UiT The Arctic University of Norway

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A Decision-Support Framework for Smart and Sustainable Reverse Logistics Network Design

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A dissertation for the degree of Philosophiae Doctor, June 2022

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ABSTRACT

The Fourth Industrial Revolution, namely Industry 4.0, has provided opportunities for digitalization and paradigm shifts in many industries and business sectors. Reverse logistics is currently being increasingly focused on by worldwide companies and governments due to the pressure on sustainable development and circular economy. Through the gradual but steady adoption of several disruptive technologies in Industry 4.0, the traditional reverse logistics operations will be dramatically improved with the increasing use of the internet of things (IoT), cyber-physical systems (CPS), artificial intelligence (AI), digital twin, smart robots and machines, etc., which may eventually lead to a smart and sustainable transformation of *Reverse Logistics 4.0*.

However, there is a lack of a systematic analysis of the impacts of these Industry 4.0 technologies on reverse logistics. Moreover, the adoption of new technologies will further complicate the reverse logistics network design at the initial stage, which involves many stakeholders with often contradictive objectives. To fill these gaps, this Ph.D. project first presents a comprehensive literature review and conceptualization of *Reverse Logistics 4.0* in order to provide a holistic and systematic analysis of the implications of disruptive technologies and Industry 4.0 for smart and sustainable reverse logistics transformation. Based on the conceptualization, an improved two-level decision-support framework, which combines both multi-objective optimization and dynamic simulation, is proposed to better help with robust strategic decisions under high dynamicity and uncertainty.

The methodological integration leads to the development of a conceptual framework for the digital reverse logistics twin. It represents a high level of methodological and system integration that can potentially connect the physical system and data with various analytical models for both proactive and real-time decision supports in reverse logistics management. Finally, this Ph.D. project presents several managerial implications and research implications for both industrial practitioners and academic researchers.

LIST OF SELECTED PAPERS

Number	Publications
Paper 1	Xu Sun, Hao Yu, Wei Deng Solvang, Yi Wang, and Kesheng Wang, 2022. “The Application of Industry 4.0 Technologies in Sustainable Logistics: A Systematic Literature Review (2012—2020) to Explore Future Research Opportunities”, *Environmental Science and Pollution Research*, 29, 9560-9591.
Paper 2	Xu Sun, Hao Yu, and Wei Deng Solvang “Towards the Smart and Sustainable Transformation of Reverse Logistics 4.0: A Conceptualization and Research Agenda”, submitted manuscript.
Paper 3	Xu Sun, Hao Yu, Wei Deng Solvang, and Kannan Govindan “A Two-Level Decision-Support Framework for Smart and Sustainable Reverse Logistics Network Design”, submitted manuscript.
Paper 4	Xu Sun, Hao Yu, and Wei Deng Solvang, 2022. “System Integration for Smart Reverse Logistics Management” Proceeding of *the IEEE/SICE International Symposium on System Integration (SII 2022)*, pp. 821-826, IEEE, 2022.
Paper 5	Xu Sun, Hao Yu, and Wei Deng Solvang “A Digital Reverse Logistics Twin for Improving Sustainability in Industry 5.0”, submitted manuscript.

LIST OF THE OTHER PUBLISHED PAPERS

Number	Publications
Paper 6	Xu Sun, Hao Yu, and Wei Deng Solvang, 2020. “Industry 4.0 and Sustainable Supply Chain Management”, *International Workshop of Advanced Manufacturing and Automation. Springer, Singapore, 2020.*
Paper 7	Xu Sun, Eugenia Ama Andoh, and Hao Yu, 2021. “A Simulation-Based Analysis for Effective Distribution of COVID-19 Vaccines: A Case Study in Norway” *Transportation Research Interdisciplinary Perspectives*, 11, p.100453.
Paper 8	Hao Yu, Xu Sun, Wei Deng Solvang, and Xu Zhao, 2020. “Reverse Logistics Network Design for Effective Management of Medical Waste in Epidemic Outbreak: Insights from the Coronavirus Disease 2019 (COVID-19) in Wuhan” *International Journal of Environmental Research and Public Health*, 17(5), p.1770.
Paper 9	Hao Yu, Xu Sun, Wei Deng Solvang, and Gilbert Laporte, 2021. “Solving a Real-World Urban Postal Service Network Redesign Problem” *Scientific Programming*, 2021.
Paper 10	Xu Sun, Hao Yu, and Wei Deng Solvang, 2019. “Solving the location problem of printers in a university campus using p-median location model and AnyLogic simulation” *International Workshop of Advanced Manufacturing and Automation.* Springer, Singapore, 2019.
Paper 11	Hao Yu, Wei Deng Solvang, and Xu Sun, 2019. “An Improved Bi-Objective Stochastic Model with SAA-based Solution Method for Reverse Logistics Design of Hazardous Materials” *2019 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM).* IEEE, 2019.
Paper 12	Hao Yu, Wei Deng Solvang, and Xu Sun, 2019. “A Stochastic Closed-Loop Supply Chain Network Optimization Problem Considering Flexible Network Capacity” *International Workshop of Advanced Manufacturing and Automation.* Springer, Singapore, 2019.
Paper 13	Hao Yu, Xu Sun, Wei Deng Solvang, Gilbert Laporte, and Carman Ka Man Lee, 2020. “A Stochastic Network Design Problem for Hazardous Waste Management” *Journal of Cleaner Production*, 277, p.123566.
Paper 14	Xu Sun, Hao Yu, and Wei Deng Solvang “Measuring the effectiveness of AI-enabled chatbots in customer service using AnyLogic simulation”, submitted manuscript.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AM	Additive Manufacturing
AR	Augmented Reality
B2B	Business-to-Business
B2C	Business-to-Consumer
CE	Circular Economy
CPS	Cyber-Physical Systems
EEE	Electrical and Electronic Equipment
ELVs	End-of-Life Vehicles
EOL	End-of-Life
EOU	End-of-Use
EPR	Expanded Producer Responsibility
EU	European Union
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GIS	Geographical Information System
ICT	Information and Computer Technology
IoT	Internet of Things
IEEE	Institute of Electrical and Electronic Engineers
IEEM	International Conference on Industrial Engineering and Engineering Management
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
PDFs	Probability Density Functions
PSO	Particle Swarm Optimization
SII	IEEE/SICE International Symposium on System Integration
UAV	Unmanned Aerial Vehicle
WEEE	Waste Electrical and Electronic Equipment
WoS	Web of Science

1 INTRODUCTION

Recently, rapid economic growth and technological development have not only improved people's lives but also accelerated waste generation. Drastically increased waste generation and improper waste management have become significant concerns for worldwide urban communities. Meanwhile, Circular Economy (CE) and sustainable development have attracted increasing attention in order to alleviate the problems of scarcity of resources, stringent legislation, and emerging business models, which further motivate and drive the recovery of value and materials from end-of-use (EOU) and end-of-life (EOL) products [1]. Reverse logistics is the core process of the value and material recovery from EOU and EOL products, which has gained increasing importance as a profitable and sustainable business strategy [2].

Reverse logistics is a complex system for dealing with possible reuse, re-fabrication, remanufacturing, recycling, and disposal for efficient management and resource recovery from EOU and EOL products. The main activities and operations of a reverse logistics system consist of the collection of EOL/EOU products from consumers, the appropriate inspection, sorting, disassembling, and/or pre-processing, the distribution of different products, components, and materials to respective locations and facilities for further treatment, e.g., reuse, refurbishing, remanufacturing, recycling, energy recovery, and for proper disposal of non-recyclable, as well as the planning of facility operations and transportation [3].

A reverse logistics network consists of several facilities/stakeholders and the links among them. Thus, designing a reverse logistics network is one of the most important strategic decisions, which has a long-term impact on the economic performance, environmental impacts, and social responsibility of a reverse logistics system. On the other hand, reverse logistics network design is complex, and several key decisions, e.g., facility location, capacity allocation, transportation, etc., need to be made by considering several conflicting objectives. Furthermore, the coming digital era with the increasing adoption of disruptive technologies in Industry 4.0 provides various opportunities for increasing the smartness and sustainability of reverse logistics systems, which may eventually lead to a smart reverse logistics transformation. However, this smart transformation further complicates the reverse logistics network design at the initial stage, it is thus imperative to develop new methods and frameworks for better decision support in a more dynamic and uncertain environment.

The remaining value needs to be recovered from the EOU and EOL phases of products. However, the challenges faced by many companies are the lack of models and methods to support the key decisions, e.g., facility upgrade with Industry 4.0 technologies, in the development of reverse logistics operations and business. In this Ph.D. project, the implications of descriptive technologies for smart reverse logistics transformation are first analyzed. A two-stage decision-support framework that combines both multi-objective optimization and dynamic simulation is then developed to help with making robust strategic decisions and evaluating the system configuration in a dynamic, stochastic, and realistic operating environment. Finally, the conceptual framework of the digital reverse logistics twin with a high level of system integration is formulated.

