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Research on Service Design of Garbage Classification Driven by Artificial Intelligence

Jingsong Zhang [1], Hai Yang [2,*] and Xinguo Xu [1]

[1] School of Design and Architecture, Zhejiang University of Technology, Hangzhou 310014, China; kingsun@neocross.cn (J.Z.); incamike@zjut.edu.cn (X.X.)
[2] Hangzhou Zhongwei Ganlian Information Technology Co., Ltd., Hangzhou 310023, China
* Correspondence: hyang@zwglink.com

Abstract: This paper proposes a framework for AI-driven municipal solid waste classification service design and management, with an emphasis on advancing sustainable urban development. This study uses narrative research and case study methods to delve into the benefits of AI technology in waste classification systems. The framework includes intelligent recognition, management strategies, AI-based waste classification technologies, service reforms, and AI-powered customer involvement and education. Our research indicates that AI technology can improve accuracy, efficiency, and cost-effectiveness in waste classification, contributing to environmental sustainability and public health. However, the effectiveness of AI applications in diverse city contexts requires further verification. The framework holds theoretical and practical significance, offering insights for future service designs of waste management and promoting broader goals of sustainable urban development.

Keywords: AI; municipal solid waste classification; garbage classification; service design; intelligent recognition; management strategy

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1. Introduction

Since 2019, Chinese provinces and prefecture-level cities have advocated solving problems of "garbage siege" and carrying out the environmental protection policies like the "Ban on Free Plastic bags", both of which have put forward the overall requirements of "reduce, reuse, and recycle" for municipal waste classification [1,2]. Compared with other countries, there are big differences in the treatment modes and actual results of garbage classification due to different economic strengths, resource demands, technical levels, and legal policies. With the reuse, superimposition, and crossover collaboration of "Internet plus", "AI plus", big data, Internet of Things, and other technologies in recent years, the exploration of the technology and service changes in garbage classification, a systematic project, is particularly prominent and important in the round of the comprehensive management of garbage classification in major cities of China [3]. This paper, based on the scientific concept of service design, studies the latest development trends of AI 2.0 technology and the driving factors in combination with waste classification service management. It proposes a solution for the assistant tool for urban solid waste classification management in the project practice in Hangzhou, China [4,5]. At the same time, it introduces the case of the ZRR2 waste classification robot used in the waste classification processing plant in Barcelona [6]. By comparing the two cases, it more prominently highlights the huge potential of AI in waste management strategies.

The main research outcome of this paper is the proposal of a framework model for AI-driven waste classification service design and management. The results of the project practice summarize several forward-looking strategic plans for AI-driven service design and management in future urban solid waste management. In addition, this paper discusses the environmental constraints, challenges faced, driving factors, and future research perspectives on future urban waste management. This research helps in understanding the potential application of AI technology in the field of waste classification management and provides practical guidance for the development of future waste classification policies and initiatives. This study also reveals the importance of community service co-creation and value network systems in environmental management under the concept of service design, especially in the context of promoting sustainable urban development.

2. Literature Review

Municipal solid waste (MSW) classification management comprises the activities associated with the collection, transfer, treatment, recycling, resource recovery, and disposal of solid waste generated within urban locales [7]. The process extends from the point of waste generation to its ultimate disposal, with efficiency and productivity being critical considerations. Artificial intelligence (AI) technology has emerged as a promising tool in bolstering the efficiency and precision of MSW classification. Artificial intelligence-based technologies like smart garbage bins, garbage sorting robots, predictive models for waste production, and optimizing the performance of waste processing facilities. The details are shown in (Table 1). Notably, Finland, Japan, and the United States have pioneered the R&D of automatic garbage-sorting robots. ZenRobotics Recycle system (ZRR) from Finland, the first garbage classification robot globally, can efficiently differentiate mixed waste, useful, and non-useful waste within MSW. Japan's FANUC garbage sorting robots utilize the AI vision analysis system to analyze wood quality and discriminate polymer from plastic. The Computer Science and AI Laboratory at the Massachusetts Institute of Technology has developed 'Rocycle', a garbage recycling and sorting robot that can distinguish paper, metal, and plastic by touch [6].

The application of AI in waste management transcends waste classification. AI modeling methods can accurately predict waste generation quantities, facilitating the design and operation of effective waste management systems [8]. AI has also been instrumental in forecasting waste generation, managing construction waste, and optimizing landfill site selection [9]. Other studies have employed non-parametric models to track the temporal productivity changes in waste management services, considering both economic and environmental aspects [10].

In essence, AI technology, in conjunction with the Internet of Things (IoT), plays a vital role in the classification and management of MSW. These technologies enable precise waste classification, waste collection and transportation optimization, and the establishment of efficient waste management systems. AI modeling and DEA-based models are employed to measure productivity from various perspectives, thus providing comprehensive insights into the performance of waste management services in terms of productivity and eco-productivity [10].

In China, the government initiated a new MSW classification strategy in 2017, with Hangzhou being one of the first pilot cities. The policy aims to ensure effective MSW classification implementation via measures like AI- and computer vision (CV)-based approaches [11]. The implementation of IoT technology in MSW classification and management can enhance the classification level and optimize waste collection and transportation, thereby reducing costs and environmental pollution. The COVID-19 pandemic has amplified the challenges of MSW management due to the surge in medical and household waste [12]. This scenario has highlighted the criticality of waste collection, recycling, treatment, and disposal services. Concurrently, the pandemic has exposed the complexities of waste management, emphasizing the importance of efficiency, health considerations, and customer satisfaction. In this context, factors such as waste collection frequency, age, educational status, and family size play a crucial role in customer satisfaction [13].

Table 1. The main application of artificial intelligence to waste management [14].

