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From data to value in smart waste management: Optimizing solid waste collection with a digital twin-based decision support system

Linard Barth [a,b,*], Lukas Schweiger [c,d], Rodolfo Benedech [c], Matthias Ehrat [b]

[a] Faculty of Business and Economics, Mendel University, Zemědělská 1665/1, Brno, 613 00, Brno, Czech Republic
[b] School of Management and Law, Zurich University of Applied Sciences, Theaterstrasse 17, Winterthur, 8400, Zürich, Switzerland
[c] School of Engineering, Zurich University of Applied Sciences, Technikumstrasse 81, Winterthur, 8400, Zürich, Switzerland
[d] Department of Industrial Engineering, University of Florence, Viale Morgagni 40, Firenze, 50139, Tuscany, Italy

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ABSTRACT

The importance of waste management, including collection, separation, recovery, and recycling, increases with the growing amount of waste. Technological innovations such as smart connected products, the Internet of Things, and digital twins are driving the development of smart management systems. Investments in necessary product-service systems are justified by cost savings and improved service quality, especially in affluent societies like Switzerland. However, there is a trade-off between cost savings and service quality that raises the question of optimal balance. Using a Swiss municipality as an example, this paper models the trade-off between cost savings and service quality using waste bin sensor modules. Simulation results demonstrate the impact of cost savings on service quality reduction and that substantial cost savings are possible without a service quality compromise. We also introduce a digital process twin as a decision support system that is able to leverage a growing database. These results contribute to research, firstly through the field study with 98 waste bins equipped with fill level sensor modules, secondly through the model-based analysis of the trade-off between cost savings and service quality, and thirdly by conceptualizing a digital twin-based decision support system. The results further contribute to practice, firstly by providing benchmarks for implementing similar systems in other municipalities without having to create their own simulations, secondly by presenting an innovative key performance indicator to measure service quality, and thirdly with a model that can be used for simulations to determine the individual optimum between costs and service quality.

1. Introduction

1.1. Relevance

Waste management is one of the three main objectives of the European Union's (EU) waste policy for protecting the environment and human health while promoting its transition to a circular economy [1]. Waste management deals with various activities, from waste collection and separation to waste recovery and recycling. It is a vital issue as the volume of waste is increasing rapidly due to steadily rising living standards and rapid urbanization [2] as well as industrial development and changing consumer behavior [3]. In 2018, the total waste generated by all households in the EU amounted to 698 million tons. The collection and management of this enormous quantity imposes huge costs, both economically and with respect to human resources, time, and environmental impact [1]. Switzerland is the focus of this study, as an innovation project from the municipality of Herzogenbuchsee in the Canton of Bern was the basis for the case study presented later in this paper. Switzerland is located in the heart of Europe, and its waste management challenges are comparable to other heavily populated regions of Western Europe. Considering such densely populated and highly developed economies such as Switzerland, it can be observed that the amount of waste per capita has stagnated for more than a decade after a phase of sizeable increase from 300 kilograms per year in 1970 to 700 kilograms per year in 2006, as seen in Fig. 1 [4]. This means that even in a small municipality like Herzogenbuchsee, with just under 10,000 inhabitants, more than 7000 tons of waste is generated annually. Due to the growing population in Switzerland, the absolute amount of waste continues to increase, which is why efficient waste management is becoming more relevant [5].

At the same time, large and dense residential areas and the urgent need for urban environmental protection create difficult conditions for waste management [6]. Therefore, to improve the quality of life for citizens and minimize the negative impact on the environment, efficient and proper waste management is a fundamental challenge [3].

* Corresponding author at: School of Management and Law, Zurich University of Applied Sciences, Theaterstrasse 17, Winterthur, 8400, Zürich, Switzerland.
E-mail address: linard.barth@zhaw.ch (L. Barth).

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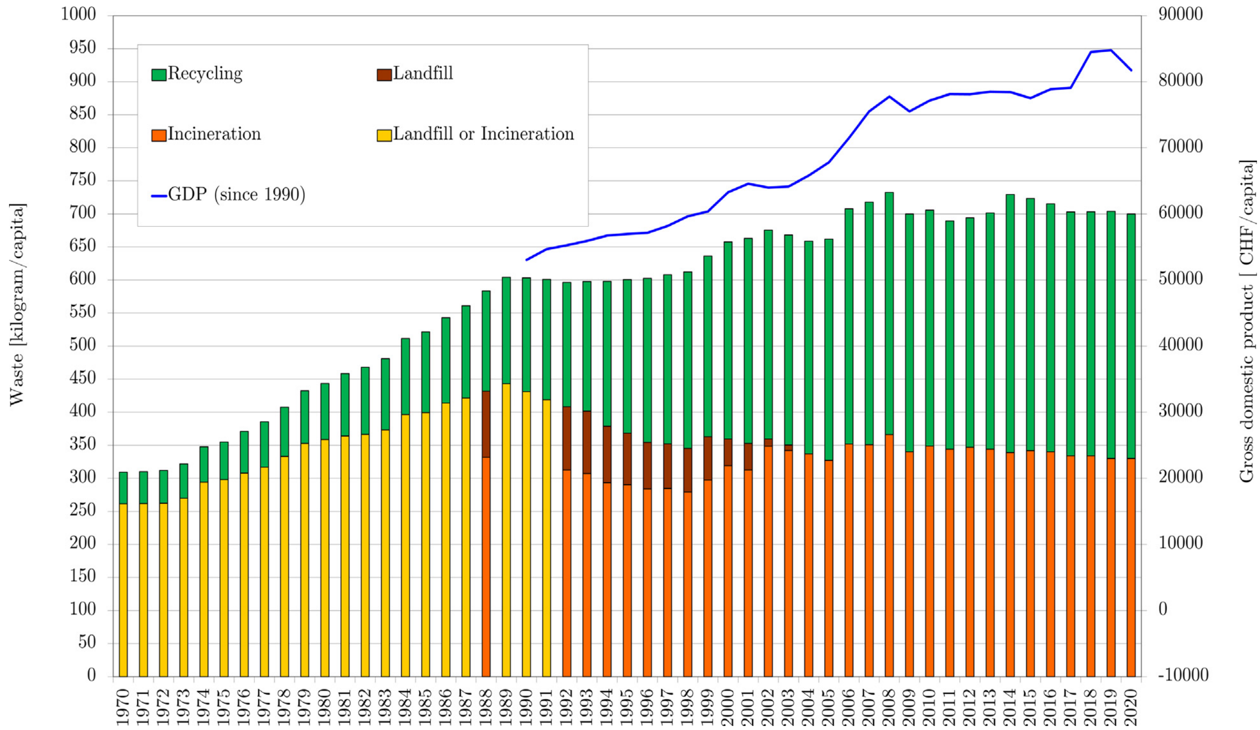

Fig. 1. Municipal waste per capita in Switzerland, 1970–2020 [4].

To achieve efficient waste management, stakeholders and operators must critically address the issues of cost and cost-effectiveness of infrastructure and processes.

1.2. Technologies and concepts

Information and communication technologies (ICT) offer a broad range of opportunities for developing solutions to the problems and challenges of waste management. Developments and progress in ICT transform traditional products into smart, connected products (SCP) by connecting them to the Internet of Things (IoT), which in turn transforms ecosystems and competition in many industries [7,8]. Therefore, the IoT is expected to change municipal waste management fundamentally in many areas, such as adaptive schedules for equipment use and maintenance, waste collection, and vehicle routing [9]. Furthermore, IoT and related concepts and technologies play a vital role in waste management systems as they allow for processing various types of information and thus help optimize the whole system [9]. SCP and smart systems allow for smart waste management (SWM) and are, therefore, considered an important part of smart city concepts [10]. The concept of the digital twin (DT), originated by Grieves [11], can be defined as a digital representation of a real-world counterpart, which can receive and provide data to create value within a use case [12]; despite this, there is still no common definition in the industry when it comes to the term DT [12,13]. With DTs, companies seek to create value in both the internal dimension (internal processes regarding product lifecycle) and the external dimension (during the usage phase in the market) [14–16]. The counterpart of a DT is often a physical object. However, in practice, any real-world entity with a recognizably distinct existence and relevance for creating value can be digitally represented by a DT [12]. In the case of processes, the term digital process twin (DPT) is used accordingly [17]. A real-world entity's representation in the digital realm can be categorized into two subsets. The first encompasses DTs symbolizing physical assets, frequently called "equipment twins". The second category, contrastingly, represents non-physical entities and is often referred to as "DPT". Such DPTs are more abstract, encapsulating processes, systems, or services instead of physical objects. They offer an innovative approach to visualizing, tracking, and enhancing various operational or business processes, thereby improving efficiency and productivity.

1.3. Research questions and innovative contribution

The focus of existing publications in the field of SWM concerns either maximizing profits, minimizing costs, or minimizing environmental impact through emissions by optimizing the routes of waste collection vehicles. The impact of SWM on service quality has been insufficiently explored until now, and the trade-off between cost savings and service quality has not yet been elaborated. It is, therefore, of great relevance to investigate the application of new technologies and concepts, such as DPT, in SWM with respect to their impact on cost savings and service quality. In this paper, we make an innovative contribution to ongoing research by addressing the following research questions:

- RQ 1 How can decision-makers balance the trade-off between cost savings and service quality in waste management?
- RQ 2 How can a DPT, in combination with an area-wide sensor module system, create value for decision-makers in waste management companies?
- RQ 3 How can a DPT be designed, and what specific functions are essential for a DPT to create value?

1.4. Structure of the paper

The remainder of this paper is structured as follows: First, we present a literature review (Section 2), elaborating on the key research and findings regarding SWM and the process by which we derived the research gaps and composed the research questions. Section 3 presents the methods and the research procedure used to answer the research questions, while Section 4 introduces and explains the use case for this study. In Section 5, the results are presented along with the main topics of data resources, the generated SWM model, and achieved optimizations. Section 6 then discusses the major findings along with the research questions and in reference to existing research in this field. Finally, in Section 7, we conclude by elaborating on our contribution to practice and science, conceding limitations, and suggesting avenues for further research.

2. Literature review

This paper aims to contribute significantly to two fields: (i) SWM, which serves as the primary focus, and (ii) the DT concept, which forms the foundation for our novel decision support system approach. Concerning SWM, the emphasis is placed on enhancing customer satisfaction and reducing costs by optimizing collection routes. A comprehensive exploration of this perspective on SWM can be found in Section 2.1 below. As our literature review shows, the focus of existing publications concerns either maximizing profits, minimizing costs, or minimizing environmental impact by optimizing the routes of waste collection vehicles. Very few publications address the impact on service quality, and we found no work elaborating on the trade-off between cost savings and service quality. Additionally, the concept of the DT will be examined in Section 2.2, with a specific focus on the notion of DPTs as a distinct subclass of DTs and the methodology employed in their structure.