This Ph.D. thesis consists of two sections. The first section including Chapters 1-4 is an introductive section that aims at giving the background information, motivation, research questions, literature gaps, objectives, research design and methods, contributions, and future works. The second section is a collection of five selected papers, which forms the main contributions to this Ph.D. project.

1.1 Background

Today, the rapid pace of technological innovation and development has not only improved people's living standards and changed consumption patterns, but also significantly shortened the product lifecycles and accelerated the generation of EOL and EOU products [4, 5]. For instance, the annual generation of end-of-life vehicles (ELVs) in the European Union (EU) countries increased by 22% from 5.54 million tons in 2011 to 6.732 million tons in 2018 [6]. Furthermore, waste electrical and electronic equipment (WEEE/e-waste) generation has become one of the fastest-growing waste streams worldwide [7]. As shown in **Figure 1-1**, the volume of e-waste generation worldwide has been gradually increasing since 2010, which reached a peak level of 53.6 million metric tons in 2019, showing a rise of 21% in just five years [7]. According to forecasts in **Figure 1-2**, this trend is expected to continue. With projections showing that by 2030, the global e-waste generation will increase by approximately 30% to reach 74.7 million metric tons [8], which is equivalent to nearly double the 2012 figure. If the current trend continues, the worldwide e-waste generation will exceed 120 million metric tons per year by 2050 [9]. From another perspective, the carbon emissions from the manufacturing and the use of consumer electronics, e.g., PCs, laptops, smartphones, monitors, etc., will account for 14% of total emissions by 2040 [9].

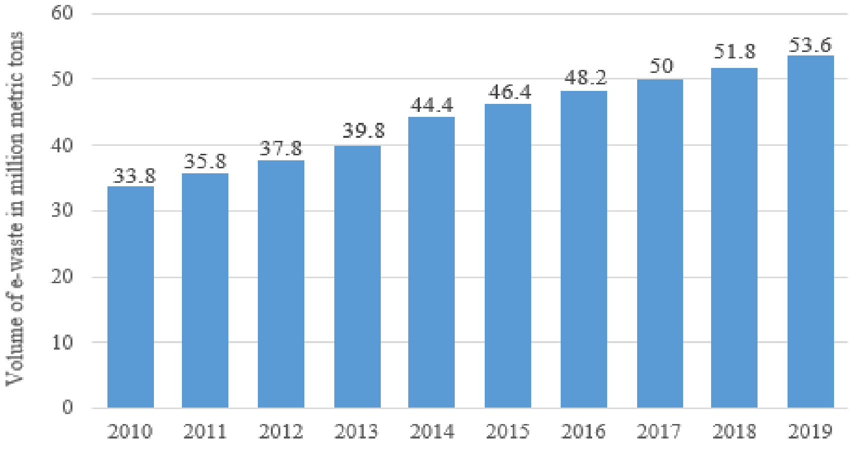

Figure 1-1 Global e-waste generation from 2010 to 2019, in million tons [7].

While the rate of e-waste generation is undoubtedly a key issue, another issue is that the increase in collection and value recovery activities have not complied with the rate of e-waste generation [10]. **Figure 1-3** shows an overview of the volumes of electrical and electronic equipment (EEE) that are put into the market and the volumes of WEEE collected, reused, and recycled in the EU during the period of 2011–2019. Even though EU countries have played a leading role in the world for e-waste recycling, the average collection rate of WEEE is 48.5% [11], and only 35% of WEEE is officially recorded as formally recycled in the EU [9]. The global average recycling rate of e-waste is much lower, which is only 20% [12]. Instead, large volumes of WEEE as well as other EOL products with high remaining values usually end up in landfill sites or are improperly recycled and disposed of in developing countries by workers under harsh working conditions and environments. As shown in **Figure 1-4**, due to the legal and regulatory requirements, the transportation of WEEE can be complex and fragmented. The illegal shipment of WEEE from developed countries to developing countries has already become another huge and global challenge [9].

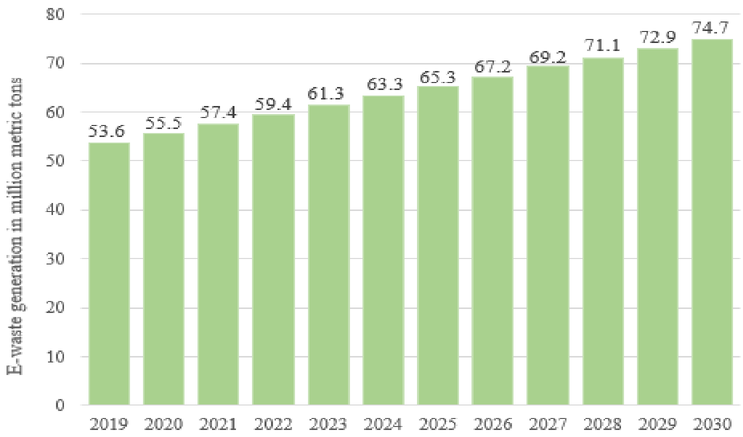

Figure 1-2 Projected volume of e-waste generation worldwide from 2019 to 2030, in million tons [8].

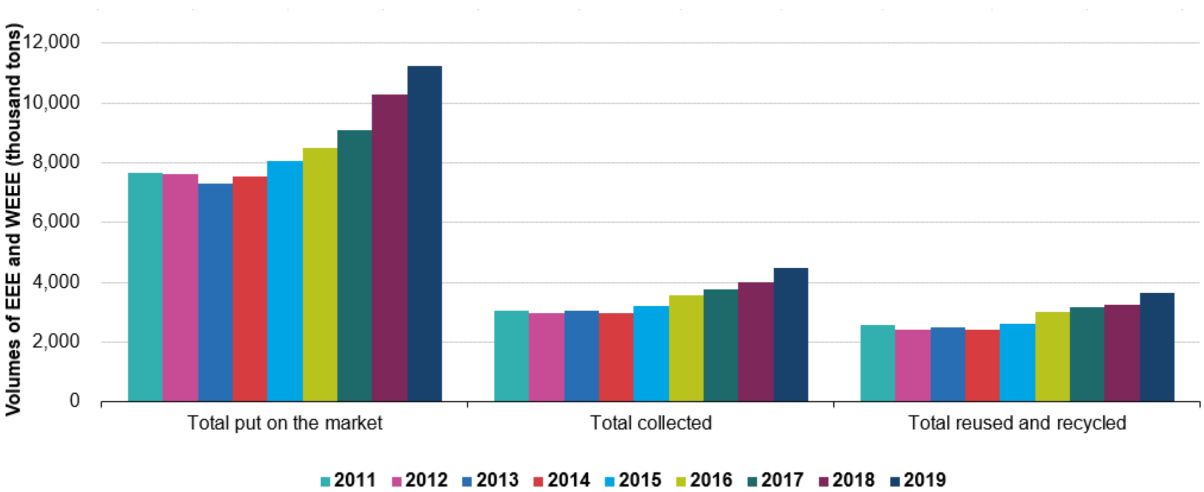

Figure 1-3 An overview of the volume of EEE put on the market, collected, reused and recycled volumes of WEEE in the EU in the period of 2011–2019, adapted from [12].

According to the report, the annual value of WEEE produced exceeds $62.5 billion, which is more than the GDP of most countries [9]. From the short-term perspective, WEEE may remain largely unused, but in the long run, almost all of them are likely to be recovered due to the growing consumer demand and the scarcity of precious resources. For instance, a ton of WEEE contains nearly 100 times the amount of gold found in a ton of gold ore [12]. Furthermore, resource extraction from complex WEEE streams is more cost-effective, practical, and energy-efficient than mining metal ore from the ground [9]. Due to the hazardous materials that are commonly used in consumer electronics (including arsenic, cadmium, lead, mercury, and certain flame retardants), WEEE is not biodegradable, and some components can even be toxic. In this regard, the lack of recycling network and capacity not only causes significant economic losses in wasting resources, e.g. the precious metals from WEEE, but may also lead to severe environmental pollution and accumulation of hazardous elements in ecosystems including soil, air, water, and organisms [9]. These may pose several health risks and result in irreversible long-term environmental and public health threats.