Type of AI Technology	Types of Waste	Measures of AI	Key Information	Results/Benefits	References
Smart garbage bin	Solid waste	Sensor network	1. Garbage bin monitoring 2. Collect data 3. Analyze information	Used to collect municipal waste	Khan et al. (2021) [15]; Ghahramani et al. (2022) [16]
	Solid waste	Ultrasonic sensors	1. Garbage will not overflow 2. The lid will open automatically 3. Automatic detection of garbage	Digital garbage bin	Wijaya et al. (2017) [17]; Praveen et al. (2020a) [18]
	Solid waste	Ultrasonic sensors Red external sensor	1. Identify garbage 2. tracking the vehicle and IR sensors 3. Garbage level monitoring	Instantly detection of the status of Bins: Filled or Empty	Pawar et al. (2018); [19]
Garbage-sorting robot	Reusable garbage	Computer vision Robotic framework	1. Gripping 2. Motion control 3. Material categorization	Success rates: glass: 79% plastic: 91%	Wilts et al. (2021) [8]; Kshirsagar et al. (2022) [20]
	Solid waste	Computer vision simultaneous localization and mapping	1. Automatic navigation 2. Garbage recognition 3. Pick up automatically	Recognition accuracy is 94%, even without path planning	Bai et al. (2018) [21]; Lee, K.-F. (2023) [6]
	Seven types of garbage	Skin-Inspired Tactile Sensor	1. Quadruple tactile sensing 2. Object recognition 3. Garbage classification	Recognizing 7 types of garbage, accuracy of 94%	Li et al. (2020) [22]; Lee, K.-F. (2023) [6]
Predictive model for waste production	Hazardous waste, construction site waste	Genetic algorithm-adaptive neuro-fuzzy inference system	1. Defining targets for waste production 2. Optimizing resources 3. Reporting and conducting inspections 4. Compared with different AI prediction models	Raised proposed measures for waste reduction prediction	Haque, M.S. et al. (2021) [12]; Bang et al. (2022) [10]
	Solid waste	Proximate analysis	1. Generation rate and waste composition 2. Quantified, characterized, and evaluated energy potential and nutrient value of solid waste	Reduce tons of carbon dioxide equivalent greenhouse gas emissions.	Fetene et al. (2018) [13]
	Solid waste	Eco-Productivity Analysis	1. DEA-based models 2. Sampling and characterization 3. Carbon emissions evaluation of MSW disposal system	Decline of daily carbon emission in MSW disposal system after waste sorting.	Lo Storto, C. (2017) [9] Wang, Y. et al. (2021) [11]

Therefore, it is imperative to conduct further research to unravel the multiple roles of AI technology or AI agents in waste classification management systems. These technologies function not only as technical components of the service system but also as collaborative agents alongside human operators [23]. The aim is to explore how AI influences service design and management practices for MSW from different perspectives. This investigation would provide constructive insights for future service ecosystem innovation, preparing us to better handle unforeseen events and navigate the multifaceted challenges of our evolving social environment.

Service design models the social, material, and relational elements that support the customer experience [24,25], integrating the various silos of the organization into a coordinated service offering [26]. It applies human-centered and collaborative methods to explore the experiences of different stakeholders. This ability to integrate stakeholders enables service design to develop solutions that are relevant to customers while considering the structural context of the organization [27,28]. However, the relationship between artificial intelligence and service systems is a complex and evolving new one [29]. Some believe a key aspect of the relationship between AI and service systems is that AI has the potential to complement rather than completely replace human labor [30]. While AI can automate certain tasks, it also amplifies the comparative advantages of human workers in areas such as problem solving, adaptability, and creativity. To fully leverage the potential of AI in service systems, it is crucial to study and implement strategic frameworks [31]. This framework should consider the nature of service activities, service processes, and other specifics [32].

Consistent with all service-dominant logic premises, the AI-driven service system guides the description of the situation at three levels: Value constellation, whole picture view of the system, service activities, and other specifics. According to Alter [32], there are three frameworks for service systems, namely the Work System Framework, the Service Value Chain Framework, and the Service Lifecycle Framework. The Work System Framework provides a systematic perspective for understanding and analyzing any system that performs work within or between organizations. The Service Value Chain Framework extends the Work System Framework by introducing functions that are particularly relevant to services. The Service Lifecycle Framework emphasizes the evolution of service systems, including the creation, operation, and planned and unplanned changes to services. Therefore, AI technologies or AI agents are set to become vital focal points in the construction of new service systems, interactive experiences, and value co-creation [32,33].

3. Materials and Methods

This research proposes a propositional AI-driven waste classification service design and management framework (hereafter referred to as AI-MSWSS). The research strategy combines literature review, case study, and Practice-oriented Design Research (PDR) [34]. The focus of the research process is on summarizing reflections or conducting empirical analysis from Municipal Solid Waste (MSW) service design practice, aiming to uncover innovative findings and new theoretical frameworks.

Literature Review: A propositional literature review was conducted to identify existing theories and practices related to AI-MSWSS. This process helped establish a theoretical foundation in service design and artificial intelligence and identified the undefined role of AI in service design and management methodologies, as well as the opportunities and challenges AI technology poses for service design [14,24]. These gaps in knowledge are addressed in this research. We utilized academic databases for sourcing relevant literature and critically analyzed the collected articles, books, and reports to understand the current state of the field.

Case Study: We conducted in-depth research on selected cases, specifically selecting a case of a waste classification helper, and a case garbage sorting robot [8], to gain a deeper understanding of the practical applications of AI-MSWSS and to facilitate the comparison and evaluation of relevant design and management experiences. Solutions were iteratively refined based on the challenges encountered in practice. The goal was to derive practical insights and lessons that could be generalized to other similar contexts.

Practice-oriented Design Research (PDR): In this research strategy, the focus is on generating new knowledge through service design practice. In our study, we implemented the PDR process via four stages: problem framing, understanding and defining, designing the service concept and architecture, and evaluation based on results [35]. Knowledge artifacts and practical experiences gathered during the PDR process were critically reflected upon and analyzed. The aim was to generate innovative knowledge and theoretical insights that could contribute to the establishment of AI-MSWSS and contribute to the broader field of practice.