2.1. Smart waste management

According to Jatinkumar Shah et al. [3], studies that have addressed information technology-based waste collection objectives can be categorized into four main groups:

1. Studies that have focused on the development of data acquisition technologies such as sensor-based technology, geographic information systems (GIS), and image processing technologies;
2. studies that have discussed data transformation platforms for transferring data collected through data acquisition technologies to central control platforms used by municipalities;
3. studies that have developed analytical models to demonstrate the application of capabilities of IoT-enabled technologies for proper waste collection activities; and
4. studies that have shown the capabilities of information technology in real case studies.

However, not all studies can be easily assigned to one of these four categories; most make contributions in more than one. In the following section, we summarize the pivotal and recent studies across the four groups defined by Jatinkumar Shah et al. [3]. Table 1 shows an overview of the relevant papers, which SMW topics they cover, their focus, main findings, and gaps. At the end of this Chapter, the distinguishing features and innovative contributions of this paper are elaborated.

2.1.1. Data acquisition technologies

Vicentini et al. [6] designed a testing prototype of four intelligent waste bins for Pudong, Shanghai. This early study focused on measuring the composition (weight, density, and water content) and quantity of waste per site. Waste bin collection was triggered when the bin was full, and no consideration was given to the threshold when a waste container should be considered for the next collection so that it would not be overfull at the time of collection. Moral et al. [18] presented a methodology to automatically generate geolocated waste container maps using algorithms that analyzed a video sequence and provided automatic discrimination between images with and without containers. Pardini et al. [19] developed an IoT-based sensor system to display fill levels in real-time to attempt to influence the littering behavior of the public.

2.1.2. Data transformation platforms

Vasagade et al. [20] developed a dynamic, intelligent waste management system by integrating RFID, GSM, and GIS to manage waste in an automatic waste monitoring system. Lozano et al. [21] introduced a waste monitoring and management platform for a rural environment in the region of Salamanca in Spain and were able to demonstrate a 28% reduction in distance driven to collect waste. Barth et al. [22] followed a holistic approach, combining technology and process development to increase the effectiveness and efficiency of multiple processes in the SWM ecosystem in Switzerland. Baldo et al. [23] developed a multi-layer approach for data transfer via LoRaWAN in SWM product-service systems (PSS). Ijemaru et al. [24] proposed an Internet of Vehicles (IoV)-based technique as an energy-efficient alternative to IoT-based data collection and transmission techniques for waste management applications in smart cities. For further information on IoT-based technologies, frameworks, and solutions for waste management in smart cities, we refer readers to the comprehensive review offered by Ijemaru et al. [24].

2.1.3. Analytical models

Most studies on IoT-enabled SWM have focused on optimizing the routing and deployment of waste collection vehicles in smart cities [3]. However, studies in recent years have focused on developing dynamic models with the goal of reducing overall cost, time, and distance. Two relatively early studies dealing with dynamic routine models for waste collection in smart cities were developed by Anagnostopoulos et al. [26,27]. Anagnostopoulos et al. [32] also presented an extensive review paper of an analytical model for route optimization for waste collection vehicles in smart cities in 2017. Asimakopoulos et al. [28] proposed several algorithms to solve dynamic routing problems using real-time monitoring of the fill level of waste bins. Sharmin and Al-Amin [29] developed an ant colony algorithm to find the shortest route for waste collection vehicles in a smart city to minimize transportation costs. Mohammadi et al. [48] achieved a 32% cost reduction compared to the previous static routing by employing a discrete choice model to streamline the process of re-optimization in dynamic vehicle routing problems in a use case. Hashemi-Amiri et al. [49] designed a multi-objective model to maximize the probabilistic profit of a SWM network while minimizing the total travel time and transportation costs. Rahmanifar et al. [46] proposed a two-echelon waste management system to minimize operational costs and environmental impact. They also employed existing meta-heuristic algorithms and several novel heuristics developed based on the problem's specifications and compared their performance based on a network of eight waste bins.

Some studies have pursued other goals besides minimizing operating costs through route optimization. For example, Rada et al. [25] investigated the waste separation efficiency and cost reduction in several aspects of a Web-GIS application in multiple municipalities in northern Italy. Others, such as Anghinolfi et al. [30], aimed to minimize costs and environmental impact. To our knowledge, they were among the first to explicitly define a key performance indicator (KPI) for "quality of service" and even presented considerations to quantify the trade-off with cost savings. Ali et al. [39] showed that IoT-based SWM PSS are more effective than traditional methods and introduced a pollution ratio KPI as an approach to quantify service quality. Dereci and Karabekmez [43] applied multiple heuristics and meta-heuristic algorithms to find the optimal routes for waste collection vehicles with two scenarios — an optimal route focus or a customer satisfaction focus. Roy et al. [44] presented an innovative approach to increase the service quality in SWM PSS by introducing a time-dependent penalty for operators.

Table 1
Overview and comparison of smart waste management literature.

Publication	Year	Data acquisition technologies	Data transformation platforms	Analytical models	Case studies	Focus	Main findings	Gaps
[6]	2009	◗			◗	IoT-based SWM in Shanghai, China.	Design of data acquisition and information flow including necessary hardware.	Old and short paper; no route optimization.
[25]	2013	◗	◗	◗	◗	Four case studies comparing developed (Italy) and emerging economies (China, Malaysia) for feasibility of Web GIS systems.	Aspects related to the implementation of a Web-GIS based system are analyzed and the economies compared.	Old and short paper; no route optimization; service quality not considered.
[26]	2014		◗	●		New framework for SCP in SWM.	Comprehensive overview of existing efforts in using IoT for SWM.	No case study; no real data; data acquisition not covered.
[27]	2015			●	◗	Extending the dynamic routing process by collecting high-priority bins immediately to comply with service quality.	Improved pathfinding in the case of high-priority bins.	Data acquisition and transformation not covered.
[28]	2016		◗	◗		Efficient algorithms for dynamic routing of collection trucks.	Theoretical cost savings of 50,000 Euros.	Data interpretation not covered; no clear case study.
[29]	2016		◗	●		Finding optimal routes with ant colony optimization approach using sensor data.	Algorithm for pathfinding based on fill level of bins.	Very short paper; no real-life data; experiments based on small artificial network.
[30]	2016			●	●	Tactical planning of SWM logistics of recycling for Italian municipalities, considered "quality of service" (QS) and acknowledged a trade-off between QS and cost reduction.	A multiobjective optimization model is proposed, aimed at minimizing both operational costs and negative environmental impacts. Cost savings of 23%.	Data acquisition and transformation are not covered; use case without IoT-system.
[31]	2016	◗	◗	◗	◗	Design and implementation of a novel agent-based platform for SWM.	Present prototypes of low-cost sensor, route system and mobile application for SWM.	Holistic but short paper; no real-life case study; service quality not considered.
[20]	2017	●	◗			Sensor design for smart bins.	Fully automated, sensor-based SWM system to optimize collection and encourage proper bin use.	No model using sensor data; no real-life case study.
[32]	2017	◗	◗	◗	◗	Meta-case study; ICT-enabled SWM models for efficient planning of collection activities.	SWM taxonomy; strengths and weaknesses of various models.	Meta-review; service quality not considered.
[33]	2017			●	◗	Algorithms to optimize the routes of a recyclable SWM system for Moron, Argentina.	An integer programming model with a solving procedure built around a subtour-merging algorithm and elimination constraints; now, 100% of the city blocks are covered compared to 84% before.	Data acquisition and transformation are not covered; use case without IoT-system.
[34]	2017			◗	●	Discrete-event simulation model to optimize zones and routes of solid waste collection in Phuket, Thailand.	Trips for solid waste collection reduced by 9.1%; average distance by 7.4%; and time by 7.1%.	Short paper, data acquisition, and processing are not covered; use case without IoT-system.
[35]	2017		◗	◗		IoT architecture and multi-agent platform to simulate real-time monitoring and collection decisions in SWM.	Simple Netlogo multi-agent simulation.	Service quality not considered; collection frequency not changed; simple route optimization; no use case.
[36]	2017	◗	◗		●	Real use case with 200 waste containers equipped with sensor modules to measure fill level.	Cost savings of 30%.	Very short paper; service quality not considered; collection frequency unchanged.
[3]	2018			●		Stochastic optimization model to minimize the total transportation cost while maximizing recovery of value.	New model for value recovery aspect in waste collection.	Data acquisition and transformation are not covered; no real-life case study.
[21]	2018	●	●	◗	●	Introduces a waste monitoring and management platform for rural environments.	Distance saving of 28% through route optimization.	Service quality not considered; collection frequency unchanged.
[10]	2019			◗	◗	Smart city development in Russia.	Formalization of logistic optimization for modeling of autonomous intelligent agents in Any Logic.	Very short paper; service quality not considered.
[37]	2019				●	Green and smart cities; recycling.	Where to locate waste-sorting stations and how to involve citizens in SWM implementation.	Data acquisition, transformation, and analytical models are not covered.
[38]	2020	◗	◗	◗	◗	Challenges related to wireless data transfer, battery lifetime, and IoT infrastructure for SWM,	Hardware & software architecture; filling behavior for glass containers; strategies to overcome challenges.	Short paper; route optimization not explained; cost savings not quantified.
[19]	2020	●	◗		◗	Using IoT sensors to show fill levels of smart bins to the public.	Proven positive influence on citizens' littering behavior.	No solutions for waste collection.

(*continued on next page*)

Table 1 (*continued*).