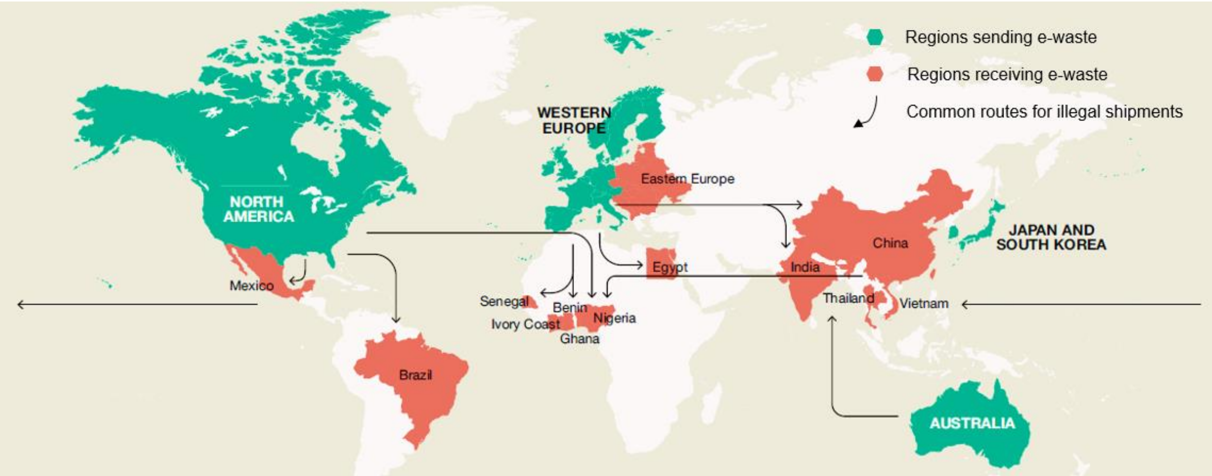

Figure 1-4 Mapping out e-waste, reproduced from [9] with permission from Creative Commons Attribution-NonCommercial-NoDerivs 4.0 Unported License.

As the traditional "take, make, use and dispose" model poses serious impacts on both environment and human society, e.g., negative effects on health, climate change, global warming, etc. The EU proposals aim to increase recycling objectives to transform the traditional linear economy into a circular economy and support long-term growth aligned with environmental sustainability [13]. The circular economy approach decouples the value creation of the economy from resource consumption by keeping resources in use for as long as possible, extracting the maximum value in use, and then recovering and regenerating products at the end of their service life [14]. The Directive 2012/19/EU launched in August 2018 sets the minimum recovery targets by category, for instance, the recovery rate and the reused and recycling rate for large equipment of WEEE are 85% and 80%. Compared with that in 2015, they have increased by 5% and 10%, respectively [15]. The increase in recovery and recycling rates is mainly due to the EU's determination to continuously strengthen the regulation and develop the corresponding legislative mechanisms, e.g., expanded producer responsibility (EPR) [16]. Typically, the majority of laws and ordinances have geared toward producers [17]. The recent EU directive, known as the "right to repair," is with a view to saving costs for consumers, which aims at empowering consumers for the green transition by giving them greater rights to repair rather than discard away [18]. Current and future purchasing patterns and consumer behaviors may be directly influenced by this EU directive.

In addition to stricter legislative requirements, another key driver for companies and organizations to actively participate in the value recovery activities of their EOU and EOL products is the push from the growing environmental awareness among the consumers. While the conversion of customers' intentions and behaviors to green and sustainable consumption is a time-consuming process, an increasing percentage of consumers are willing to pay extra for green and sustainable products and services [19]. Currently, the start-of-the-art technologies in Industry 4.0 can provide competitive advantages in cost reduction, operations flexibility, product quality improvement, increase in efficiency as well as less waste generation [20]. Besides, it has the potential to tackle many ecological and social challenges and limitations of traditional industrial practices [21]. Recent studies have shown that more focus and investments in enterprises’ sustainable practices not only help them to build up a socially responsible image but also improve their overall sustainable performance in both economic and environmental dimensions [22]. Finally, these smart and sustainable actions may convert into long-term competitiveness. Thus, many enterprises have started to rethink their business models and transform their businesses and operations into more sustainable ways [23].

However, managing value recovery activities of EOL and EOU products is a complex task, which involves different operations and communications among multi-layered and non-homogeneous stakeholders, i.e., waste collector, waste transporter, distributor, facility managers of reuse, remanufacturing, recycling, and disposal. This is not a self-contained endeavor, it needs the collaboration of the state, government, firms, organizations, research institutes as well as the general public. Furthermore, adopting improper value recovery operations can also result in environmental and health risks as well as the loss of profit and valuable resources. To better manage this, it is of imperative importance to move towards smart and sustainable reverse logistics management, which helps to better achieve the sustainable development goals and circular economy. Thus, reverse logistics is considered a crucial step to holistically and systematically managing those activities for recapturing and reclaiming the value of EOL and EOU returns, which can bring various profits for companies in the competitive markets [24]. To manage this exponential increase trend in the generation of EOL and EOU products, worldwide research attention has been given to the development of both regional and international reverse logistics systems. However, significant work needs to be done to better support the smart and sustainable reverse logistics transformation in a more dynamic and uncertain environment.

1.2 Motivation

The advancement, adoption, implementation, and integration of several disruptive technologies in Industry 4.0 provide new opportunities for smart and sustainable reverse logistics [25], which can potentially shift and improve traditional reverse logistics operations through the increasing use of smart data analytics and autonomous technologies. For instance, the increased data availability can improve the prediction and traceability of EOL products, and this minimizes the uncertainty of the reverse flows and improves the planning of different operations, e.g., collection [26] and remanufacturing [27, 28]. The high-quality data also improves the outputs of the model-based optimization and simulation approaches for critical decisions [29]. In addition, the increased use of AI-enabled smart robots can replace human workers from harsh working environments and can also enhance the interaction among different partners and stakeholders via a highly connected digital platform to achieve a high level of inter-company information sharing and resource utilization.

On the other hand, reverse logistics network design is a strategic decision that has long-term impacts on the overall system performance, which requires the balance of the trade-offs among economic, environmental, and social objectives in a highly dynamic and uncertain environment. The recent technological innovation and development of Industry 4.0 have opened up new opportunities for configurational upgrades and smart transformation. Eventually, these technological drivers will significantly alter the operations and several key operational parameters of a reverse logistics system within the planning horizon. It's worthy to note that adopting new technologies is typically not a one-time endeavor, but rather a dynamic process in which the change of system configurations occurs gradually over several periods. However, considering the configurational and technological changes of a smart reverse logistics system will dramatically increase the complexity, dynamicity, and uncertainty at the initial network design stage. Moreover, the currently existing methods have several limitations that may significantly hinder their usage. Thus, it is of imperative importance to develop an improved decision-support framework that incorporates different analytical models and methods for smart and sustainable reverse logistics network design.

Based on the discussions above, the motivation of this Ph.D. project is to first thoroughly investigate the impacts of different Industry 4.0 technologies on reverse logistics and the potential changes in various reverse logistics operations. This aims to provide a holistic and systematic conceptual development and framework for a better understanding of the implications of disruptive technologies for smart reverse logistics transformation. The obtained comprehensive understanding may eventually lead to the emergence of highly intelligent and autonomous operations in *Reverse Logistics 4.0*. This investigation also aims to identify whether there is a clear need for a decision-support framework for smart and sustainable reverse logistics network design, when multiple objectives are subjected and smart transformation, practical operational policies, and a realistic geographical information system (GIS) and planning horizon need also to be considered. With a high level of methodological integration in this decision-support framework, this project aims also at presenting a conceptual framework for future system integration and the development of digital reverse logistics twin.

1.3 Research Questions

Through the extensive literature review, conceptual development, and methodological development and validation, this Ph.D. project aims at answering the following research questions:

- *RQ1:* What are the impacts of disruptive technologies on smart and sustainable logistics/reverse logistics operations?
- *RQ2:* What is the potential smart reverse logistics transformation in Industry 4.0?
- *RQ3:* How to design and configure a smart and sustainable reverse logistics network?
- *RQ4:* How to develop a smart digital reverse logistics twin?

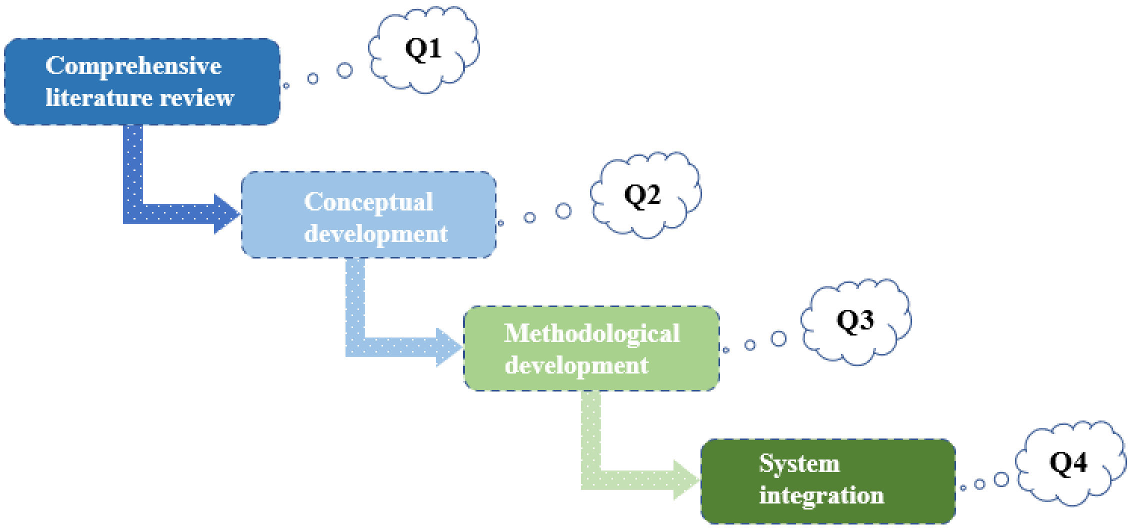

Figure 1-5 Research approaches associated with research questions in this Ph.D. project.