The research process placed significant emphasis on empirical analysis and reflection from practice. The overall goal was to extract innovative findings and develop a new theoretical framework that can enhance the practical understanding of AI-MSWSS and enrich the knowledge construction in the interdisciplinary field of service design and artificial intelligence.

4. Case Study: Service Design and Management of MSW Classification Based on AI Technology

4.1. Case Study 1: BinBin Helper

The BinBin Helper applet, primarily developed to aid in waste classification and management, serves a crucial role in the urban management of Hangzhou's Binjiang district in China. This project, commissioned by the Urban Management Bureau, is an embodiment of the effective use of artificial intelligence (AI) and Internet of Things (IoT) technologies in managing municipal solid waste (MSW).

As shown in Figure 1, the applet's user interface (UI) is designed with simplicity in mind, utilizing a unique shade of blue as its main color and featuring intuitive visual icons of sorted trash cans. These design elements aim to assist citizens and community workers in navigating and using the applet effectively. One of the applet's noteworthy features is its use of AI technology. With capabilities such as image recognition, speech recognition, and text search, the applet assists users in accurately classifying waste with an average accuracy rate of 92%, which is 9.5% higher than the competing control group. This not only helps users improve their waste classification practices but also aids the Urban Management Bureau in the data sampling of garbage bins and waste transfer stations, thereby enhancing the efficiency of urban environmental sanitation work. Another major component of the project is the creation of an IoT monitoring platform. Based on Geographic Information System (GIS) maps, the platform oversees garbage disposal and urban administration patrol management. During the COVID-19 pandemic, the platform was used to develop a map and supervision system for discarded mask drop-off points in the Binjiang district. This initiative helped alleviate environmental pollution and health concerns among the residents, demonstrating the responsiveness and adaptability of the system to unexpected challenges.

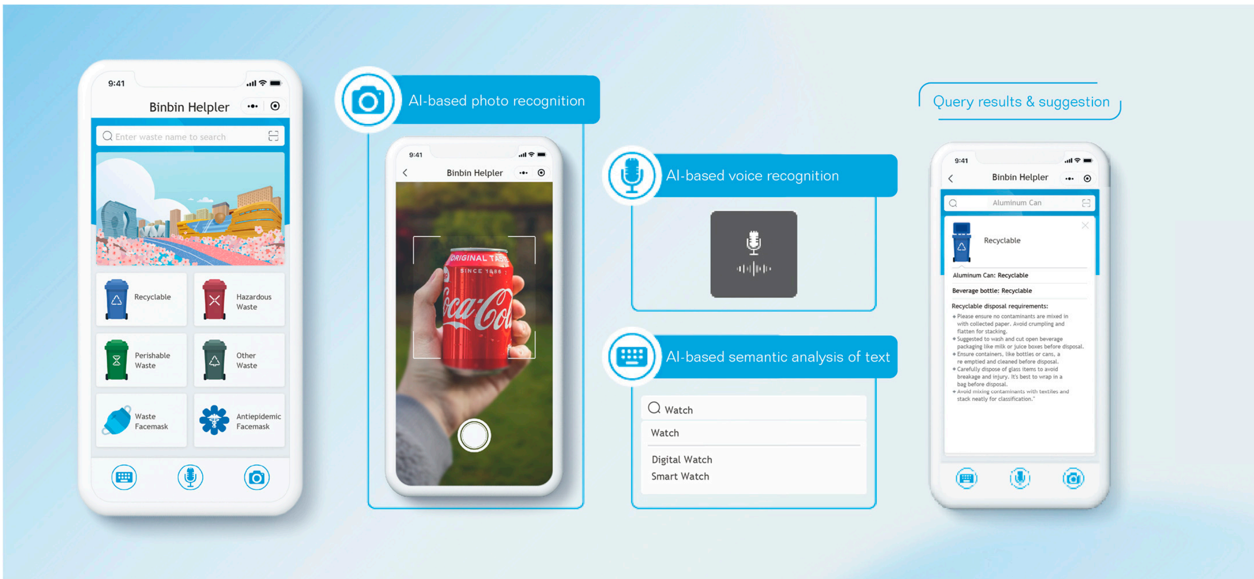

Figure 1. AI-related features and UI design of BinBin Helper applet.

4.2. Case Study 2: ZRR2 Robot Applied in Garbage Sorting [8]

As shown in Figure 2, in Barcelona's Ecoparc4 waste treatment facility, a ZRR2 robot from ZenRobotics was utilized to explore its potential in solid waste sorting, aimed at testing and evaluating the automation of municipal waste sorting plants by supplementing or replacing manual sorting. The objectives were to increase the current recycling rates and the purity of the recovered materials, to collect additional materials from the current rejected flows, and to improve the working conditions of the workers, who could then concentrate on, among other things, the maintenance of the robots.

Figure 2. ZRR2 robot applied in garbage sorting [35].

The ZRR2, equipped with dual mechanical arms, advanced sensors, and deep-learning software, could identify and sort a variety of waste materials, including metal, plastic, and cardboard. Researchers trained and tested the robot using 13 different types of residential and industrial waste. Post-training, the robot demonstrated the ability to accurately classify different waste materials, achieving over 90% purity in most categories. In the next phase, the throughput was gradually increased until the desired throughput for production was achieved. In some cases, a monolayer of the material could no longer be guaranteed, objects began to overlap, touch, and cover each other. Under such conditions, the ZRR2 robot showed increasing difficulties in detecting and handling objects. Although the recovery rate test results for ZRR2 were not satisfactory, averaging only 67%. This case study provides initial evidence that robots and artificial intelligence can potentially enhance traditional urban waste sorting processes, improving precision and efficiency. However, it also identified some challenges in optimizing the entire system for robotic use [8].