[39]	2020	◗	◗	●		Efficiency and cost of IoT-based SWM solutions; pollution ratio as service quality KPI.	Showed that collection with IoT-based SWM is more effective with traditional methods.	Theoretical use case; no route optimization; per-day costs decrease but distance driven increases.
[22]	2021	◗	●	◗	◗	Holistic approach from data to services.	Optimized collection routes reduces working time by 14% and total cost by 16%.	Short paper; simple route optimization.
[40]	2021		◗	◗	●	Analyzed 40 cases of urban digital twin applications.	Classified cases according to four criteria and discussed future direction with three perspectives.	No waste management focus.
[23]	2021	◗	●		●	SWM infrastructure based on the LoRaWAN.	Multi-layer approach to data transfer via LoRaWAN.	Only surveillance solution; no improvement in waste collection.
[18]	2022	●			◗	Visual model for waste container detection; evaluated in eleven Spanish cities.	A methodology to automatically generate geolocated waste container maps.	Data transformation and analytical models not covered; no route optimization.
[24]	2022	●	◗	◗		Comprehensive literature review; focus on energy consumption; analyzed different routing algorithms.	Proposal of IoV (V=vehicles) to reduce energy consumption of data transmission; ant-based routing algorithms for energy efficient SWM.	No case study.
[41]	2022				●	Holistic and comparative assessment of volume reduction, segregation, and collection costs of waste in 16 Polish cities.	Volume of waste per capita and cost for waste management increasing in most cities; smart cities are among the least effective.	Meta-case study, data processing, transformation, and analytical models not covered; service quality not considered.
[42]	2022				●	Longitudinal Finnish case study.	Evolution from one-bag dumping to SWM PSS.	Technical aspects of PSSs, route optimization, and cost savings are not covered.
[43]	2022			●	◗	Optimal routes in a real case study with two scenarios: optimal route focus and citizen satisfaction focus.	Comparison of different (meta-) heuristic algorithms to determine optimal routes.	Data acquisition and transformation not covered; only historical data and collection frequency unchanged.
[44]	2022	◗		●	◗	IoT-based waste bin allocation with monitoring system and ant colony based vehicle routing algorithm.	Innovative approaches to increase service quality (time-dependent penalty) and collection efficiency (collection of neighboring bins if vehicle has capacity).	Data processing and transformation not covered; limited use case (15 locations).
[45]	2022		◗		●	SWM for 32 bins with dashboard for decision-makers; correlation between fill levels and date or month.	Reduced collections from 28 to 6 times per month (80% reduction).	Very short paper; no route optimization.
[46]	2023			●		Two-echelon SWM system to minimize operational costs and environmental impact.	Several meta-heuristic algorithms to optimize a capacitated vehicle routing problem are analyzed and ranked.	No holistic approach: no case study; cost savings not quantified; service quality not considered.
[47]	2023			◗	◗	Zero-defect concept for value chains and the notion of DT enabled planning to reduce food waste in grocery retail.	Juxtaposition of causes of food waste and DT capabilities.	No route planning; no collection; municipal waste not in focus.
[48]	2023			●	◗	Discrete choice model to streamline re-optimization of dynamic vehicle routing problems; use case with 220 bins and seven trucks.	Several algorithms are applied to the problem and compared; 32% cost reduction by changing from static to dynamic routing.	Data acquisition and transformation not covered; service quality not considered.
[49]	2023			●		SWM framework based on IoT.	Multi-objective model to maximize the probabilistic profit of network while minimizing total travel time and transportation costs.	No real data used; data transformation and transmission from bins to model not covered.
[50]	2023	◗		◗	●	DT model to experiment with a garbage collection mechanism using wind blowers and pipes.	Delivers the practice of designing, experimenting, and calibrating a DT system for SWM.	Different system with no collection vehicles; no quantification of savings.
[51]	2023			●	●	Collection routing problem with workload concerns in SWM; large case study with 800 bins.	Solution methodology consisting of two phases (when and which bins to collect).	Data acquisition and transformation not covered; service quality not considered.
[52]	2023	◗			◗	Context ontology.	Provides a unified model for SWM contextual data, a solution to implement IoT according to different waste contexts, waste objectives, and waste activities.	Very short paper.
This paper	2023	◗	◗	●	●	Holistic approach; complete process from data acquisition to value creation explained in a use case with 98 bins covering the whole collection area; trade-off between service quality and cost savings.	DPT to optimize collection frequency and routes; quantified trade-off between cost savings and service quality; defined a new KPI to measure service quality.	Simple route optimization.

Key: ● = category in focus, ◗ = category covered, *empty* = category not covered.

2.1.4. Case studies

Many studies are based on real cases; for example, Braier et al. [33] presented a waste collection case from Morón, Argentina, and proposed an integer programming model to optimize the dynamic routes of collection vehicles. Banditvilai and Niraso [34] developed a heuristic approach for assigning waste collection zones and routings, and proposed a simulation framework for modeling the night shift solid waste collection in Phuket, Thailand. Oralhan et al. [36] presented the results of a relatively large real use case with 200 waste bins equipped with sensor modules, which achieved a 30% reduction in waste-collection costs. In a Russian case study, Mingaleva et al. [37] analyzed where to locate waste-sorting stations and how to involve

Properties	Definition	Comments / Explanatory Notes
	A digital twin …	
Authenticity	… is a sufficient authentic digital representation…	Regarding fidelity and synchronization
Counterpart	... of a distinct real-world entity…	Entity with i) a recognizably distinct existence and ii) which are relevant for the creation of value
Creation	… that exists as a prototype…	Containing all the information required to create the real world entity, as well as the DT instance
	… from which instances to accompany these real-world entities are derived.	A specific instance of an individual entity that remains linked to it throughout its life
Communication	… has interfaces to communicate with users bidirectionally...	Users include humans via Human-Machine-Interfaces (HMI) as well as other objects and DTs via Machine-to-Machine-Interfaces (M2M)
	… receives raw and preprocessed data...	From own sensors, internal systems, external systems or users
	… to provide data, information and services…	Reactively or proactively offered
Purpose	… to create value…	For defined stakeholders
	… within a specific use case.	Is individually customized for use cases

Fig. 2. Application-oriented definition of DT according to Schweiger and Barth [12].

citizens in successfully implementing SWM PSS. Zakharova and Fedorova [10] showed automation directions for solving environmental problems in the Sverdlovsk region and data of Yekaterinburg. Jonek-Kowalska [41] investigated what results smart cities in Poland have achieved regarding waste volume reduction, waste separation, and collection costs. Peura et al. [42] presented a longitudinal case study that elucidates how waste management in a Finnish region evolved from a one-bag system towards PSSs. An et al. [45] demonstrated the potential of IoT and dashboards for decision-makers to reduce the amount of waste collection in a case study with 32 smart waste bins in an Australian municipality. Yun et al. [50] used a DT model to experiment with a garbage collection mechanism using wind blower and pipes instead of collection vehicles in Sejong City, South Korea. An exceptionally large case study with 800 waste bins was conducted by de Morais et al. [51] who presented a solution methodology consisting of two phases to decide (i) when and (ii) which bins to collect.

2.1.5. Innovative contribution of this paper

Our study can predominantly be assigned to the fourth category (see above) but contains elements from the other three categories. It contributes through its holistic approach covering the whole process from data acquisition to value creation in SWM PSSs. Our study differs from other studies as it does not focus on optimizing the routing but considers possible cost savings by reducing the number of collection trips per week and the number of waste bins included in the tours depending on the threshold fill level. We also introduce an innovative approach to measure and quantify the service quality level; this topic is often overlooked, with a KPI influenced by the number of overfull waste bins. Furthermore, our study is based on data from a field test with 98 waste bins, which cover the entire collection area of the community in question. In contrast, many previous studies with field tests had only a limited number of bins or did not cover the whole collection area.

2.2. Digital process twins

The DT concept, initially introduced by Grieves [11] from NASA, has evolved since its inception in a 2003 PLM lecture. NASA's 2012 definition described DTs as multiphysics, multiscale, probabilistic simulations relying on historical, real-time, and physical model data [53]. This definition is still being discussed and developed further by many different researchers (e.g., [54–56]). A significant debate revolves around the nature of the DT counterpart. While early definitions predominantly emphasized the exclusive representation of physical entities, recent perspectives have shifted towards a more inclusive interpretation of what a DT can embody [55]. Schweiger and Barth [12] investigated the defining characteristics and properties of DTs in scientific research and by industrial companies and presented an application-oriented definition. The definition shown in Fig. 2 is detailed and, at the same time, generic enough to be used in various application areas. In their publication, Meierhofer et al. [57] proposed a distinction between the equipment twin and the DPT as two sub-components of the DT. They contend that a logical dependency exists between these elements within a company's decision-making process. According to their perspective, value creation occurs through a series of steps that begin with the equipment twin and inherently evolve into a DPT. The approach outlined by Meierhofer et al. [57] was further examined in a study by Schweiger et al. [58], which highlighted the close relationship between the term DPT and the concept of symbiotic simulations, as employed, for example, by Onggo et al. [59]. Additionally, Schweiger et al. [58] demonstrated that the different sub-components of the DT, as described in Meierhofer et al. [57] under the term "DT sequence", possess intrinsic value individually. The development process for a DPT is elaborated on in a publication by Schweiger et al. [17], in which they advocate the use of the term DPT, drawing support from Verdouw et al. [60] and Tjahjono and Jiang [61]. However, with the industry, especially a service-focused one, attempting to fully automate service, it becomes increasingly important to standardize and fully understand the processes. According to Ganz and West [62], this lays the foundation for automated services. Here, the DPT could support this general development. In conclusion, Schweiger et al. [17] emphasized that further investigation is needed to understand the integration and interaction between equipment twins and DPTs to maximize their potential benefits within decision support systems [63] for companies.

2.3. Research gap

Although many studies address vehicle routing for waste collection in the literature, the number dealing with this topic is insufficient, according to Dereci and Karabekmez [43]. Furthermore, as shown by de Morais et al. [51], the objective of those studies is either maximizing profits, minimizing costs, or minimizing environmental impact caused by emissions. We have found only two studies that also offer an innovative approach to measure and optimize the service quality of a SWM system [39,44].

Our review of the existing literature in the relevant field reveals several key studies and approaches concerning decision analytics (including, e.g., [24,32] for the topic of waste management and, e.g., [59, 60] for DPTs). While these contributions have advanced our understanding of the field, they are not without limitations. The most notable gaps in the current body of research on SWM systems and DPTs include the following:

RG 1 A trade-off analysis that shows the relationship between cost savings and service quality.
RG 2 A field study that includes an area-wide sensor module usage in the collection area.
RG 3 A prototype of a DPT showing how equipment twins and DPTs generate value in combination.

Addressing these gaps is crucial for the continued development of decision analytics in waste management. By deepening the understanding of the interaction between cost reduction and service quality, studying the waste collection system behavior under real-life circumstances, and improving the understanding of the value creation of DPTs in combination with equipment twins, we contribute to a better understanding of the complex system of waste collection in communal areas under the restriction of cost efficiency and service quality (in the sense of no overfilled or even overflowing bins). In this paper, we propose a novel approach that aims to fill these identified gaps, thereby advancing the field of decision analytics and contributing to more effective decision-making processes in the domain of waste management.

2.4. Research questions

In this section, we formulate three research questions that directly address the three identified gaps in the field of waste management. By establishing clear and concise research questions, we guide our investigation towards meaningful and beneficial findings. The resulting research questions are:

RQ 1 How can decision-makers balance the trade-off between cost savings and service quality in waste management?
RQ 2 How can a DPT, in combination with an area-wide sensor module system, create value for decision-makers in waste management companies?
RQ 3 How can a DPT be designed, and what specific functions are essential for the DPT to create value?