Figure 1-5 shows the focus of each research question related to the comprehensive literature review, conceptual development, methodological development, system integration, and developing digital twin in this Ph.D. project.

2 THEORETICAL BACKGROUND, RESEARCH GAPS, AND OBJECTIVES

2.1 Reverse Logistics

Reverse logistics commonly refers to the backward movement of materials, parts, and products in the supply chain, which focuses on the value recovery from EOL and EOU products and the proper treatment of non-recyclables [30, 31]. In the early 1990s, the concept of reverse logistics was first put forward to depict all relevant activities and logistics flows from the end customers to different remanufacturers, recyclers as well as other actors. The main activities and operations of a reverse logistics system consist of the collection of EOL/EOU products from consumers, the appropriate inspection, sorting, disassembling and/or pre-processing, the distribution of different products, components, and materials to respective locations and facilities for further treatment (e.g., reuse, refurbishing, remanufacturing, recycling, etc.), and the planning and scheduling of facility operations and transportation [3, 31, 32].

Reverse logistics has already been practiced in many industries resulting in long-term environmental and resource benefits. The motivation of reverse logistics comes initially from two aspects [32]. From the ecological and environmental perspective, reverse logistics drastically improves the utilization of various materials and hence aids in solving the global resource depletion issues. On the other hand, it may provide companies with opportunities to cut down their cost and improve profitability through product recovery operations. However, in practice, several factors, e.g., the low-profit margin [33], the possible competition with new products [34], the uncertainty related to market acceptance [35], the uncertainty of reverse flows [36], and the complexity of managing reverse flows, may significantly hinder the value recovery activities through reverse logistics. Furthermore, while reverse logistics has been considered a fundamental and critical component of sustainable development and circular economy, improper recycling practices may have detrimental environmental and social consequences. For example, the large export volume of WEEE from developed countries, such as the United States, the European Union, Japan, etc., to the developing countries in southeast Asia, not only results in increased greenhouse gas (GHG) emissions due to maritime transportation, but also poses significant risks to the workers and the environment due to the primitive and low-tech recycling methods used. Thus, the effective design and operation of a reverse logistics system will help to create more sustainable practices in many countries.

Since the early 2000s, the network design and planning of a reverse logistics system has become a highly focused topic [37]. It is commonly recognized as a strategic decision issue that is of prime importance [38, 39]. Strategic decisions have long-term impacts on a reverse logistics system since they are difficult or extremely expensive to alter in the later operational stage. Besides, several major determinant performances will potentially affect the performance of a reverse logistics network in many different ways, i.e., the determination of the number and locations of potential facilities, capacity planning, identification of transportation mode, determination of transportation and operational strategy, selection of service providers, establishment of distribution channels for the treatment of recovery products as well as the judgment of remanufacturing and recycling technologies application [40-42].

2.1.1 End-of-Use (EOU) Product and End-of-Life (EOL) Product

Reverse logistics comprises several value recovery activities including reuse, repair, refabrication, remanufacturing, recycling, and disposal [31, 43]. Reuse is to give the secondary usage of a functional product from a used/retired one, which is typically used for the same purpose for which it was designed [1]. Repair/refurbishing is to bring the damaged/non-functional components back to their original functions through the process of refinishing in order to extend the lifespan of the product [44]. Remanufacturing transforms used/worn-out components or parts into units or products with an 'as good as new' condition that satisfies all the same quality and other standards [45] and uses them for the production of new products. Remanufacturing targets the maximum recovery of high-value EOL products and may require a higher quality standard than the original products. Recycling is the reprocessing of scrap for its original use or being degraded into new materials for other use [1]. Finally, disposal is to handle the non-recyclable components and hazardous materials either for energy recovery or for incineration and landfill.

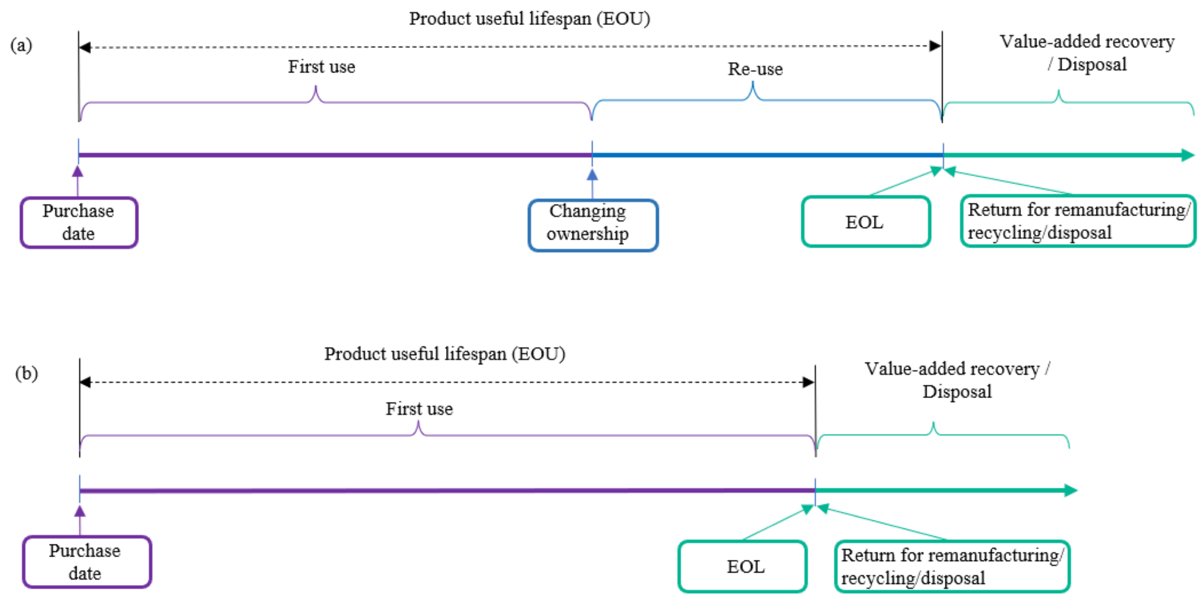

Figure 2-1 Illustration of End-of-Use and End-of-Life points with the product's lifespan, adapted from [10].

Circular economy is becoming more widely recognized as a promising sustainable business strategy that aims to keep the value of products, materials, and resources in the economic loop for as long as possible while promoting waste reduction throughout establishing product life cycles [44, 46]. When a product reaches the end of its product life cycle and is withdrawn from the market, it is known as EOL [47]. EOU return signifies the product that comes out of service due to some reasons, e.g., unwanted or obsolete [48]. The difference between EOU and EOL products is discussed from the standpoint of a product's useful lifespan. EOU products can be returned at every stage of the product's useful lifespan, not necessarily end-of-life [49]. **Figure 2-1** illustrates two cases of EOU and EOL points within the product's useful lifespan. The value recovery options vary depending on the difference in product quality between EOU and EOL returns. In Case (a), typically, the total product's useful lifespan is extended by reuse through changing ownership due to the returns are still reusable that can be simply and properly treated through repair and refabrication before re-introducing into the primary (usually at a lower price) and second-hand markets. For instance, the product has become obsolete and replaced by functionally richer technology, but it is still reusable. In case (b), due to the long useful lifespan and the issue of product quality, the EOL products are usually lost their functionalities with worse quality conditions. Thus, they can be directly sent to the value recovery stage for further treatments including remanufacturing, recycling, and disposal. As can be seen, the EOU and EOL stages are the keys to circulating the product's life cycle, rather than direct disposal.

2.2 Reverse Logistics Network Design

Reverse logistics management covers a wide range of problems and decisions, which are typically divided into three categories, namely, strategic, tactical, and operational [50]. At the strategic level, several factors and decisions are typically about the number and locations of potential facilities, capacity planning, the establishment of distribution and collaboration channels for the recovery of products and materials, remanufacturing and recycling technologies, transportation strategy, and so forth [40, 41, 50]. Tactical decisions are usually related to the determination of production policy, inventory policy [51], fleet management, and vehicle routing [52]. Operational decisions are the short-term decisions, which are normally associated with dynamic control of product recovery operations, dynamic inventory control, real-time vehicle routing and scheduling problems, service level enhancement [53], risk analysis, and so forth [50]. Network design is typically considered to be a cross-level decision-making problem that involves both long-term and mid-term decisions [51, 54].