4.3. Comparative Study: The BinBin Helper vs. the ZRR2 Robot

This case study primarily focuses on the innovative design and management of waste classification services regardless of the project type. It represents an evolution and integration of previous service design methodologies, realized via three distinct stages: problem framing, understanding the experiences and goals of multiple actors, and ideation for the design of service concepts and architecture [36].

The first stage, problem framing, involves mapping the value network and identifying all actors in the waste classification service, and their inter-relationships. The second stage delves into the goals and experiences of various actors. For instance, during the initial promotion of waste classification in Shanghai, residents were required to deposit waste at fixed times and locations. This approach required significant community human and material resources for classification supervision [11]. Recognizing these issues and the fact that Hangzhou did not have the same level of resources to invest, Hangzhou improved its regional implementation methods. This resulted in a more resource-efficient solution such as a digital assistant tool. This multi-actor perspective provides a comprehensive view of the service ecosystem and identifies areas of the service encounter that require improvement.

The third stage involves ideation to create a service blueprint for waste classification. This blueprint includes the determination of the service interface and process, ensuring a balance of different actors' goals, and supporting real-time network interactions. These architectures are not rigid representations with formal language; instead, they provide a flexible visual experience for a collaborative and iterative service design process. Using ZRR2 as an example, the design of the service blueprint must consider the differences between actual working environments and optimal experimental environments [35]. Therefore, understanding how AI technology integrates with software and hardware facilities is crucial, which includes corresponding improvements to process design. In real working environments, there may be various unforeseen challenges and constraints that require adjustments and optimizations in the service design so that AI technology can integrate more effectively with facilities to achieve optimal results.

In comparing the BinBin Helper and the ZRR2 robot, it is clear that both solutions utilize AI technology to tackle waste management, albeit in different ways and contexts. Their respective service designs and management strategies reflect the unique demands of their environments.

BinBin Helper integrates AI technologies into a user-friendly applet. The design focuses on user experience, with an intuitive UI that employs recognizable icons and an appealing color scheme. This design choice encourages user interaction and aids in the proper classification of waste. The ZRR2 robot, designed for an industrial setting, prioritizes operational efficiency and accuracy. It incorporates AI and advanced sensors to autonomously sort various types of waste materials [35]. The management strategy of BinBin Helper involves aiding the Urban Management Bureau in waste management. The applet not only enables users to classify waste accurately but also provides valuable data on waste generation patterns, facilitating more efficient management and planning. The ZRR2 robot's management strategy focuses on automation and enhancing operational efficiency within waste treatment facilities. The robot also aims to improve working conditions by taking over tasks usually performed by humans [8].

In conclusion, comparing these case studies provides valuable insights into the diverse applications of AI technology in waste management. It highlights the importance of tailoring the service design and management strategy to the specific context and user needs. Despite the different approaches, both case studies (Table 2) demonstrate the immense potential of AI in enhancing waste management efficiency and effectiveness, as shown through the value networks of different service systems.

Table 2. Summary of the comparative case study on the BinBin Helper and the ZRR2 robot.

Project Case Study	Types of Artificial Intelligence	Types of Waste (Top 5–10)	Duration or Frequency of Use/Trial	Classification Quality	Efficiency Optimization	References
1. Garbage sorting helper in China Hangzhou	Baidu EasyDL platform [37]	Mainly four-category waste sorting, including: Plastic bags, Milk cartons, Sunflower seed shells, Eggshells, Plastic products	Total of users: 37,800+ Active Users: 6800+ Numbers of Queries: 1,000,279	Accuracy: 92%, compared with control group + 9.5%	\	Yuan, J et al. (2020) [38]
2. The Ecorparc4 municipal waste sorting plant in Barcelona [8]	ZenRobotics ZRR2 [6]	Solid waste: PET bottles, plastic films (LDPE), aluminum, ferrous metals, PE boxes, large PE bottles, paper/cardboard, PP, (untreated) wood, textiles, Tetra Pak and vegetable substances	A trial period of 15–30 min, feeding rate (about 1000 picks/h).	Average purity: 97%	Average recovery: 67%	Wilts et al. (2021) [8]

4.4. Findings and Further Study

The integration of AI in service design brings both opportunities and challenges, the distinctiveness of AI-driven service design as a commodity and design object will bring new design concepts and methods that revolve around service design. Co-creation in service contact points now includes both common issues and complex uncertainty issues. The traditional service co-creation process is an innovation process similar to participatory and collaborative forms [39]. With the participation of AI, human–computer co-creation has become a "recommend-select-feedback" cycle process, transitioning human–computer interactions from "one-way dependence" to "two-way training" [40]. By introducing this kind of classification correction function into a waste classification inquiry and result pages, both the accuracy of waste classification and user interaction can be improved.

Based on these findings, although the service system is not a new area of theoretical research or social practice, we believe a new theoretical framework is needed to better guide the design and management of service systems in the context of the AI era. The following section will detail and explain this new theoretical framework, including its theoretical basis, main components, and application scenarios. It will also discuss how it helps us understand and address the problems encountered in this case study and provide useful insights for more complete and complex service systems in the future.

5. Results: A Proportional Framework for AI-Driven Garbage Classification Service Design and Management (AI-MSWSS)

Building upon the service design framework and stakeholder value network theory, the aforementioned case study presents research findings on the key elements and stakeholders of AI-MSWSS. Compared to traditional urban service systems, this new framework offers several advantages, as it is designed to address the evolving complexities of waste classification and management in urban environments. Beyond its immediate application in waste management, this framework's significance extends to addressing broader challenges in complex service systems, challenges that have become increasingly prominent in the AI era [34].