These research questions serve as the foundation for our investigation, helping us to explore the research gaps identified.

3. Methodology

3.1. Case study

The basis of our research was a single case study, which allowed us to study the development, use, and value creation of a DPT with real data. The case study is described and elaborated in detail in Section 4. According to Yin [64], one of the rationales for a single case study, as opposed to a multiple-case design, is the availability of a representative or typical case, where the objective is to capture the circumstances of an everyday or commonplace situation. Furthermore, the essence of a case study is to illuminate a decision or set of decisions to answer questions such as why they were taken, how they were implemented, and with what results [65].

In the case of optimizing waste management in a residential area by using SCPs and DT applications, a single case study illuminating such decisions can produce transferable findings for other cases. This is because the challenges and constraints of why and how to realize such an intelligent PSS, as well as the desired results, are similar worldwide. A single case study with in-depth analysis is, therefore, a suitable method to contribute to closing the research gaps identified.

3.2. Reference framework

Two specific methods were applied in the case study. First, the application-oriented conceptual reference framework for the value creation with DTs by Barth et al. [16] was used to develop the envisioned system conceptually. The framework incorporates primary dimensions of external and internal value creation and data resources. It also discusses the product life cycle, the real-world counterpart, value creation in the ecosystem, and the generational aspect of the DTs.

3.3. Mixed model simulation

Second, we employed a mixed-model simulation approach, combining an agent-based simulation (ABS) model with discrete event simulation (DES) elements. We utilized AnyLogic® as the modeling tool due to its suitability for our purposes, as highlighted by Abar et al. [66]. AnyLogic® is a versatile graphical model editor that integrates discrete event, agent-based, and system dynamics models within a single modeling environment. Moreover, AnyLogic® facilitates incorporating geographic information system (GIS) maps, enabling the simulation of agent behavior on realistic travel routes in a true-to-life environment. The GIS environment relies on OpenStreetMap (OSM) as its map provider. The specific model used in this paper will be presented in Section 5.2. The baseline model construction approach, the foundation for subsequent simulations and experiments, was published by Schweiger et al. [17]. The model structure was similarly employed by Ding et al. [67].

3.3.1. Data collection

Data for the model were sourced from industry partners or collected during field visits. Industry partners provided information on smart bin locations, vehicle counts, and routing details. Data collected from field visits included emptying schedules for the smart bins and incineration plants. Furthermore, we used our industrial partner's platform to obtain the sensor data for the smart bins on which we based the filling behavior of the bins. Due to confidentiality, this data, as well as the validation data, will not be shared.

3.3.2. Experiments

We conducted an optimization experiment using the pre-designed optimization experiment feature of AnyLogic® based on the waste management system model. Such optimization experiments aim to discover optimal solutions while examining system behavior under specific conditions. This approach enabled us to determine the optimal fill levels for smart bin collection. AnyLogic® employs the OptQuest® optimization engine, which utilizes metaheuristics to guide its algorithm towards a solution closer to the optimum. The engine integrates tabu search, scatter search, integer programming, and neural networks into a single, efficient algorithm for identifying optimal scenarios. Additionally, we used the AnyLogic® parameter variation experiment to show the different results depending on the collection threshold for the smart bins.

We focused exclusively on simulating the service ecosystem, comprising waste bins, collection vehicles, and disposal points. Instead of recalculating routes using a traveling salesman algorithm or a bin-packing algorithm, we utilized predefined routes provided by our industry partners. Our model then identified the waste bins that could be skipped, thereby optimizing the collection process. The results were validated based on historical data from the industrial partners.

Fig. 3. Sensor module (top left), waste bin (bottom left), and analytic platform (right).

4. Case study

The project that served as a basis for the case study was entitled "Development of the Waste Management Ecosystem based on a Smart Connected Product-Service-System (PSS)". It was funded by the Swiss Innovation Agency Innosuisse and conducted by a consortium of institutes from the Zurich University of Applied Sciences and four private companies over two years between 2020 and 2022. The goal of the project was to initiate a SWM ecosystem in Switzerland. The basis was provided by a dense network of existing waste bins equipped with sensor modules to measure various data regarding their status (e.g., fill level) and transmit this information for analysis and process optimization (cf. Fig. 3).

To achieve this, a new, smart PSS was developed and validated to digitally map, analyze, and optimize cross-company processes in waste management. According to the five proposed development phases of traditional products into smart systems of systems in the seminal model by Porter and Heppelmann [7,8], the project aimed to realize SCPs according to phase three and thus to form the basis for a SWM system according to phase four, as seen in Fig. 4. At the core of the integrated PSS of phase four is a DT of the PSS consisting of waste bins, collection vehicles, and waste recyclers or incineration plants. Starting from the initial situation, the following main tasks were carried out:

1. Developing reliable technical measurements in the waste bins (raw data collection using sensors).
2. Designing the processing and analysis processes for the generated data (processing the raw data into information).
3. Developing models and workflows for decision-making (using the information to determine actions).

The focus was on existing processes regarding managing waste collection bins, their maintenance, and the emptying and collection processes. However, by taking a holistic view of the waste management ecosystem, further innovation potential regarding the integration into subsequent and higher-level systems such as smart cities was also considered and advanced. To develop and depict the value creation with DTs of smart connected waste containers conceptually, an application-oriented DT framework (DTF) was used. For a detailed explanation of this application-oriented DTF, its parts, and their interaction, we refer to the publication by Barth et al. [16], which also includes an instantiation of the DTF for a use case with a digital twin for a ship. To instantiate the framework for the case at hand, first, the current state of the SWM processes was analyzed according to the dimensions and specifications of the application-oriented DTF and graphically depicted. With this basis, the framework was complemented in workshops with the project partners and other stakeholders of the ecosystem with additional elements to depict the desired future system. The resulting framework in Fig. 5 depicts the whole PSS for SWM, with the parts covered in this article highlighted by a green frame. The physical counterparts of the DT, referred to as *things*, are depicted in the bottom section. These are one of the three data source categories (next to internal and external systems) and provide DT applications with information about the real world. The smart analysis box is where the data are structured and interpreted to receive information and make necessary decisions to realize services that, in turn, create value in the three categories of availability, performance, and quality.

This paper focuses on the simulation-based DPT developed for the service of static route optimization provided to external users. However, as seen in Fig. 5, a range of other services have been developed and partially implemented, some of which are only used by internal users. For example, field service employees can use bin asset management applications connected to the DT to locate installed waste bins, call up service checklists, and document their work visibly for the customer, for example, by providing smartphone images.

All three categories of value creation could be improved for the municipality in the pilot project. However, a trade-off between (i) performance and (ii) quality (cf. Fig. 5) was identified for route optimization based on the fill levels of the waste bins in regard to cost savings as a (i) performance measurement and service quality as a (ii) quality measurement. We, therefore, simulated scenarios using different thresholds of fill levels to find the individual optima in this trade-off. On the part of the practice partners, the optimum was defined as minimizing costs as much as possible while allowing for a maximum of 1% overfilled waste bins.

Many of the developed services have already been enabled by the smartness maturity level "Control" (cf. [14,16]). The allocation of individual waste bins to the next collection tour based on the current fill level and the threshold defined with the help of the simulation functions entirely automatically. This means that the interpretation of pre-structured data is carried out purely by the DPT, and no human intervention is required.

However, for most services assigned to the smartness maturity level "Optimization", humans are still required for an interpretation step. Based on the collected data over a more extended period, the DT can suggest how the static route planning (i.e., the frequency of collection tours and their routes) could be optimized. However, a human still makes the final change in the route planning as this decision influences many other factors, such as employee capacity planning and short-term traffic restrictions due to construction sites or other unforeseen events. When enough data have been collected in the DT, the quality of interpretations by the DPT will become sufficiently high for humans to trust its decisions, allowing these services to be carried out without human intervention. After this intermediate step, it is planned not only to carry out static but also dynamic route optimizations independently with the help of the DTs, namely the route being adapted in real-time based on fill levels, traffic, and other factors during the collection tour.

The smartness maturity levels, together with the seminal model by Porter and Heppelmann [7,8], which shows the development phases from a simple product to a system of systems, outline the long-term development directions of the project.

5. Research results

In this Chapter, we present the results regarding the service of static route optimization with the DPT. The structure of this Chapter is based on the process shown in the *smart analysis* box in Fig. 6, which is an extract of Fig. 5, where incoming raw data are first processed and structured before they can be interpreted by the DT. Section 5, therefore, has the following sections: The section on data resources 5.1 explains how the raw data is collected and structured, the next Section 5.2 explains how this data is interpreted with the help of a DPT, and Section 5.3 presents the findings from the case study.

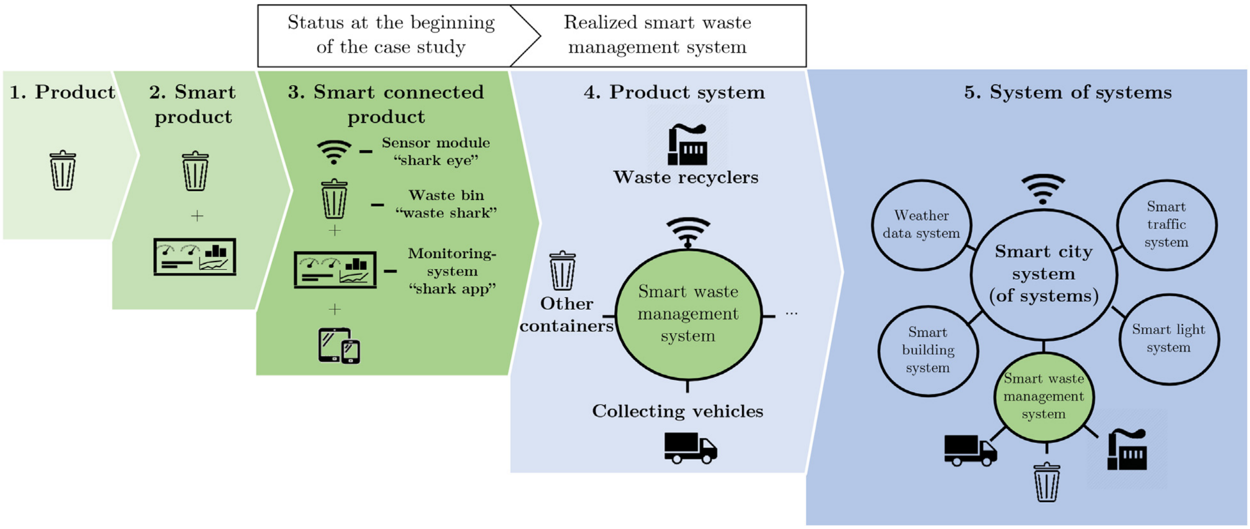

Fig. 4. Development phases from product to system of systems in the waste management context [22].