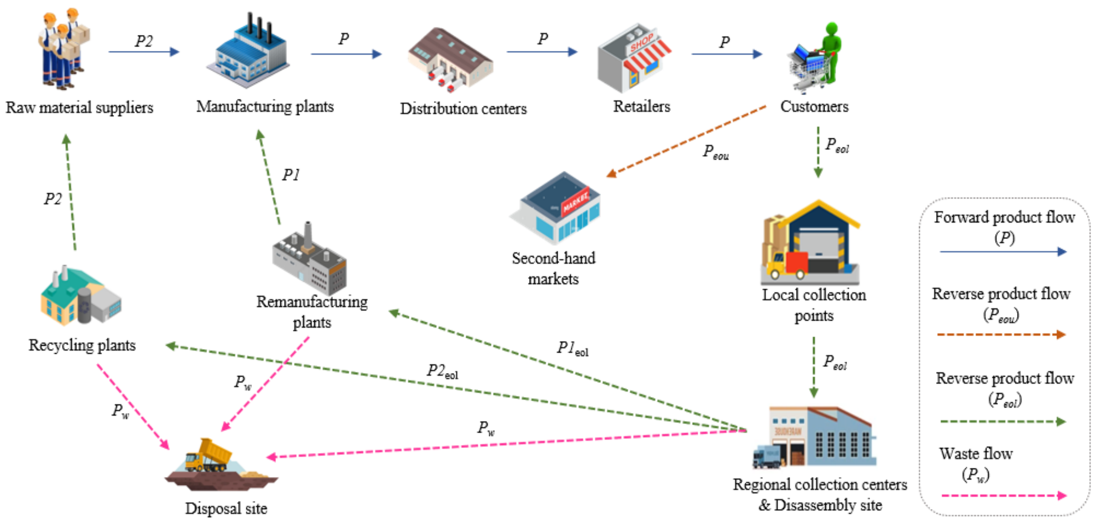

Figure 2-2 A conceptual framework of the reverse logistics system.

Reverse logistics network design is a complex decision-making problem and has gained increasing importance as a sustainable business strategy [2]. From a broader perspective, there are five types of material flows in reverse logistics activities: product recalls, B2B/B2C commercial returns (e.g. unsold products, wrong/damaged deliveries), manufacturing returns (e.g., raw material surplus, quality-control returns, production leftovers), warranty and service returns, and EOU and EOL returns [55]. Compared with other returned flows in reverse logistics, EOU and EOL return for value recovery and waste disposal have been attracted more focus in the research field due to two main reasons: 1) The potential economic and environmental value behind the large generation of EOL and EOU products is enormous, and 2) the network structure is more complex. Thus, this Ph.D. project puts the focus on the management of the reverse flows of EOL and EOU products. As shown in **Figure 2-2**, a reverse logistics network consists of different facilities, i.e., local collection points, regional collection/disassembly centers, remanufacturing plants, recycling plants, and disposal sites. It is noteworthy that some operations, e.g., disassembly, may take place at different facilities. The material flow in a reverse logistics system starts from the end-users and moves toward various facilities for the further treatment of value-added recovery or proper disposal.

Reverse logistics network design primarily determines the locations of different types of facilities and the material flows among the facilities [56]. Essentially, it is a two-stage decision-making problem, where the first-stage location decisions configure the reverse logistics network, while the second-stage decisions explore the best use of the network [57]. Considering the nature of these two types of decisions, the first-stage decisions need to be robust to withstand the change in both internal and external environments. On the other hand, the second-stage decisions are more flexible to be adjusted in order to optimize the use of the reverse logistics system. Research has also been done to support various second-stage decisions, e.g., routing, inventory, etc.[58, 59]. Literature addresses reverse logistics network design problems mainly by leveraging relevant quantitative models in two groups, namely, mathematical optimization and simulation. Mathematical models, e.g., multi-objective models, stochastic models, etc., are used to primarily solve combinatorial optimization problems and find out the optimal decisions among a large number of alternatives under different conditions, while, on the other hand, simulation models are used to provide a comprehensive analysis of several scenarios in much more details.

2.3 Smart Reverse Logistics System

2.3.1 Industry 4.0 and Its Impact on Logistics

Industry 4.0 represents the fourth industrial revolution. This concept was first put forward at the Hannover Fair of Industrial Technologies in 2011 to enhance the competitiveness of the German manufacturing industry [60]. It has shown a blueprint of the next-generation manufacturing systems with the adoption of disruptive manufacturing technology and information and computer technology (ICT). At the global level, several countries have launched their own strategies, e.g., the United States' National Network for Manufacturing Innovation, Japan's New Robot Strategy, and China's Made in China 2025, in order to strengthen their manufacturing industries as well as other business sectors through the utilization of the latest technological advancements [61]. According to a collaboration report by the World Economic Forum and McKinsey & Company, the innovation and adoption of the disruptive technologies in Industry 4.0 will generate inclusive growth and potentially create up to $3.7 trillion for the global economy by 2025 [62], and approximately 68% companies interviewed seeing it as their top strategic plan [20].

Compared with the past three industrial revolutions in history, where the major results were the mechanization of production, the use of electricity and mass-production systems, and the automated and flexible manufacturing systems [60], Industry 4.0 predominantly emphasizes the combination of Internet-based communication technologies, digitalization, and future-oriented intelligent manufacturing technologies in order to build smart machines and systems, implement smart manufacturing and logistics processes, and provide smart products and services [61]. From the technological perspective, an Industry 4.0 manufacturing system emphasizes the internet/5G-based communication and the connectivity of different smart devices and cyber elements, which enable real-time data collection, autonomous system control, and effective human-machine interaction [63]. Another significant feature is the computational intelligence brought by AI, big data analytics, and advanced optimization and simulation tools, which enables better proactive decision support with better prediction and real-time data-driven decision makings. From the commercial perspective, these Industry 4.0 technologies pave the way for new business models [64], individualized customization, better resource planning and sharing, and more sustainable production and logistics management [21, 65].

Empowered by the disruptive technologies in Industry 4.0, there is an opportunity to develop a smart production network characterized by real-time monitoring, autonomous operations, responsive communication, smooth material flows, and self-organized and integrated production system. Over the past two decades, the productivity of workers in the manufacturing industry has improved by 47% in the United States, which is mainly driven by the innovation and adoption of new technologies [62]. Technological advancements have also created opportunities and new business models for value creation and value proposition by targeting individualized product demands and services [66]. According to the McKinsey Global Institute, current technologies can realize more than 60% automation of all manufacturing tasks [62]. Previous studies [67-69] have revealed the 12 fundamental enabling pillars of Industry 4.0, which are the internet of things (IoT), cyber-physical system (CPS), big data analytics, artificial intelligence (AI), cloud technologies, autonomous robots, blockchain, unmanned aerial vehicle (UAV), additive manufacturing (AM), augmented reality (AR), virtual technologies and simulation, cybersecurity. These technologies may not only change the paradigm of the manufacturing industry but also dramatically impact other industries and business sectors through improved digitalization, connectivity, and intelligence. In addition, digital twin is one of the most promising concepts in Industry 4.0, which combines several ICT and virtual technologies to re-create a physical object or a physical process/system in the digital world. A digital twin can help to capture all the variables of an object or a system, perform tasks faster, and enable companies to better understand the working condition and optimize reactions and decisions under various scenarios. With the help of simulation, different experiments can be performed to determine the optimal solution in a risk-free environment and with much lower resource commitments in terms of time, money, or manpower. A better understanding of the features of new technologies and the prompt awareness of the potential critical issues are of significant importance for successful business innovation and transformation in the Industry 4.0 era [20].

The phrase "4.0" has been extensively used to depict the future paradigm shift in many industries, which are brought by disruptive technologies and increased digitalization. Traditionally, Logistics is considered a labor-intensive industry, which will be dramatically affected by the coming Industrial Revolution. With the emphasis on the role of Industry 4.0 technologies, the concept of Logistics 4.0 was proposed in 2014 [70]. Logistics 4.0 is believed to be a conceptual extension of Industry 4.0, and it emphasizes the real-time ability, autonomous operations, fast decision supports, and convertibility of a new IT system empowered by CPS. Logistics 4.0 provides new prospects as a result of technological advances in the logistics sector, and several major elements are highlighted by Strandhagen, Vallandingham [68] and Yu and Solvang [71] as follows:

- Demand-driven individualization and personalization
- Product-service system
- Digitalization
- Autonomous operations
- Resource sharing
- Green and sustainable logistics

To achieve these goals, increased digitalization and system integration at both intra- and inter-enterprise levels are required to facilitate effective interactions among stakeholders, better data utilization, real-time decision-making, streamlined and autonomous operations, and fewer resource utilization in a logistics system.