5.1. A Proportional AI-Driven Service Design Framework

The service design basis for an AI-driven Municipal Solid Waste (MSW) service system should be established using service design methodologies and stakeholder value network concepts. Following the design thinking process as described by Brown [41] and Stickdorn and Schneider (2010) [28], the construction of the entire service design framework can be divided into four stages: problem framing, understanding, ideation, and implementation. However, to effectively leverage AI technology and address the challenges of designing services for value networks, it is necessary to explore the dual or multiple roles that AI technology can play within the service system. This understanding should then be translated into value network service concepts and service architectures.

Building upon the aforementioned case, the service design basis should not only consider the tasks, processes, personnel allocation, interactive behaviors, and value exchanges at each stage of the waste management lifecycle but also how AI technologies can continuously refine and optimize these elements. AI brings challenges to almost all stages of a typical design process (Figure 3). As shown in the triangular colot block area in Figure 3, the proposed AI design methods and tools have mostly focused on the two ends of this creative process, either helping designers to understand what AI is and can do generally or enhancing the evaluation of the final design [42].

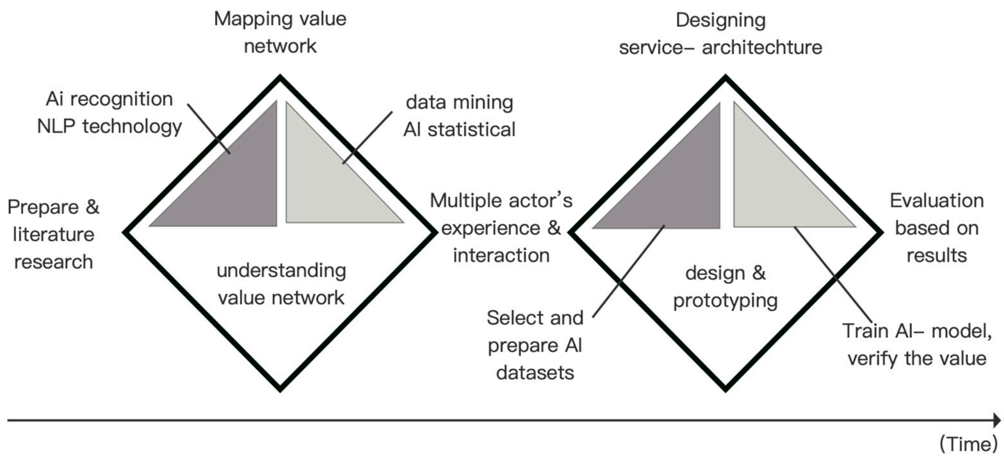

Figure 3. Mapping AI technology challenges onto a design process (based on Double Diamond [43]).

The four stages that can be employed in AI-driven service design include the following:

Stage 1. Plotting the Value Network

As shown in Figure 4, the first phase focuses on plotting the value network of the municipal solid waste (MSW) service system. This involves identifying all key stakeholders and their respective roles in the system. These can include waste generators such as individual households and businesses, waste collectors, waste treatment facilities, and regulatory bodies supervising waste management [44]. Tasks in this phase include stakeholder identification, role definition, and relationship mapping. Interactions in this phase primarily involve decomposing the elements of the service system, understanding the role positioning and network relationships of different participants, and establishing a comprehensive understanding of the service ecosystem. AI can play a crucial role in this phase, helping analyze the complex stakeholder network and the AI agent itself can also become part of the network structure. For example, machine learning algorithms can identify waste generation patterns among different stakeholder groups, helping to highlight key contributors or potential inefficiencies within the system.