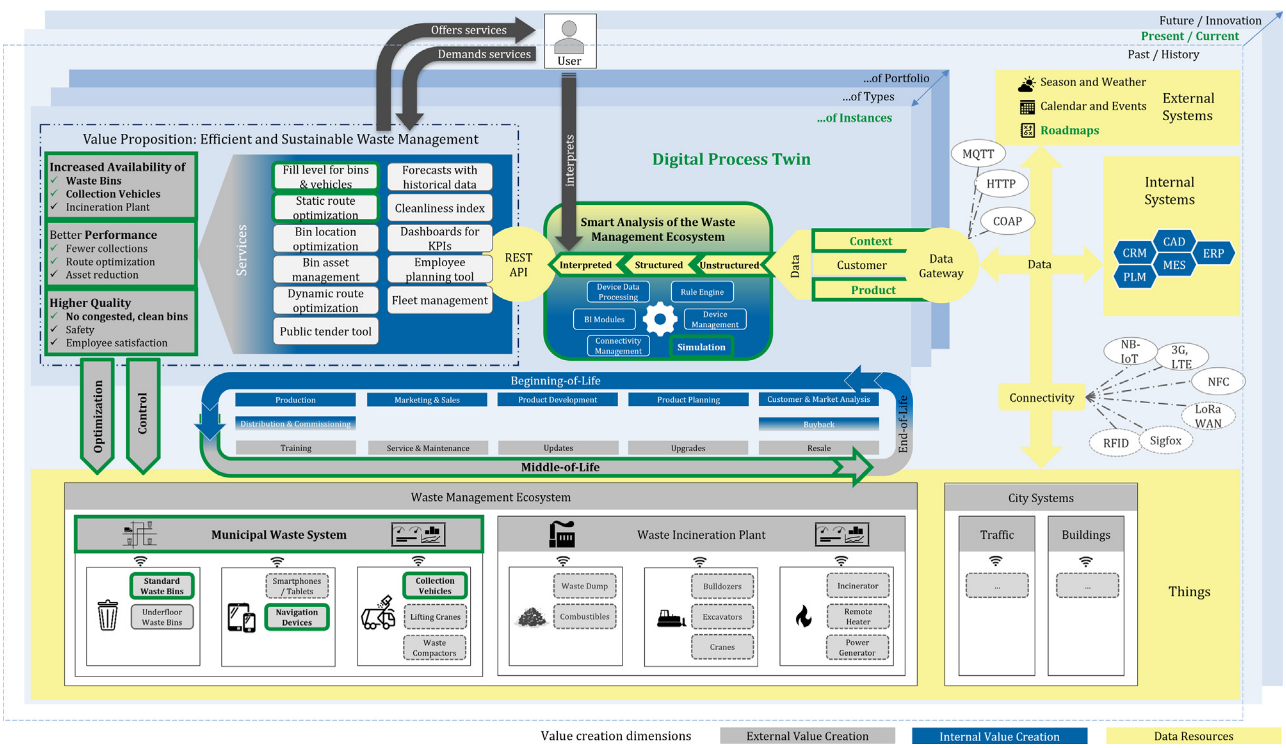

Fig. 5. Value creation with DTs in the SWM ecosystem; topics covered in this paper are highlighted by a green frame.

5.1. Data resources

This section describes how the raw data is obtained, processed, and structured in the use case.

5.1.1. Data collection

In this project, a large quantity of data from different sources were connected with the DT, as shown in Fig. 5. In addition to information about the waste bins, collection vehicles, and the waste incineration plant generated directly by the *things*, other data from internal and external systems were used. These included the standard routes for waste collection from the municipalities or the locations and capacities of the waste bins. However, the most significant challenge in the project and the central information for the DPT (in making decisions for the service of static route optimization) were the fill levels of the waste bins (cf. Item 1 in Fig. 7), which is why these sections focus on the generation and processing of these data.

Several types of sensors can be used to measure a fill level in a waste bin. We tested ultrasonic sensors, radar sensors, and time-of-flight sensors in the project (cf. Item 2 in Fig. 7). Ultrasonic and radar sensors did not provide reliable data because waste is a very heterogeneous mass, with materials of different densities and reflective properties, and also forms cones of dump (cf. Item 3 in Fig. 7). For these reasons, a time-of-flight sensor of the type Espros 611 with 64 distance measuring points was chosen to obtain the raw data (cf. Item 4 in Fig. 7).

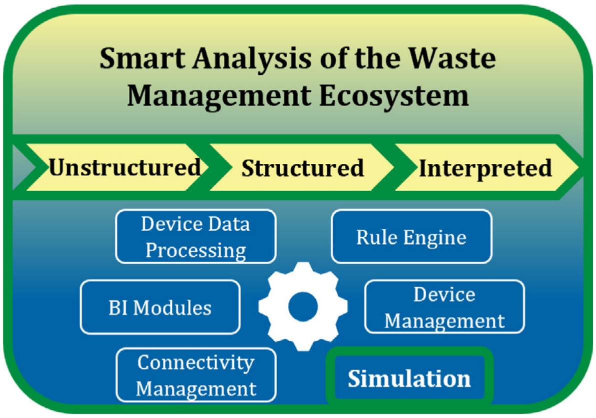

Fig. 6. Smart analysis with a simulation-based digital process twin.

5.1.2. Data structuring

The unstructured data generated do not yet form a sufficient basis for interpretations and decisions. To achieve this, incoming sensor data must be structured and processed to ensure the DT reproduces reality in the desired manner. In the SWM project, another sensor in the form of a wildlife camera was used for labeling the fill levels measured by the time-of-flight sensor. With a scale placed in the waste container, an assistant entered the actual fill levels to label the measured values with "ground truth" values. Item 5 in Fig. 7 shows how the initial sensor values (dashed red line) were approximated to the ground-truth level (blue line) in several stages. In the first step, the approximation to the real fill levels was achieved with weighted exponential smoothing to reduce the noisy signal of the data and a simple rule to discard heavy outliers. By generally discarding heavy outliers at low-fill levels and with a smoothing factor of $\alpha = .2$, the raw sensor values were brought much closer to the ground-truth values (solid red line). When analyzing the results, it became apparent that the solid red line representing the structured fill level data represented the real values much more precisely although it suffered from a systematic deviation towards the bottom. Therefore, in the final step, the results obtained were increased by 13% to compensate for this. As seen in Item 5 of Fig. 7, the resulting structured data of the fill level (yellow line) is sufficiently close to the ground-truth value for interpretation and decision-making by the DPT.

5.2. Data interpretation with a process twin

Once the data of the fill levels were available in a sufficiently structured format, they could be interpreted with a DPT. In this project, the DPT was built with a mixed method model based on an ecosystems analysis of the use case described in Section 4 and as described in Schweiger et al. [17]. The model incorporates the following SCPs or systems, which are also depicted in Fig. 5: smart waste bins, collection vehicles, and a waste incineration plant. These components operate within a GIS environment facilitated by AnyLogic®. In the subsequent sections, we will introduce the model, input data, KPIs, optimization experiment, and resulting findings.

5.2.1. Model description

For the model $M(t)$ of a communal waste management system, let $B_b(t)$ denote the bth smart bin at time t, where $b \in \{1, 2, \ldots, n_B\}$ and n_B is the total number of smart bins in the population. Similarly, let $V_v(t)$ denote the vth collection vehicle at the time t, where $v \in \{1, 2, \ldots, n_V\}$ and n_V is the total number of collection vehicles in the population. Let I denote the waste incineration plant and GIS denote the GIS environment for the model. Then, the state of the overall model at time t can be represented by the time-dependent set:

$$M(t) = \{B(t), V(t), I, GIS\} \tag{1}$$

Table 2
Sets and indices of model M.

Sets and indices	Description
B	Set of smart bins
V	Set of collection vehicles
I	Set of waste incinerators
b	Smart bins index
v	Collection vehicle index

Table 3
Parameters of model M.

Parameter	Description
g_b	Category of B_b
t_b	Tour index of B_b
k_b	Capacity of B_b
d_b	Discharge time of B_b
s_b	Sensor in B_b
l_b	Location of B_b
k_v	Capacity of V_v
$c_{h,v}$	Cost per hour of V_v
$c_{k,v}$	Cost per kilometer of V_v
t_v	Tour of V_v
d_v	Discharge time of V_v
d_i	Discharge time of I_i
l_i	Location of I_i

Table 4
Variables of model M.

Variable	Description
$f_b(t)$	Fill level of B_b
$f_v(t)$	Fill level of V_v
$v_v(d)$	Speed of V_v
$l_v(t)$	Location of V_v

where $B(t) = \{B_1(t), B_2(t), \ldots, B_{n_b}(t)\}$ is the state of the smart bins at time t, $V(t) = \{V_1(t), V_2(t), \ldots, V_{n_V}(t)\}$ is the state of the collection vehicle at time t (cf. Table 2).

Each B_b has the following parameters and variables: category denoted by g_b, tour denoted by t_b, capacity in liters denoted k_b, fill level in liters denoted by $f_b(t)$, discharge time denoted by d_b, sensor denoted by s_b, location denoted by l_b. Similarly, each V_v has the following parameters and variables: speed in km/h denoted by $v_v(d)$ where d is the distance to the next B_b, capacity in kg denoted by k_v, fill level in kg denoted by $f_v(t)$, the cost per km denoted by $c_{k,v}$, the cost per hour denoted by $c_{h,v}$, the location denoted by $l_v(t)$, tour denoted by t_v where $\{t_v \in B \mid t_b = x\}$, and the discharge time denoted by d_v. Furthermore, the waste incineration plant $I(t)$ has the following changing parameters: location denoted by l_i, and the discharge time denoted by d_i (cf. Tables 3 and 4).

5.2.2. Heuristic of route provider

In the context of our model, the route provider plays a key role, acting as the planning entity of the waste collection organization. This agent is responsible for evaluating the fill level $f_b(t)$ of each bin B and determining the collection sequence to be followed by the collection vehicles V.

Our project revealed that waste collection organizations already have routes optimized for their collection vehicles, considering the practical restrictions of road layouts and other geographical factors. To make our model simpler and more efficient, we have incorporated this pre-existing collection sequence. The route provider utilizes this sequence as a foundational framework, removing any bins with a fill level $f_b(t)$ lower than a predefined threshold from the list before forwarding the updated sequence to the collection vehicles V.