2.3.2 Smart Reverse Logistics Transformation

Even though Logistics 4.0 has gained increasing attention in recent years, there is still a lack of research focus on reverse logistics, particularly from a holistic and systematic perspective [72, 73]. With the help of technological advancements of Industry 4.0, reverse logistics is being influenced in an accelerated way [29], and efforts have been made to improve the smartness and sustainability of various operations and activities in a reverse logistics system [25, 74]. The improved digitalization, connectivity, and smartness brought by Industry 4.0 have changed the paradigms of reverse logistics predominantly in three ways: data, service, and operations, respectively. In this regard, a thorough understanding and conceptualization of *Reverse Logistics 4.0* are of critical importance to provide a systematic and holistic overview of the technological impacts of reverse logistics. Based on the main characteristics of Industry 4.0, the concept of *Reverse Logistics 4.0* can be defined as follows:

Reverse Logistics 4.0 is the sustainable management of all relevant flows and activities for value recovery and/or proper disposal of EOL products by using data-driven and smart technologies enabled individualization and innovative services.

As can be seen, *Reverse Logistics 4.0* emphasizes the use of data and technologies to achieve innovative reverse logistics services and operations, through which the harmony among the three pillars of sustainable development can be better achieved by taking into account economic benefits, environmental friendliness, and social responsibility. Herein, individualization represents the service innovation enabled by new technologies in a reverse logistics system. For example, the collection service of EOL products may be performed based on the filling data of the recycle bins or the request from individual customers, and the use of emerging technologies, i.e., IoT, AI, real-time optimization, etc., can help to optimize the task allocation and resource utilization so that both service level and operating efficiency can be well-balanced.

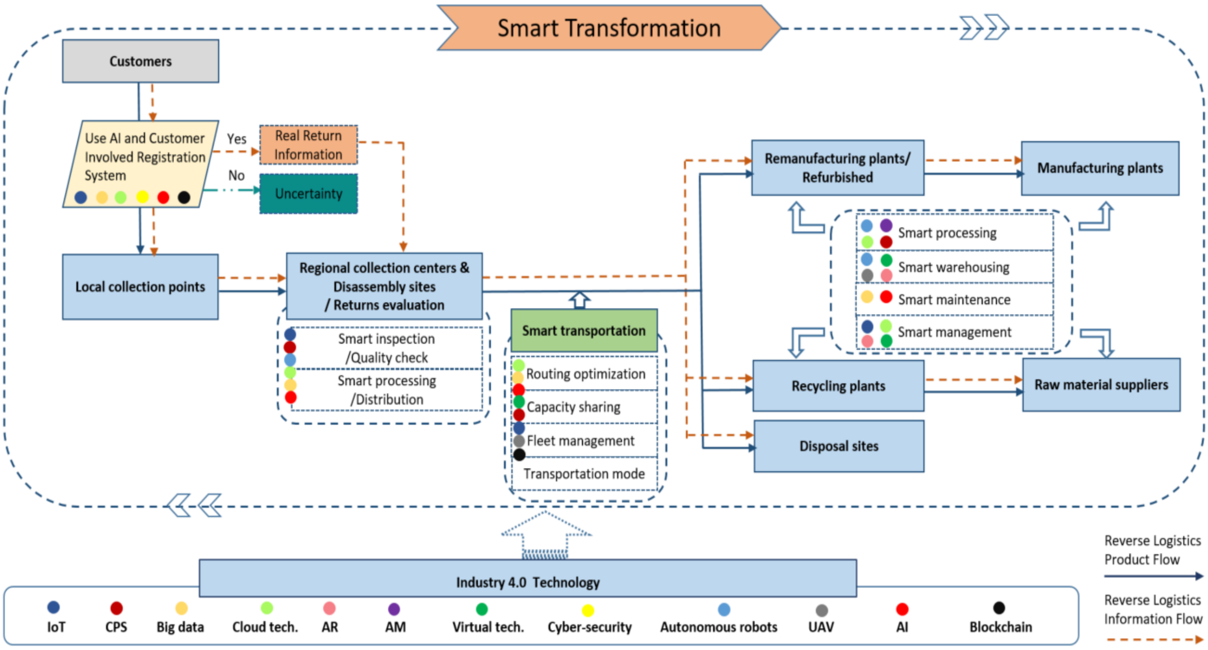

Figure 2-3 Smart reverse logistics transformation [75].

The term "smart transformation" refers to a paradigm shift fueled by innovation and the accelerating utilization of smart and disruptive technologies. As shown in **Figure 2-3**, a smart transformation will result in a paradigm change toward highly interconnected, intelligent, and autonomous reverse logistics systems, where data-driven decision-making and operations with both accurate prediction and real-time data are of significant importance. From the planning perspective, the value of data and information are predominately emphasized in a smart reverse logistics system, with which the impact of uncertainty of the EOL and EOU products can be significantly minimized. For example, a product-based digital twin of consumer electronics can effectively bridge the information gaps between end-users and reverse logistics companies. The collectors can have a clearer overview of when and where these EOL and EOU products will be returned, based on which the collection can be better planned and scheduled. The quality data can also be collected via a cloud-based information system or from the end user's registration via smartphone, which can help to organize the repairing and remanufacturing activities in a more effective and efficient fashion. On the other hand, various reverse logistics operations can become autonomous with the help of intelligent robots, UAVs, and AI-enabled autonomous vehicles and smart devices. This may drastically reduce the need for human operators, which occupy the largest share of the operating costs in a traditional labor-intensive logistics system. Meanwhile, the environmental impacts and safety issues can also be minimized.

The wide and increasing adoption of emerging technologies in Industry 4.0 enables a high level of automation and intelligence and will eventually lead to a smart reverse logistics transformation in different aspects, i.e., smart collection of EOU and EOL products, smart sorting and process management, smart transportation, smart remanufacturing and recycling, and smart disposal [76]. For instance, in the automotive remanufacturing process, the sustainability benefits of digitization could be significant. It has been revealed that the adoption of data-driven remanufacturing enhances sustainable practices, which may reduce the machine downtime by 20–30%, inventory level by 12–20%, and quality costs by 30–50% [14]. Meanwhile, the forecasting accuracy can be increased by up to 80% [14]. Besides, research has shown that AR may help to achieve up to 25% improvement in operator productivity while providing a better and safer working environment [77, 78]. Digital twin plays an essential role to connect the physical world with the digital world in order to achieve a high level of system integration, and remanufacturing has become one of the most focused areas of the adoption of digital twin [79]. In addition, emerging technologies will also yield significant impacts on transportation through the increased use of cleaner energy and improved fuel efficiency [80], and the use of intelligent transport systems and truck platooning has the potential to reduce CO_2 emissions by 10-25% in the near future [80, 81].

2.4 Smart Reverse Logistics Network Design

Even though Industry 4.0 provides new opportunities for smart reverse logistics transformation, the adoption of new technologies is usually not a one-time endeavor but rather a gradual and dynamic process throughout the whole lifespan of a reverse logistics system. However, this will further complicate the reverse logistics network design problem in the initial strategic planning stage. Reverse logistics network design is a complex decision-making problem that needs to balance the long-term trade-off between the economic, environmental, and social performances, and the gradual adoption of Industry 4.0 technologies may result in significant changes in the way of operations, e.g., inventory policy, transportation strategy, etc., and the key parameters of a reverse logistics system, e.g., costs and carbon emissions related to facility operation and transportation. Thus, the planning of a smart and sustainable reverse logistics network needs not only to consider the external fluctuations, e.g., generation of EOL and EOL products, fuel prices, etc. but also to take into account the internal configurational changes and performance improvement through the adoption of Industry 4.0 technologies within the planning horizon.

Recently, Govindan and Gholizadeh [82] studied a sustainable and resilient reverse logistics network design problem using a scenario-based robust optimization model. This research considers the impact of big data analytics, which is one of the most important Industry 4.0 enablers, on reverse logistics network design, where the volume, velocity, and variety (big data’s 3V feature) are modeled as uncertain parameters related to the quality and quantity of EOL returns. This research is the first one that considers the impact of smart reverse logistics transformation on strategic network decisions, however, the method is oversimplified and cannot fully account for the dynamicity, uncertainty, as well as other real-life characteristics of the problem. Besides, even though significant modeling efforts have been made, no research has been conducted to simultaneously investigate the smartness, sustainability, uncertainty, and dynamicity in reverse logistics network design. Thus, new models and methods are needed to better support the decision-making of smart and sustainable reverse logistics network design in Industry 4.0.

2.5 Research Gaps

Despite significant advancement have been achieved in terms of Industry 4.0 technologies, reverse logistics, and strategic network design, there is no research at present time has been conducted that integrating these key concepts. This hinders a holistic understanding of the importance of Industry 4.0 to reverse logistics and thereafter properly designing smart and sustainable reverse logistics networks. Besides, from the methodological perspective, there is a lack of an effective combination of different analytical methods in reverse logistics network design. **Table 2-1** presents a vis-à-vis comparison of 85 research papers focusing on the development of analytical models for reverse logistics network design with either mathematical optimization or simulation methods. In the literature search, the Web of Science (WoS) database is used with a set of keyword combinations, i.e., “reverse logistics network design”, “reverse logistics network planning”, “reverse logistics”, “optimization”, and “simulation”. The search results are limited to journal articles published from 2011, and the most relevant research papers are selected based on the full-text reading.