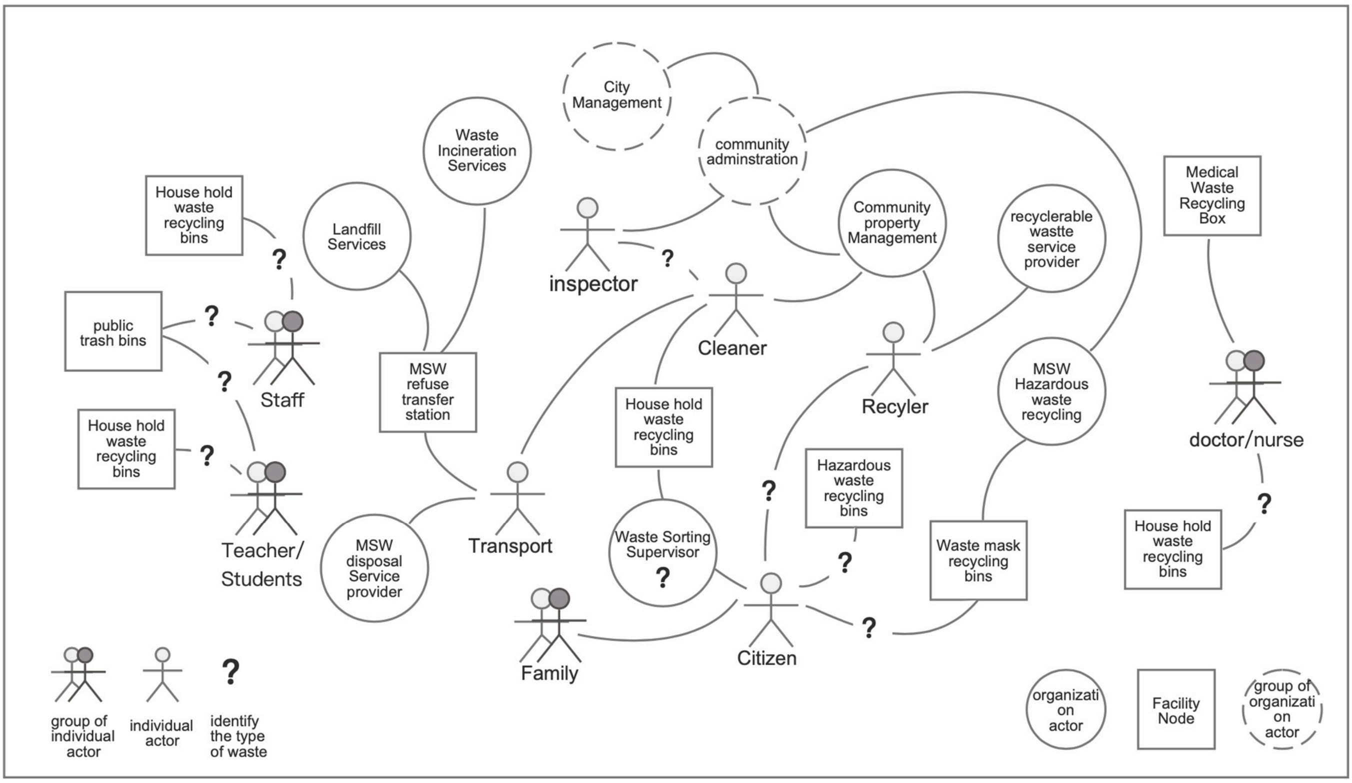

Figure 4. Plotting value network of the AI-MSWSS [44].

Stage 2. Understanding the Experiences and Interactions of Multiple Participants

As shown in Figure 4, the second phase involves empathizing with various stakeholders to understand their experiences, needs, and pain points in the waste management process. The means include qualitative research methods such as user interviews, surveys, and observations (Table 3). Process tasks may include developing user personas, journey mapping, and empathy mapping. Interactions mainly involve contact with stakeholders, activities, interactions of multiple users, goals, and conflicts of multiple users, and the value goal is to discover unmet needs and opportunities to improve the service [36]. AI can provide assistance in this phase by analyzing large amounts of user feedback to identify common themes or sentiments. For example, user-generated content can be used for social network analysis, survey feedback, media commentaries, and internet public sentiment about waste management.

Table 3. Mapping AI technology challenges onto the AI-MSWSS [36].

Actor's Goal	Subgoal	Quotes
1. quality of garbage classification	accuracy	What the hell are dry batteries? Is it hazardous waste? (inspector)
	complete	Do we need to break the bag of perishable garbage? Under what circumstances do not need to break the bag? (citizen)
	understandability	Why are the classification marks on the trash cans inconsistent? (city management)
2. efficiency of garbage reduction	source classification	There are too many types of garbage, how to quickly memorize and identify them? (company representative)
	recycling efficiency	There are so many types of garbage, how do you know which ones are recyclable? (community management)
	transfer and treatment efficiency	We need to optimize the transportation routes for garbage collection to reduce the time and cost of delivery to the landfill (city management)
	labor saving	Disposal supervisors are not doing a good job (inspector)
3. relationship among actors	citizen centered	Garbage classification is beneficial to the people rather than disturbing the people (community management)
	majority support	Good garbage classification reflects the level of the community (community)
	mostly value recognition	If the garbage classification in the community is done well, the value of the real estate will increase a lot (citizen)
4. information sharing	regulatory compliance	We need to make sure that all stakeholders are aware of the regulations and guidelines for garbage reduction (community property)
	uniform standards	The standard of classification in Hangzhou is different from that in Shanghai, and the names are also different (city management)
	easy to use	We must first teach the elderly and children to sort garbage, and others will naturally (community management)

Stage 3. Designing the Value Network Service Architecture

The third phase involves designing service prototypes and architecture based on insights gathered from the previous two phases (Figure 5). This involves defining the customer journey, touchpoint interfaces, and the service architecture that will deliver value to the stakeholders. The research methods used are primarily participatory design, service blueprinting, and prototyping. Tasks in this phase may include service blueprinting, process modeling, and technology selection. Interactions here mainly involve collaborative design work, ensuring the balance of customer value constellations and activities and goals of multiple user roles. The goal of constructing the value network is to integrate service concepts and architectures for different participants, thereby creating an effective and efficient service process [36,44]. AI can play a significant role in this phase, helping optimize the service process and integrate the technical architecture. For example, AI can offer a model service to assist in computing how front-end waste classification can adjust to fit the city's MSW disposal scheme, ultimately achieving an optimal allocation scheme with maximum economic benefits.

Stage4. Evaluation Based on Results

The final phase involves testing and evaluating the service design. This includes prototype testing and field testing and involves measuring the performance of the service system according to defined metrics, as well as a qualitative assessment of customer satisfaction and other subjective indicators in the value network. The research methods used can include the Analytic Hierarchy Process (AHP) and satisfaction surveys [45]. Tasks in this phase may include prototype testing, field pilot testing, performance testing, and satisfaction surveys. Interactions mainly involve testing and collecting feedback, and the value goal is to validate the service design and identify areas for improvement. AI can provide advanced analytical capabilities in this phase. For instance, machine learning algorithms can analyze operational data and identify patterns or trends that may not be apparent to human analysts. This can help gain a deeper understanding of the service system's performance and provide recommendations for further optimization.