The process of generating a new collection sequence is initiated daily. All existing lists carrying data from the previous day are purged to ensure a clean slate for the new day's operations. Next, each bin is

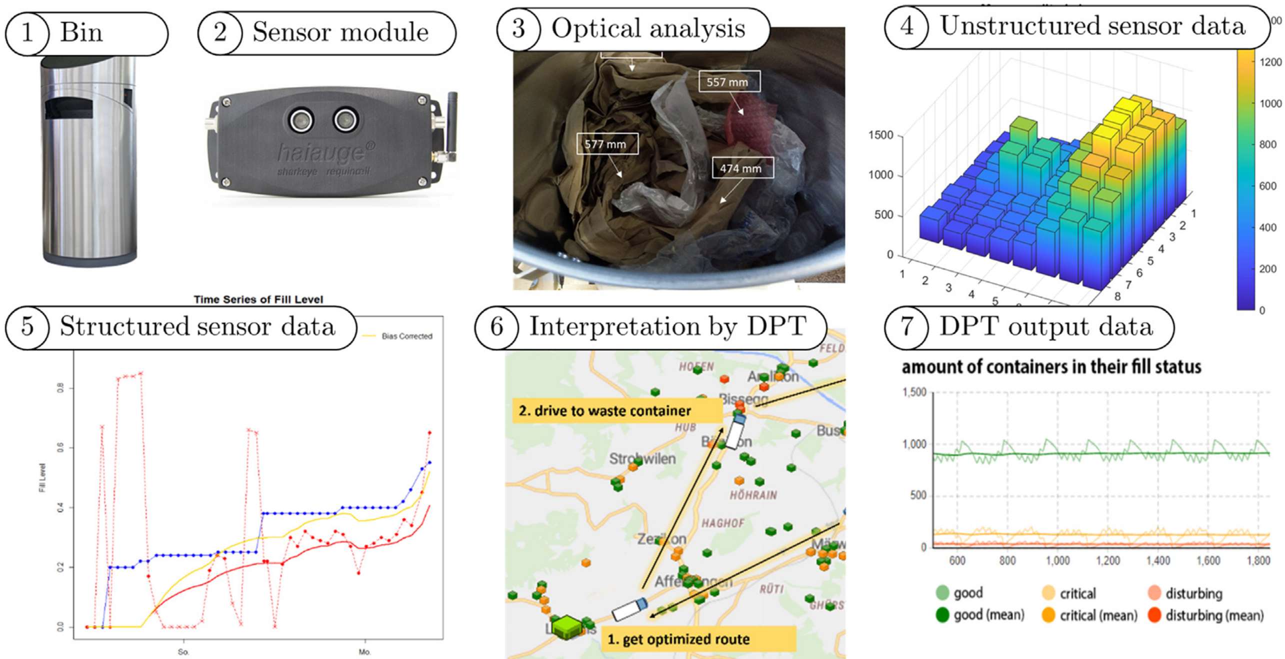

Fig. 7. From sensor to decision in a SWM system.

pinged to relay its current fill level $f_b(t)$, facilitating the creation of a new collection list composed of each bin B_b and their respective fill levels. Subsequently, a set threshold filters out any B_b with fill levels lower than the cut-off value from the collection list. Then, a function queries each bin for the date it was last emptied. Any bin B_b that has not been emptied in the past two weeks is added to the collection list to prevent unpleasant odors and ensure regular cleaning of the bins. To prevent any bin B_b from being serviced multiple times in a single day, we adhere to the collection order provided by the waste collection company. This is accomplished by sorting the collection list according to day t_b, a numeric value representing the collection sequence. Once sorted, this finalized collection list is stored and then transferred to the collection vehicles V_v, directing them where to collect waste from the bins B_b. This methodical process ensures efficient waste management, adhering to the principles of both sustainability and practicality.

Heuristic of route provider:

1. Request fill level $f_b(t)$ from smart bins B at time t, immediately before the collection.
2. Add all B, from the tour t_j, to the collection list that are overdue, and all that have not been emptied for 14 days.
3. Add all B from the t_j to the collection list whose level is above the threshold.
4. Sort them by the day-tour index.
5. Transmit the list to the collection vehicle.

Algorithm 1 Route Provider Heuristic

procedure ROUTE PROVIDER(t, x, tfl, V, B)
 V.collectionList $\leftarrow \emptyset$
 for each bin B_b in B **do**
  $f_{B_b}(t) \leftarrow$ REQUESTFILLLEVEL(B_b, t)
  if $f_{B_i}(t) >$ threshold or not emptied for x days **then**
   V.collectionList $\leftarrow V$.collectionList $\cup \{B_b\}$
  end if
 end for
 V.sortedList $\leftarrow$ SORTBYDAYTOURINDEX(V.collectionList)
 HANDOVERTOCOLLECTIONVEHICLE(V.sortedList)
end procedure

5.2.3. Input data

The model introduced utilizes a set of input data to set the initial state denoted as e_0. For each $B_b(0)$, a location l_i is set by loading the coordinates from a database of the internal data management system of the waste management company. Similar to the location of the smart bins, a starting location for each $V_v(0)$ is loaded from internal data management systems as $l_v(0)$. Furthermore, the initial fill level $f_b(0)$ for each B_b is loaded from the sensor data of each smart bin. For strategic simulations, the $f_b(t)$ can also be simulated in order to replicate more than one week.

5.2.4. Key performance indicators

The model can calculate several KPIs; for example, each B returns one of the following levels for each point in time: good, critical, and overfull. Those levels are based on the fill level of the B as the thresholds are >60% for critical and >90% for overfull. Other available KPIs include, but are not limited to, kilometers driven by the V during trips, included B in a collection tour t_v, the yearly cost of waste collection based on $c_{k,j}$ and $c_{h,j}$ and the respective hours of each V. The following KPIs of the model are used in our analysis:

The yearly cost of waste collection is based on $c_{k,j}$ and $c_{h,j}$ and the respective hours each V was working and how many kilometers were driven. The total distance driven by vehicle V_v in a week is denoted as D_v, and the total hours worked by vehicle V_v in a week is denoted as H_v. Then the cost for vehicle V_v in a week, denoted as C_v, can be calculated as:

$$C_v = c_{k,v} \cdot D_v + c_{h,v} \cdot H_v$$

The total yearly cost for all vehicles is then the sum of the costs for each vehicle:

$$C_{\text{total}} = \sum_{v=1}^{n_V} C_v = \sum_{v=1}^{n_V} (c_{k,v} \cdot D_v + c_{h,v} \cdot H_v)$$

Let H_b denote the number of hours a week that bin B_b has a fill level greater than 90%. The mean average of hours of all bins with $f_b(t)$ >90% can be calculated as:

$$H_{\text{avg}} = \frac{1}{n_B} \sum_{b=1}^{n_B} H_b$$

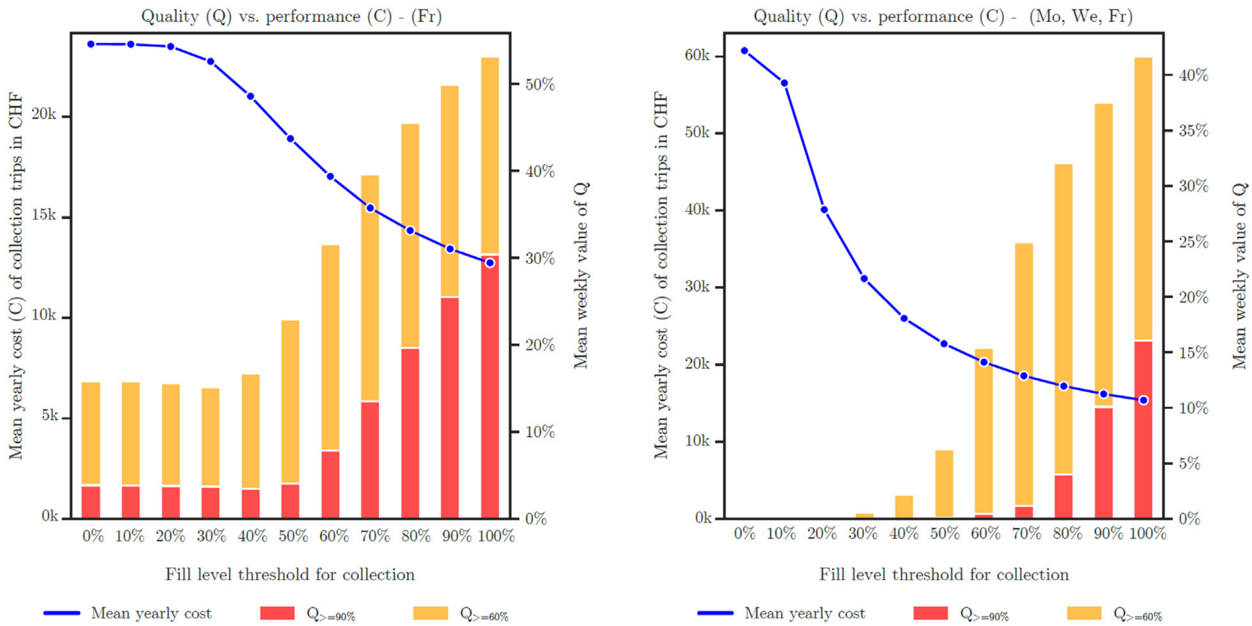

Fig. 8. Comparing scenarios where waste is collected on Friday only or on Monday, Wednesday, and Friday.

The percentage of time a bin has a fill level of ≥90% is then calculated as:

$$Q_{\geq 90\%} = \frac{H_{\text{avg}} \cdot n_B}{168 \cdot n_B} \times 100\%$$

This simplifies to:

$$Q_{\geq 90\%} = \frac{H_{\text{avg}}}{168} \times 100\%$$

The following numerical example should help to understand the defined KPI for service quality Q. Assuming there are exactly 100 bins, a value of 1% can result only if one bin has a fill level above 90% the whole week or if all 100 bins have a fill level above 90% during 1% of the week.

The selection of the KPIs is based on the requirements of the decision-makers of the waste management company described in the case study in Section 4 and also in respect of the first research question in Section 2.4.

5.3. Digital process twin output

To assist decision-makers in evaluating the trade-off between cost savings and service quality, we simulated various scenarios. These simulations enabled a comparative analysis of varying runs where the waste collection schedules were adjusted in terms of days and frequency.

For instance, in Fig. 8, we juxtaposed two scenarios — one where waste collection is conducted once a week, in this case specifically on Friday, and another where the collection occurs three times a week, on Monday, Wednesday, and Friday. This comparative approach provides a nuanced understanding of the impacts of different collection schedules on both service quality and cost-effectiveness, thereby guiding more informed decision-making.

To ensure the reliability of our simulations, multiple replications of each scenario were executed using varying seeds. This approach generated results with a 95% confidence interval, ensuring that our findings were statistically significant and robust to random variations.