The results show that majority of studies have modeled and solved reverse logistics network design problems by employing a single method either mathematical optimization or simulation [54]. A few research have incorporated a simplified simulation model, e.g., Monte Carlo simulation, as a validation method for the results from the optimization models [83]. These models can only evaluate the parametric uncertainty and find the statistically optimum with a static and oversimplified depiction of real-world situations [54]. However, they are incapable to evaluate the dynamic system transformation by adopting new technologies and test the system performance with practical operational policies, e.g., inventory control policy, transportation policy, etc. Furthermore, no research has been conducted to discuss the system integration problem, which has a significant potential to seamlessly link the physical elements, data, and various analytical models and tools in a highly integrated and cloud-based environment for supporting smart and sustainable reverse logistics management.

Table 2-1 Related research in reverse logistics network design and optimization.

Authors	**Network features**				**Analytical methods**			
	Dynamicity	Uncertainty	Smartness	Sustainability	Optimization		Simulation	
					Single	Multiple	Monte Carlo	Discrete event
Tuzkaya, Gulsun [84]	-	√	-	√	-	√	-	-
Alumur, Nickel [40]	√	-	-	-	√	-	-	-
Kannan, Diabat [85]	-	-	-	√	√	-	-	-
Li, Wang [86]	-	-	-	√	-	√	-	-
Lieckens and Vandaele [87]	-	√	-	√	√	-	-	-
Eskandarpour, Zegordi [88]	-	-	-	√	-	√	-	-
Keyvanshokooh, Fattahi [89]	√	-	-	-	√	-	-	-

Alumur and Tari [90]	√	-	-	√	-	√	-	-
Bing, Bloemhof-Ruwaard [91]	-	-	-	√	√	-	-	-
Hatefi and Jolai [92]	-	√	-	-	√	-	-	-
Litvinchev, Rios [93]	√	√	-	-	√	-	-	-
Mirakhorli [94]	-	√	-	-	-	√	-	-
Ramos, Gomes [95]	√	-	-	√	-	√	-	-
Soleimani and Govindan [57]	-	√	-	-	√	-	-	-
Suyabatmaz, Altekin [96]	-	√	-	-	√	-	-	-
Alshamsi and Diabat [97]	√	-	-	-	√	-	-	-
Aras, Korugan [98]	√	√	-	-	√	-	-	-
Ayvaz, Bolat [99]	-	√	-	-	√	-	-	-
Baykasoglu and Subulan [100]	-	√	-	-	√	-	-	-
Galvez, Rakotondranaivo [101]	-	-	-	√	√	-	-	-
Hatefi, Jolai [102]	-	√	-	-	√	-	-	-
Hatefi, Jolai [103]	-	√	-	-	√	-	-	-
Yanik [104]	-	-	-	√	√	-	-	-
Chari, Venkatadri [105]	-	-	-	√	√	-	-	-
Govindan, Paam [106]	√	√	-	√	-	√	-	-
Hatefi, Jolai [107]	-	√	-	-	√	-	-	-
Li, Wang [108]	√	-	-	-	-	√	-	-
Qiang and Zhou [109]	-	√	-	-	√	-	-	-
Yu and Solvang [110]	-	-	-	√	-	√	-	-
Yu and Solvang [111]	-	√	-	√	√	-	-	-
Yuchi, He [112]	-	-	-	-	√	-	-	-
Zohal and Soleimani [113]	-	-	-	√	-	√	-	-
Alshamsi and Diabat [56]	-	-	-	-	√	-	-	-
de Souza, Borsato [114]	-	-	-	√	-	-	-	-

Fattahi and Govindan [115]	√	√	-	-	√	-	√	-
John, Sridharan [116]	√	-	-	√	√	-	-	-
Temur and Bolat [117]	-	-	-	√	-	√	-	-
Temur and Yanik [118]	√	√	-	-	√	-	-	-
Vahdat and Vahdatzad [51]	√	√	-	-	√	-	-	-
Yu and Solvang [119]	-	√	-	√	√	-	-	-
Banguera, Sepulveda [120]	-	-	-	√	√	-	-	-
John, Sridharan [121]	-	-	-	-	√	-	-	-
John, Sridharan [122]	√	-	-	-	√	-	-	-
Liao [123]	-	-	-	-	√	-	-	-
Rahimi and Ghezavati [124]	√	-	-	√	-	√	-	-
Yu and Solvang [125]	-	√	-	√	-	√	-	-
Farrokh, Azar [126]	√	√	-	-	√	-	-	-
Gao [127]	-	√	-	√	-	√	-	-
Oyola-Cervantes and Amaya-Mier [128]	√	-	-	-	√	-	-	-
Reddy, Kumar [129]	√	-	-	√	√	-	-	-
Trochu, Chaabane [130]	√	√	-	-	√	-	√	-
Yuchi, Wang [131]	-	-	-	√	-	√	-	-
Zarbakhshnia, Soleimani [132]	-	-	-	√	-	√	-	-
Xiao, Sun [133]	-	-	-	√	√	-	-	-
Kuşakcı, Ayvaz [134]	-	√	-	-	√	-	-	-
Gonçalves, Fagundes [135]	-	-	-	√	-	-	-	√
de Oliveira, Fagundes [136]	-	-	-	√	-	-	-	√

Elia, Gnoni [137]	-	-	-	√	-	-	√	√
Ameli, Mansour [138]	-	√	-	√	-	√	√	-
Azizi, Hu [139]	√	√	-	-	√	-	-	-
Kargar, Pourmehdi [140]	√	-	-	-	-	√	-	-
Lu, Zhu [141]	√	√	-	-	√	-	-	-
Pan, Xie [142]	√	-	-	-	-	√	-	-
Reddy, Kumar [143]	√	-	-	√	√	-	-	-
Ren, Wang [144]	-	√	-	√	√	-	-	-
Safdar, Khalid [145]	-	-	-	√	-	√	-	-
Temucin and Tuzkaya [146]	-	-	-	-	-	√	-	-
Trochu, Chaabane [147]	√	√	-	√	-	√	-	-
Yang and Chen [148]	-	√	-	-	√	-	√	-
Yu, Sun [149]	-	√	-	√	-	√	√	-
Budak [150]	√	-	-	√	-	√	-	-
Gao and Cao [151]	-	√	-	√	-	√	-	-
Tosarkani, Amin [152]	√	√	-	√	-	√	√	-
Yu and Solvang [153]	-	√	-	-	-	√	√	-
Nayeri, Paydar [154]	-	√	-	√	-	√	-	-
Zarbakhshnia, Kannan [155]	√	√	-	√	-	√	-	-
Hao, Sun [156]	√	-	-	√	-	√	-	-
Hashemi [157]	√	√	-	√	-	√	-	-
Islam, Nizami [158]	-	-	-	-	√	-	-	-
Roudbari, Ghomi [159]	-	√	-	-	√	-	-	-
Song, Tian [160]	-	-	-	√	-	√	-	-
Wang, Huang [161]	√	-	-	√	-	√	-	-
Shahparvari, Soleimani [162]	-	√	-	√	√	-	-	-
Che, Lei [163]	-	-	-	-	√	-	-	-
Govindan and Gholizadeh [82]	√	√	√	√	√	-	-	-

Therefore, the research gaps related to smart and sustainable reverse logistics network design are summarized from conceptual, decisional, methodological, and integrational perspectives:

1. First, from the conceptual perspective, no research has been conducted to present a holistic overview of the impacts of disruptive technologies on reverse logistics. Besides, there is also a lack of a systematic conceptualization, definition, and analysis of smart reverse logistics transformation in Industry 4.0 and how these Industry 4.0 features can be interpreted in the context of reverse logistics.
2. From the decisional perspective, no research efforts have been given to the development of a hand-on decision-support system that can be used to better assist the smart and sustainable reverse logistics network design under various real-life scenarios considering conflicting objectives, dynamicity, uncertainty, technological alternatives, disruption, and operational policies.
3. From the methodological perspective, to solve reverse logistics network design problems, the effective combination of different analytical methods, e.g., mathematical optimization and advanced simulation remains still under-explored [164]. There is a lack of research on solving the methodological integration issues, e.g., the complexity of building respective models, data conversion between different models, setup of practical operational policies, etc.
4. Last but not the least, no research has been conducted to present a comprehensive analysis of a general framework and the associated challenges related to the system integration of different physical elements, data, and analytical models and algorithms for reverse logistics management, which may form the theoretical foundation for a highly connected, smart, and sustainable digital reverse logistics twin.

