacturing based on demand response for energy-intensive industries", *Journal of Cleaner Production*, Vol. 274, p. 123155, doi: 10.1016/j.jclepro.2020.123155.
Makarova, I., Shubenkova, K. and Pashkevich, A. (2018), "The Concept of the decision support system to plan the reverse logistics in automotive industry", *2018 26th International Conference on Software, Telecommunications and Computer Networks (SoftCOM)*, IEEE, pp. 1–6.
Marrucci, L., Daddi, T. and Iraldo, F. (2021), "The contribution of green human resource management to the circular economy and performance of environmental certified organisations", *Journal of Cleaner Production*, Elsevier, Vol. 319, p. 128859.
Marseglia, G.R., Arbasini, A., Grassi, S., Raubal, M. and Raimondo, D.M. (2015), "Optimal placement of wind turbines on a continuous domain: An MILP-based approach", *2015 American Control Conference (ACC)*, IEEE, pp. 5010–5015.
Massaro, M., Dumay, J. and Bagnoli, C. (2017), "When the investors speak: intellectual capital disclosure and the Web 2.0", *Management Decision*, Emerald Publishing Limited, Vol. 55 No. 9, pp. 1888–1904.
Massaro, M., Dumay, J. and Bagnoli, C. (2019), "Transparency and the rhetorical use of citations to Robert Yin in case study research", *Meditari Accountancy Research*, Emerald Publishing Limited, Vol. 27 No. 1, pp. 44–71, doi: 10.1108/MEDAR-08-2017-0202.
Modgil, S., Gupta, S., Sivarajah, U. and Bhushan, B. (2021), "Big data-enabled large-scale group decision making for circular economy: An emerging market context", *Technological Forecasting and Social Change*, Elsevier, Vol. 166, p. 120607.
Mourtzis, D., Angelopoulos, J. and Panopoulos, N. (2022), "A Literature Review of the Challenges and Opportunities of the Transition from Industry 4.0 to Society 5.0", *Energies*, MDPI, Vol. 15 No. 17, p. 6276.
Noy, C. (2008), "Sampling knowledge: The hermeneutics of snowball sampling in qualitative research", *International Journal of Social Research Methodology*, Taylor & Francis, Vol. 11 No. 4, pp. 327–344, doi: 10.1080/13645570701401305.
Owojori, O.M. and Okoro, C. (2022), "The private sector role as a key supporting stakeholder towards circular economy in the built environment: a scientometric and content analysis", *Buildings*, MDPI, Vol. 12 No. 5, p. 695.
Paes, M.X., de Medeiros, G.A., Mancini, S.D., Ribeiro, F.M. and Puppim de Oliveira, J.A. (2019), "Transition to circular economy in Brazil: A look at the municipal solid waste management in the state of São Paulo", *Management Decision*, Emerald Group Publishing Ltd., doi: 10.1108/MD-09-2018-1053.
Pagoropoulos, A., Pigosso, D.C. and McAloone, T.C. (2017), "The emergent role of digital technologies in the Circular Economy: A review", *Procedia CIRP*, Elsevier, Vol. 64, pp. 19–24, doi: 10.1016/j.procir.2017.02.047.
Park, J., Sarkis, J. and Wu, Z. (2010), "Creating integrated business and environmental value within the context of China's circular economy and ecological modernization", *Journal of Cleaner Production*, Elsevier, Vol. 18 No. 15, pp. 1494–1501.
Perey, R., Benn, S., Agarwal, R. and Edwards, M. (2018), "The place of waste: Changing business value for the circular economy", *Business Strategy and the Environment*, John Wiley & Sons, Ltd, Vol. 27 No. 5, pp. 631–642, doi: 10.1002/bse.2068.
Peters, G.P., Weber, C.L., Guan, D. and Hubacek, K. (2007), *China's Growing CO2 Emissions a Race between Increasing Consumption and Efficiency Gains*, ACS Publications.
Prieto-Sandoval, V., Jaca, C. and Ormazabal, M. (2018), "Towards a consensus on the circular economy", *Journal of Cleaner Production*, Elsevier Ltd, Vol. 179, pp. 605–615, doi: 10.1016/j.jclepro.2017.12.224.
Rajamanikam, A. and Solihin, M.I. (2019), "Solid waste bin classification using Gabor wavelet transform", *Int. J. Innov. Technol. Explor. Eng*, Vol. 8, pp. 114–117.

Raworth, K. (2017), *Doughnut Economics: Seven Ways to Think like a 21st-Century Economist*, Chelsea Green Publishing.
Sadraei, R., Biancone, P., Lanzalonga, F., Jafari-Sadeghi, V. and Chmet, F. (2023), "How to increase sustainable production in the food sector? Mapping industrial and business strategies and providing future research agenda", *Business Strategy and the Environment*, Wiley Online Library, Vol. 32 No. 4, pp. 2209–2228.
Secinaro, S., Brescia, V., Calandra, D. and Biancone, P. (2021), "Towards a hybrid model for the management of smart city initiatives", *Cities*, Vol. 116, p. 103278, doi: 10.1016/j.cities.2021.103278.
Singh, D. and Satija, A. (2018), "Prediction of municipal solid waste generation for optimum planning and management with artificial neural network—case study: Faridabad City in Haryana State (India)", *International Journal of System Assurance Engineering and Management*, Springer, Vol. 9, pp. 91–97.
Stahel, W.R. (2016), "The circular economy", *Nature*, Nature Publishing Group UK London, Vol. 531 No. 7595, pp. 435–438.
Tang, M. and Liao, H. (2021), "Multi-attribute large-scale group decision making with data mining and subgroup leaders: An application to the development of the circular economy", *Technological Forecasting and Social Change*, Elsevier, Vol. 167, p. 120719.
Umeda, Y., Kitagawa, K., Hirose, Y., Akaho, K., Sakai, Y. and Ohta, M. (2020), "Potential impacts of the European Union's circular economy policy on Japanese manufacturers", *International Journal of Automation Technology*, Fuji Technology Press Ltd., Vol. 14 No. 6, pp. 857–866.
United Nations. (2015), "SDGs - Sustainable Development Goals".
United Nations. (2023), *The Sustainable Development Goals Report 2023*, New York.
Upadhyay, A., Mukhuty, S., Kumar, V. and Kazancoglu, Y. (2021), "Blockchain technology and the circular economy: Implications for sustainability and social responsibility", *Journal of Cleaner Production*, Elsevier Ltd, Vol. 293, doi: 10.1016/j.jclepro.2021.126130.
Yetilmezsoy, K., Ozkaya, B. and Cakmakci, M. (2011), "Artificial intelligence-based prediction models for environmental engineering", *Neural Network World*, Vol. 21 No. 3.
Zhang, A., Venkatesh, V.G., Liu, Y., Wan, M., Qu, T. and Huisingh, D. (2019), "Barriers to smart waste management for a circular economy in China", *Journal of Cleaner Production*, Elsevier, Vol. 240, p. 118198.