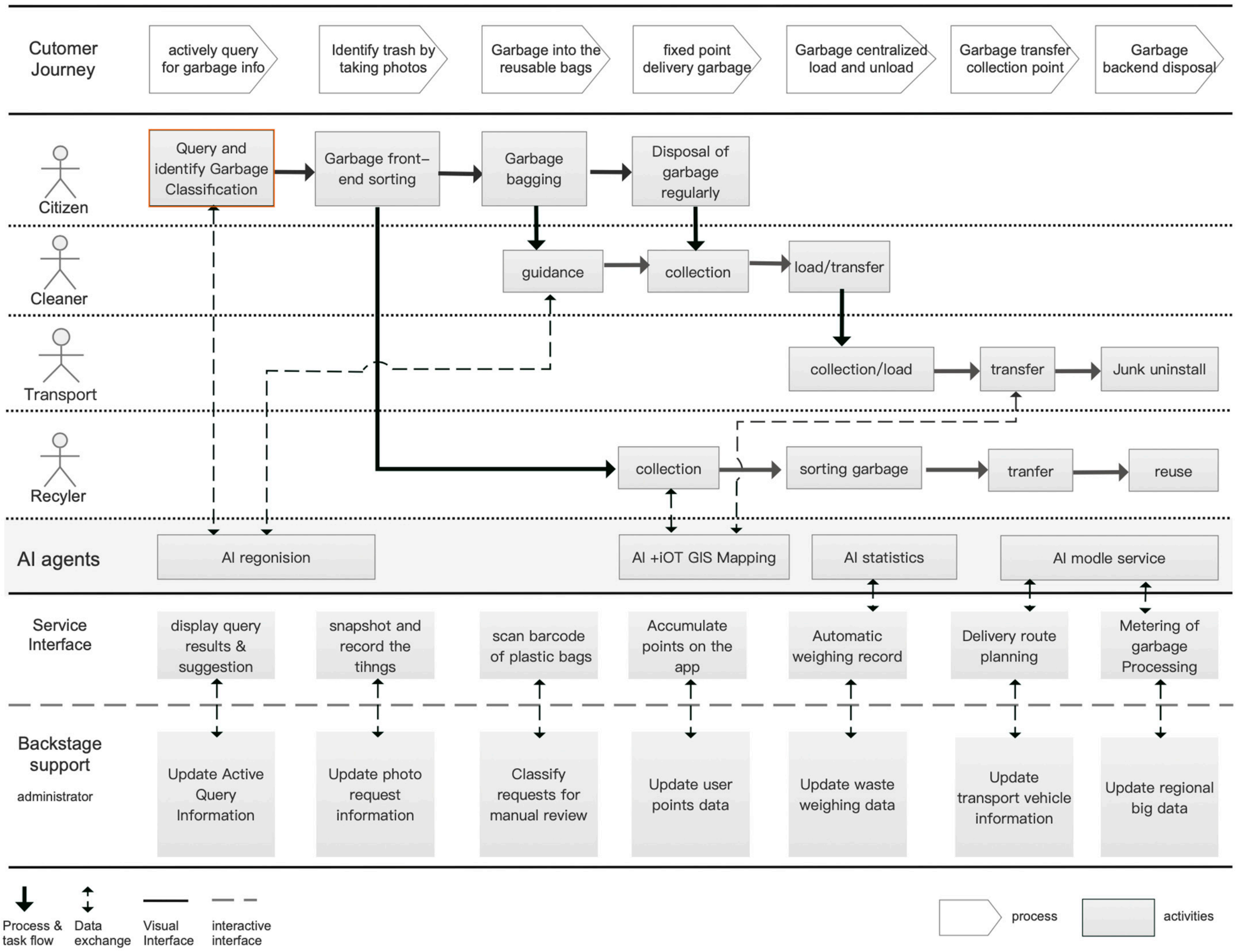

Figure 5. Designing service prototypes and architecture of the AI-MSWSS [36].

5.2. *A Proportional AI-Driven Service Management Framework*

Consistent with all service-dominant logic premises, the AI-driven service system guides the description of the situation at three levels: value constellation, whole picture view of the system, service activities, and other specifics. According to Alter's view [32], there are three frameworks for service systems, namely the Work System Framework, the Service Value Chain Framework, and the Service Lifecycle Framework. The Work System Framework provides a systematic perspective for understanding and analyzing any system that performs work within or between organizations. The Service Value Chain Framework extends the Work System Framework by introducing functions that are particularly relevant to services. The Service Lifecycle Framework emphasizes the evolution of service systems, including the creation, operation, and planned and unplanned changes of services. Therefore, AI technologies or AI agents are set to become vital focal points in the construction of new service systems, interactive experiences, and value co-creation.

In integrating AI as a specific element in the Work System Framework, a marked enhancement in the system's ability to perform tasks efficiently is observed (Figure 6). This elevation, attributed to AI technologies, presents in the form of intelligent automation, data analytics, and predictive capabilities that significantly augment traditional infrastructure.

This shift redefines the roles and responsibilities within the service system, where both service providers and receivers find their functions facilitated. The former, in leveraging AI's data analysis and decision-making capabilities, can deliver more personalized and efficient services. The latter, on the other hand, benefits from improved service experiences, facilitated by AI's ability to anticipate needs and provide timely solutions.

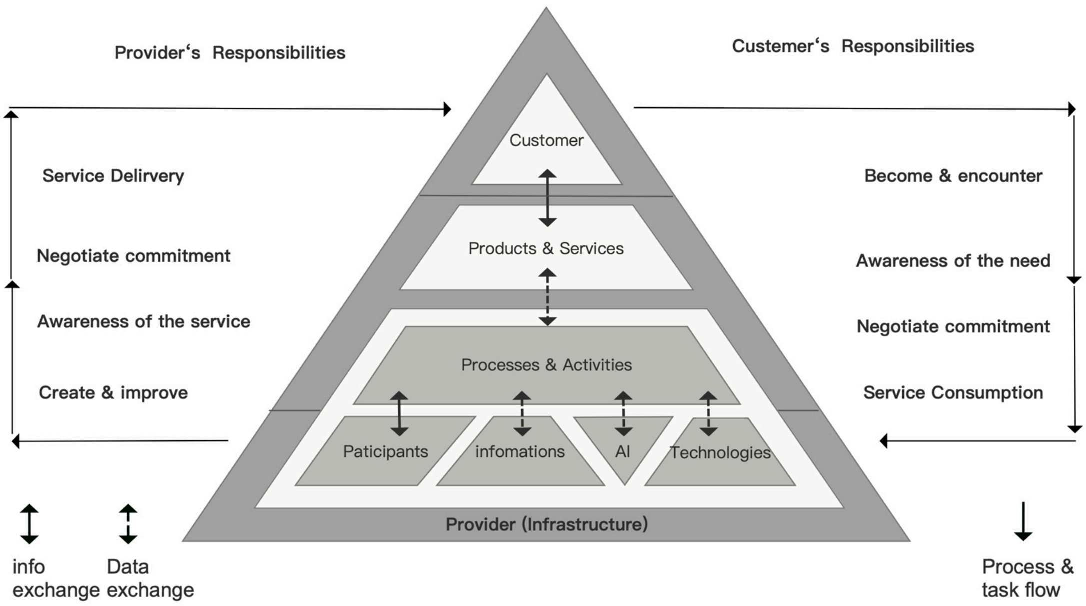

Figure 6. A proportional AI-driven service management system framework (AI-MSWSS) [32].