Fig. 9 illustrates the multiplicity of replications and the subsequent boxplot derived from the results of each simulation run. This visualization not only provides an aggregate representation of our simulation outputs but also offers insights into the statistical dispersion and skewness of our data, further bolstering the credibility of our findings.

We also conducted a more granular examination based on the optimal scenario identified through our previous comparative analysis. We utilized smaller step sizes in parameter variation for the smart bin collection threshold to locate the precise "sweet spots" that best balance the cost savings and service quality trade-off.

The results of this analysis are shown in Fig. 10. At a collection threshold of $f_b(t) = 36\%$, the service quality KPI $Q_{\geq 60\%}$ reaches 1%. By using $f_b(t) = 36\%$ as the threshold to trigger collections, the yearly collection cost can be reduced by 54.2% from CHF 60,756 to CHF 27,812.

At a collection threshold of $f_b(t) = 70\%$, the service quality KPI $Q_{\geq 90\%}$ reaches 1%, i.e., the maximum percentage of overfull waste bins accepted by the practice partners. At this threshold, the service quality KPI $Q_{\geq 60\%}$ reaches 23.8%. Using $f_b(t) = 70\%$ as the threshold to trigger collections, the year collection cost can be reduced by another 20%, lowering the total yearly cost to CHF 16,203. This translates to a total cost reduction of 73.3% when compared to the initial cost of CHF 60,756.

By executing this detailed analysis, we not only affirm the potential benefits of a strategically set collection threshold but further demonstrate its capability to enhance service quality while significantly reducing costs.

6. Discussion

The first section of this Chapter summarizes and discusses the major findings along with the research questions posed at the outset. The second section highlights and discusses the contribution of the findings to practice and research.

6.1. Major findings

To discuss the major findings, we revisit and answer the research questions derived from the research gaps identified in the literature review (cf. Section 2.4).

RQ 1 How can decision-makers balance the trade-off between cost savings and service quality in waste management?

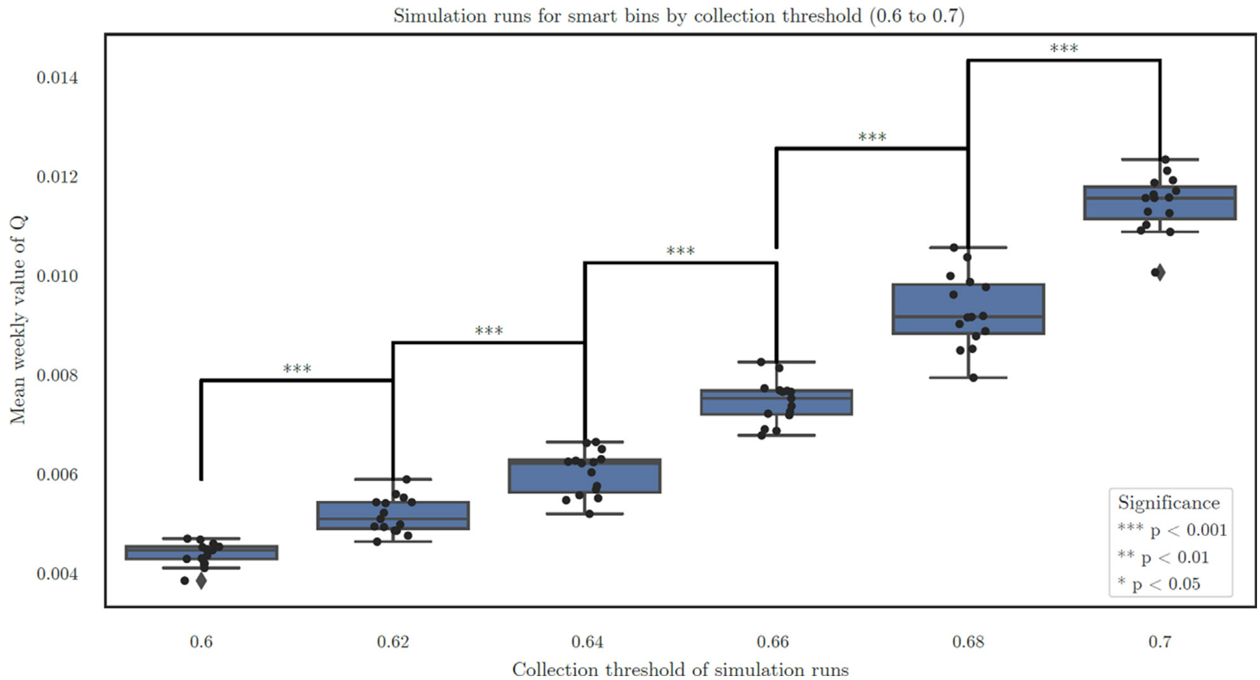

Fig. 9. Multiple simulation runs per threshold.

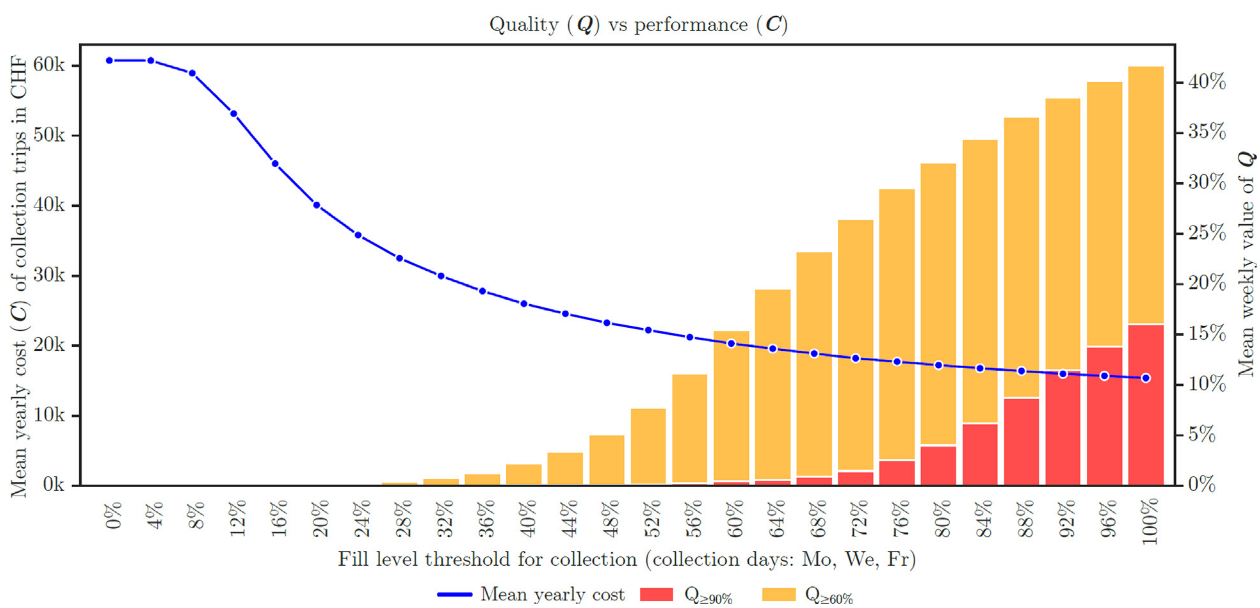

Fig. 10. Trade-off between cost savings and service quality KPI.

To balance this trade-off, decision-makers need suitable KPIs to evaluate and compare cost saving versus service quality in different scenarios. Only then can they use simulation models to evaluate the impact of different scenarios, such as using a different number of collection days per week or different fill level thresholds to assign a waste bin for the next collection trip. In cooperation with our project partners, we defined a KPI that provides a suitable representation of the service quality of a waste management system (cf. Section 5.2.4). We established two different thresholds with the stakeholders in the project to evaluate the fill level status of the waste bins and facilitate the interpretation for corresponding decisions. The first threshold value was set to 60% of the maximum fill level. This threshold was chosen because having just two statuses of waste bin (“full”and “not full”) was deemed insufficient. It was important for the decision-makers to have an additional status in between, where the waste bin had reached a certain fill level but was not yet full. This results in a much more differentiated view when considering the statuses of waste bins in a system with different thresholds for collection (see, for example, Fig. 8). The value for this threshold was set at 60% at the beginning of the project when the optimal fill level threshold to trigger a collection was still unknown. Throughout the project, this threshold value for status change became established in discussions with the stakeholders and retained accordingly. The second threshold evaluates whether the status of a waste bin reduces service quality because it is (potentially) overfull. In the case study presented in this paper, the threshold value of this second threshold was set to 90% rather than 100% for the following reasons: First, for a fill level of more than 90%, it might already be impossible to dispose of certain larger objects. In such a case, the public already perceives the bin to be full and no longer usable. Second, the waste container aperture is slightly below the maximum possible fill level, and a buffer allows for small measurement inaccuracies.

RQ 2 How can a DPT, in combination with an area-wide sensor module system, create value for decision-makers in waste management companies?

A DT of a SWM ecosystem with DPTs and area-wide sensors module provides the basis for various services that, in turn, create value in different categories (cf. Fig. 5). If the static route optimization service is considered in isolation, it becomes evident that value is created in all three categories, i.e., *availability*, *performance*, and *quality*. The *availability* of waste bins and collection vehicles is increased by only emptying bins with a certain fill level, thus avoiding unnecessary trips. In addition to better capacity utilization, this also frees up time that can now be used for maintaining and servicing waste bins and collection vehicles to avoid unscheduled downtime. By reducing the number of trips, varying levels of costs and resources can be saved depending on the selected threshold for collecting the waste bins, which increases the *performance* of the system. In addition to monetary savings due to lower costs for vehicles, fuel, labor costs, and material costs such as waste bags, the impact on the environment is also reduced accordingly. We have shown that with a fill level threshold of 70%, cost savings of 73.3% are achievable (cf. Fig. 10). These results are similar to other studies; for example, An et al. [45] reported that in their use case, the average monthly collection was reduced by an impressive 80%. However, there is no indication of whether this massive reduction has affected the service quality of trips. In contrast, through the defined service quality KPI and quantifying the trade-off with costs with the DPT, our results enable PSS providers to assure customers that cost-cutting is not so aggressive as to compromise their individually defined service quality expectations.

In reality, most municipalities and companies will not be able to reduce costs significantly, as they are unwilling to accept the decrease in quality above a certain fill level threshold. By measuring the fill level and correspondingly managed collection processes, full and overfull waste bins can be avoided. This reduces the amount of improperly disposed waste in the vicinity of the waste bin, thereby improving the area and increasing the *quality* of life of the population. Reducing environmental impact can also lead to a perceived increase in *quality* of the system; if, for example, this results in defined sustainability goals being achieved and this is actively communicated to the general public, satisfaction increases through the knowledge that the SWM system is reducing the collective ecological footprint.

However, probably the most important value is created by revealing and quantifying the trade-off between cost savings as a performance measurement and service quality as a quality measurement. For many municipalities, especially in Switzerland, the perceived *quality* of the system is more important than cost savings. Accordingly, authorities are still hesitant to make large investments in SWM systems. Using the simulation presented in our paper, this trade-off can be simulated for an individual system. This makes it possible to estimate the savings and return on investment achievable without falling short of the individual quality requirement. In turn, this reduces uncertainties regarding a decision for or against investment in a SWM system. The new service quality KPI Q defined in this paper also enables municipalities to stipulate service level agreements with PSS providers to ensure that the level of quality they require is met. Once a SWM system with area-wide sensor modules and DPTs has been installed, it is also possible to increase the values described or even create new values. After a given time, historical data can be used for further analyses, for example, to define individual fill level thresholds for each waste bin or optimize the size and location of waste bins in existing or new systems.

RQ 3 How can a DPT be designed, and what specific functions are essential for the DPT to create value?

This paper presents a mixed-method model for simulating a waste management system that measures waste bin fill levels with sensor modules to optimize the planning and execution of static collection vehicle routes. Decision-makers can determine the optimal number of collection days per week and collection-triggering fill levels of the waste bins according to their needs regarding service quality and performance regarding cost reduction.

An important function of the DPT is that it can provide a decision-making basis using both simulated and real fill level data. With simulated fill level data, the DPT can provide the necessary decision-making basis even before system implementation, for example, in terms of return on investment, possibly leading to investment in a corresponding SWM system not otherwise envisaged. With the DPT, decision-makers can simulate the effects of different thresholds for triggering waste bin emptying on the service quality and performance of the system with simulated and real data, thereby determining the optimal threshold according to individual requirements. After implementing the system, the DPT can provide decision-makers with the waste bins to be collected and the shortest route for each collection day, using real fill level data. Initially, a human decision-maker would need to review and interpret the decision-making basis. By recording interpretations made by human decision-makers and comparing these with the DPT-proposed decisions, non-human proposals can be further improved over time.

For a DPT to possess these functions, it needs to access not only the fill levels of waste bins but also additional data from internal and external information systems. Furthermore, it requires human-to-machine interfaces to communicate with human decision-makers, as well as machine-to-machine interfaces to communicate with other DTs and SCPs in the waste management product service system. Additionally, a DPT can only unleash its impact when seamlessly integrated into existing or new decision-making processes.

6.2. Contribution

This section highlights the significance and contribution of the results to practice and research.

6.2.1. To practice

The results of the use case presented in this paper and the accompanying DPT are relevant and provide valuable contributions to decision-makers in waste management systems, regardless of the digital maturity level of their own PSSs. The following itemized points briefly outline the contributions of different groups of practitioners.

1. Contribution to general discussion in practice.

Smart waste systems that measure fill levels using sensors have been available for over a decade. However, implementing such systems is still not widespread in practice due to a lack of practical experience and empirical validation with real data. This often leads to the prevailing opinion in discussions with practitioners that such systems are not yet mature enough and still too expensive. The results obtained with the DPT presented in this paper – implemented in a real use case with nearly 100 sensor modules covering a whole collection area – confirm the enormous potential for cost-saving and associated environmental impact while maintaining the desired service quality. The results, therefore, contribute substantially to the general discussion concerning the impact of implementing such SWM PSSs in practice.

2. Contribution for practitioners who cannot implement a DPT themselves.

The results presented in this paper are also valuable for practitioners unable or unwilling to use a simulation-based DPT themselves, owing to its cost, for example. As the challenges and requirements for SWM systems are similar throughout the world, the results are globally transferable. As long as users can measure the fill levels in their waste bins, they can orient themselves based on the thresholds calculated in our study to optimize their static route planning without an explicit need for their own simulation and DPT. However, in such a case, they will be unable to optimize fully the trade-off between cost savings and service quality. Nevertheless, as our results have shown, even with very conservative threshold values below 50% of the maximum fill level, relatively large cost savings could still be realized without running the risk of a noticeable decline in service quality (cf. Fig. 10).

3. Contribution for practitioners who wish to implement their own DPT.

The cost savings demonstrated in this use case can serve as a reference for practitioners to estimate the return on investment when they receive a quote for implementing their own PSS. For the dissemination and acceptance of such systems, it is crucial to demonstrate a positive return on investment after implementation and pacify the critics. Jonek-Kowalska [41], for example, found that the cost of waste management in self-declared "smart" cities in Poland was actually higher than in some other Polish cities. Our results contribute to developing systems that provide a positive return on investment by demonstrating how the cost-saving potential can be maximized using a DPT and by helping practitioners estimate whether it is worthwhile for their collection area and cost structure to invest in such a system.

4. Contribution for practitioners who already have a similar system.

Our findings are also valuable for practitioners managing waste with a similar PSS or a DPT. The KPI developed for service quality and the thresholds for evaluating the fill levels of waste bins, along with the plots illustrating the trade-off between costs and service quality, help decision-makers determine the optimal threshold for triggering waste bin collection. If users already have data from their own collection areas, corresponding calculations and assessments can be conducted. If a fully functional system consisting of area-wide sensor modules and DPTs has already been implemented, its performance can be compared to the results of our study to identify any potential for improvement. Furthermore, the new KPI for service quality Q defined in this paper enables the definition of quantified service level agreements and a measurement of compliance.

6.2.2. To research

Our findings also contribute to ongoing research, which, until now, has focused on technical feasibility and achievable optimizations. However, the concepts of a DPT, cost savings, and their trade-off relationship with service quality have had limited presence in research. After demonstrating the technical feasibility and implementations using common simulation software such as Anylogic®, future research should increasingly focus on the qualitative and quantitative values that can be created. Although this paper focuses on the well-explored topic of route optimization through fill level measurements, it also presents elements that have been hitherto less explored. Here, we have defined an appropriate KPI that can comprehensibly represent the service quality of a waste management system. This allows for the examination and comparison of different decision-making approaches not only in terms of cost and resource savings but also in terms of their impact on critically important service quality in practice. The proposed approach for deriving a threshold that triggers waste bin collection can complement the analyses of other researchers, such as Rahmanifar et al. [46], who have been working with experiential-based thresholds in their studies. Furthermore, the holistic view and presentation of the use case with additional relevant services for stakeholders in the ecosystem (cf. Fig. 5) provide important points of reference for researchers to integrate previously isolated research topics and optimization problems, which may rely on the same data, through the concept of a DT of the SWM system. By conceptually linking different interdisciplinary research areas, we contribute to their integration, which, in turn, can advance the realization of the corresponding network effects in practice, for example, with smart cities.

7. Conclusion

In this final Chapter, we first acknowledge the limitations of this present study before suggesting avenues for further research.

7.1. Limitations

The following non-exhaustive list of limitations in our research must be acknowledged.

7.1.1. Time frame

One limitation arises from the limited time frame in which data could be collected during the field test. Although data for our project were collected over several months, permitting a meaningful analysis, comprehensive data for an entire calendar year are unavailable. Owing to this lack of historical data, we could not adequately capture the seasonal nature and effects of waste disposal before the project deadline.

7.1.2. Extraordinary events

The restricted time frame is a further limitation that has to be acknowledged. In the simulation, rare but still regularly occurring extraordinary events were not simulated and thus not considered. These include, for example, extraordinary cleaning and repair work due to vandalism and events that lead to atypical fluctuations in filling behavior. Such fluctuations could be due to large public events or objects becoming stuck in the bin aperture that subsequently render it unusable, either temporarily or until the next collection.

7.1.3. Route optimization

Another limitation arises from a somewhat simplistic approach to route optimization. If a waste bin has not yet reached the chosen fill level threshold, it is simply bypassed and the collection vehicle proceeds to the next waste bin via the shortest route. The resulting route is usually shorter than the standard route, but there is no separate optimization of the route based on the reduced number of waste bins being emptied. This factor was omitted because the standard routes in existing collection areas had already been optimized based on years of experience, and thus, the described approach already produced excellent results. However, especially in cases where many bins are removed from the route and only a few are collected, a new collection route created independently from the standard route would probably be even more efficient.

7.1.4. Return on investment

For a final assessment of the cost-effectiveness and return on investment, any savings made need to be balanced against the cost of the PSS. Although the costs for purchasing and installing the equipment were known in the project, they were not utilized in this analysis as they were expected to be optimized for serial production. Furthermore, the costs for ongoing operations and maintenance were inadequately recorded as the processes in a field test differ significantly from those in continuous operation.

7.2. Further research

The use case and the simulation developed can be the starting point for further research. In the following section, we discuss a non-exhaustive selection of points that specifically address our acknowledged limitations.

7.2.1. Time frame

The collection and analysis of data over an extended period, ideally several years, will lead to additional insights and enable further optimization of the DPT and PSS. Of great interest, for example, are seasonal variations in waste generation depending on weather conditions and other factors. Additionally, historical data can be utilized to forecast the waste volume for specific bin locations, thereby allowing for individual determination of fill level thresholds for collection.

7.2.2. Extraordinary events

Extraordinary events could be considered in a variety of ways. For example, large social events that have a significant impact on waste generation in a region could be sourced from an external third party and used to improve the simulation of the DPT. Other, more unpredictable events, such as the deliberate destruction of smart bins, are harder to predict. However, with a sufficiently large data set, the average effect of these occurrences on the overall system could be extrapolated and used for decision-making, such as return-on-investment decisions.

7.2.3. Route optimization

Another factor to consider in the ongoing development of the PSS is the integration of the DPT with additional relevant data and more advanced methods for route optimization. The ultimate goal is to achieve dynamic real-time route optimization. However, this requires not only up-to-date information on traffic conditions, road construction sites, and other variables but also specialized road-map data, since collection vehicles may, for example, have special access permission into pedestrian zones that they cannot use owing to their physical size.

7.2.4. Return on investment

Our research has demonstrated that combining DPTs and PSSs in waste management can lead to significant cost savings. However, to promote the adoption of PSSs for SWM in practice, it is crucial to provide evidence of a positive return on investment after a short period of operation. To maximize the credibility of the calculated return on investment, the database should be from a real case and an independent team of researchers should perform the calculation. Based on the model presented, further possibilities emerge to simulate optimizing other resources, such as fuel and waste bags, and the resulting reduced environmental impact. In addition, the satisfaction levels of local residents could be simulated, for example, by integrating the influence of cleanliness or reduced noise pollution into the model.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Linard Barth reports financial support was provided by Innosuisse Swiss Innovation Agency. Rodolfo Benedech reports financial support was provided by Wissenschaftsverbund Vierländerregion Bodensee.

Data availability

The data that has been used is confidential.

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