The lifecycle of the service activities within this system, under the influential hand of AI, undergoes continuous evolution and iteration. AI drives this process by promoting efficiency, scalability, and adaptability, allowing the system to respond effectively to fluctuating service needs and environments. The transformative effect of AI's inclusion in the new service management framework is profound, enhancing operational efficiency while empowering the creation of innovative service offerings. Its ability to co-create value by amplifying the effectiveness of service delivery and experience underscores AI's pivotal role. Conclusively, AI is a vital catalyst in the new service management framework, driving the evolution and iteration of service activities, and enabling role players to excel in their responsibilities. As the importance of AI continues to gain recognition, its role in the future of service management frameworks is set to increase, validating its significance.

6. Discussion

Artificial intelligence (AI) technologies are observed to play a crucial role in the new service system of municipal solid waste (MSW) classification. They serve multiple roles, necessitating careful consideration of their positioning. In the context of urban solid waste management, AI is viewed not merely as a technical tool, it is seen as an active participant, automating and optimizing complex tasks. For example, AI-driven robots using advanced sensors and cameras can effectively identify, classify, and separate waste, enhancing system efficiency and reducing human exposure to hazardous waste.

However, it must be acknowledged that AI's role in the entire new service system is currently apparently local and not global. Some sorting tasks still have to be carried out manually (manual picking), e.g., the quality control of recovered material and the manual sorting of oversize and waste streams [8]. This raises a demand for setting how AI adapts to existing workflows and environments. While the advent of AI 2.0 technologies offers the possibility of AI replacing some human participants, particularly those that follow logical structures and require minimal social interaction, this transition is recognized as being not immediate and may face technical and implementation challenges. AI technology is also seen as assisting human participants in achieving their goals within the system. Ideally, it serves as a co-pilot, sharing the objective of improving process efficiency and user experience with humans. In certain circumstances, AI may turn the task of image recognition into a bidirectional training process that continuously enhances learning [42]. For instance, in the waste classification recognition process of BinBin Helpler, human intervention is still required when situations arise where multiple objects overlap and cause confusion in image recognition. This is necessary to determine the correct target for sorting and subsequent disposal actions.

In the commercial environment, services dominated by efficiency and utilitarianism can be replaced with AI, as demonstrated in various automatic telephone services launched by banks, airlines, and other operators [46]. It is expected that classification and sorting services will also be gradually replaced with AI in the waste classification field. On the other hand, the distinctiveness of AI-driven service design as a commodity and design object will bring new design concepts and methods that revolve around service design.

With the introduction of service design, the concept of 'co-creation' has evolved. Co-creation in service contact points now includes dealing with both common issues and complex uncertainty issues [39]. The ultimate concern of service design is people's experience perception in value co-creation. Users complete value co-creation in the process of service delivery and contact. The service's value is embodied in the "enable" of the platform, which provides various possibilities for participants. This concept of "enable design" can be evaluated using methods like AHP and CSI satisfaction, calculating the evaluation level of the sense of value created from service design [39,45].

In the lifecycle management of the new service system, AI also plays a critical role. If AI widely replaces some participants, it can simulate human participants' goal perception and the system's incentive for proactive behavior, enabling AI to exhibit capabilities of reinforced learning and adaptability. This plays a crucial role in managing the lifecycle of the service system. In large institutions, the role of AI can be further optimized to ensure that AI agents continue iterating to meet an ever-changing user experience. As the system evolves, AI can be trained and retrained to ensure system adaptability and durability. For instance, when new types of waste are introduced, the AI model can be updated to recognize and sort these new waste types.

However, it must also be noted that the application of AI in lifecycle management needs to consider certain constraints, such as hardware durability, software scalability, and the cost of AI updates and maintenance [32,42]. For example, predictive maintenance can foresee potential breakdowns and schedule maintenance to avoid service interruptions, which requires ample data support and highly accurate forecasting models. Additionally, AI needs ongoing supervision and adjustment in adapting to changes in waste management regulations or guidelines to ensure that services are always in compliance with legal requirements.

In discussing this topic, the possibility that AI challenges social ethics and economic activity must also be considered. The increased use of AI agents may lead to a loss of jobs requiring lower qualifications, which could obviously pose social and ethical challenges and increase uncertainties in economic activity. Future research is needed to delve deeper into this issue to ensure that the application of AI not only improves efficiency but also considers social and economic impact. This could involve developing new policy frameworks to protect workers who may be affected or providing new job opportunities through education and training.

7. Conclusions

This framework is intended to offer profound insights into advancing AI technology in waste classification management and pave a new path toward the goal of sustainable cities. By automating tasks, optimizing processes, and analyzing large volumes of data, AI holds the potential to significantly enhance the efficiency of waste classification and management, thereby reducing the environmental impact of waste. Nevertheless, while utilizing AI technology to achieve these goals, we also need to address a range of challenges including setting appropriate boundaries for AI, ensuring transparency and ethics, managing shifting human–AI relationships, and designing people-centric services. Particularly in the process of human–AI service co-creation, we need to find a way to align human and AI capabilities for mutually beneficial collaborations.

To further advance the implementation and refinement of this framework, more research is needed, including deepening community engagement, exploring solutions to uncertainties in service co-creation, and investigating how to better integrate this framework with the broader goals of sustainable urban development. We hope this framework can not only drive improvements in waste management services but also provide new ideas and tools for building more sustainable and environmentally friendly cities.

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