Through the comprehensive literature review, the four research gaps above are thoroughly analyzed and further discussed in Part II.

2.6 Research Objectives

This Ph.D. project aims at filling the identified research gaps in smart and reverse logistics network design. The research results of this Ph.D. project will be used to answer the four research questions proposed in **Chapter 1**.

With respect to the four research gaps identified, the main objectives of this Ph.D. project are given as follows:

1. This Ph.D. project aims first at providing a comprehensive analysis of Industry 4.0-enabled smart logistics in both forward and reverse channels to better understand the technological impacts on smart logistics services and operations. Specifically, systematic conceptual development of smart and sustainable reverse logistics transformation in Industry 4.0 will be focused on in order to present a clear roadmap to guide both researchers and practitioners in this field.
2. This Ph.D. project aims primarily at developing an improved decision-support framework that can be used to effectively support sustainable reverse logistics network design. This

framework will take into account of current undergoing smart and dynamic transformation, the implied uncertainty as well as other real-life conditions. The developed framework needs to be tested and validated through numerical methods or case studies to show its applicability and to obtain meaningful implications in a real-life environment.

3. Thirdly, this Ph.D. project aims also at exploring the effective way to combine different analytical models and methods, i.e., prescriptive analytics and descriptive analytics, in the decision-support framework for smart and sustainable reverse logistics network design, through which different analytical models and methods can be connected and their strengths can be better utilized to yield robust strategic decisions and comprehensive performance analyses.
4. Finally, this project Ph.D. project aims at providing a system-based framework of digital reverse logistics twin and a general structure for system integration, which potentially help to achieve a highly connected and automatic decision-support system. This general framework may help to guide future software development for smart and sustainable reverse logistics management.

3 RESEARCH DESIGN AND METHODS

3.1 Research Design

Research design is a comprehensive plan developed for answering specific research questions or testing specific hypotheses using empirical data [165], which plays the most important and fundamental role in each type of research. A well-planned research design will help to ensure that the research methods employed are appropriate to achieve the research goals and that the correct type of data analysis is adopted. A well-devised research design will also guarantee that different parts can work harmoniously together in order to promote efficient and successful functioning [166]. As shown in **Figure 3-1**, a systematic framework of research design is presented by Maxwell [166], which includes five key components, namely, research questions, goals, conceptual framework, research methods as well as validity. These five elements create logical and workable relationships, and the linkages among each element are strongly tied to several others. The top triangle is more conceptual, which is generally regarded as the initial stage in developing a research project. On the other hand, the lower triangle is more operational and is usually the next step considering the implementation of research methodologies and the verification of validity and feasibility [166]. The research questions play a vital role and should have a clear relationship to link the other elements in the research design.

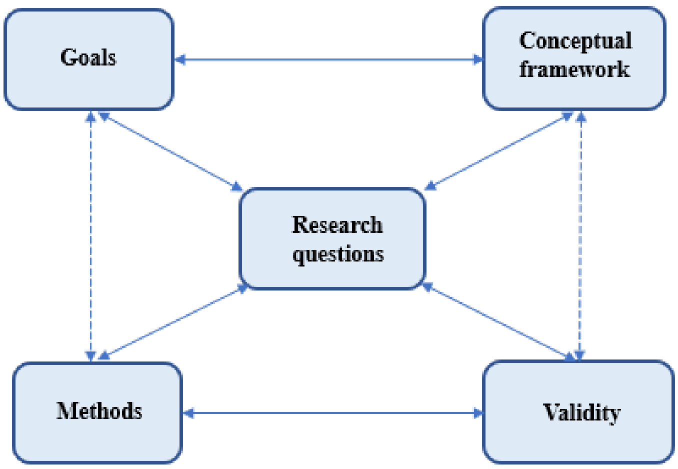

Figure 3-1 Research design for a research project [166].

Basically, there are three general categories of research methods, i.e., qualitative, quantitative, and mixed methods, respectively. From a broader perspective, it reflects the research strategies that could have impacts on which data collection and analysis techniques can be used. At the most basic level, qualitative research uses data that is not number-based, which focuses on words, concepts, ideas, feelings, and so forth. Therefore, it is a more subjective method. In contrast, the quantitative method emphasizes the use of numerical values and statistics to measure and evaluate differences and relationships. However, it is noteworthy that both subjective values and objective values may be employed in the quantitative method. The mixed-method is the combination of both qualitative and quantitative methods. The proper selection of the research methods depends on the research questions and objectives.

3.2 Research Design of the Ph.D. Project

Based on the definition of the five fundamental elements, the research design framework of smart and sustainable reverse logistics network design is given in **Figure 3-2**. First, the research questions are clearly identified, based on which the research objectives and goals are proposed. In order to achieve these research objectives and goals, conceptual development and quantitative models are given for answering the proposed research questions while seeking ways to improve and enhance the existing decision-support methods for smart and sustainable reverse logistics network planning. In the following sub-sections, these five fundamental elements are discussed.

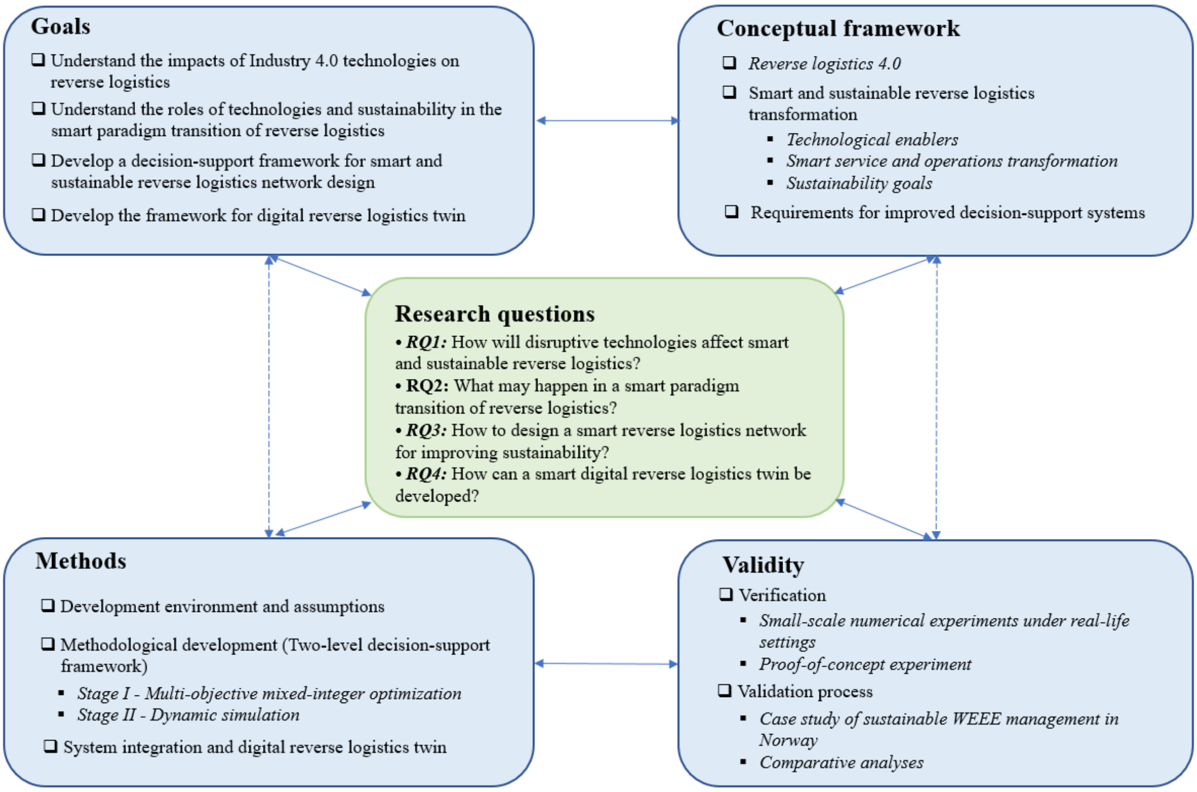

Figure 3-2 Research Design for the Smart and Sustainable Reverse Logistic Network Design.

3.2.1 Research Questions

Smart and sustainable reverse logistics network design is a complex decision-making problem that has gained increasing importance as a sustainable business strategy [2]. Based on the heterogeneous characteristics of the EOL and EOU products received, various operations are performed for either recapturing their remaining value or proper disposal. As shown in **Figure 3-3**, a reverse logistics network consists of different nodes, i.e., local collection points, regional collection/disassembly centers, remanufacturing plants, recycling plants, and disposal sites. They are linked by the material flows starting from the collection from end-users to different destinations. The collected EOL and EOU products are transported to regional collection centers for inspection and disassembly. The components with high residual value are sent either for repair and re-sell at second-hand markets or for remanufacturing and refurbishing for function restoration. The others are sent to recycling plants to be degraded into new materials and then sold to the raw material suppliers. The non-recyclable components and hazardous materials are sent either for energy recovery or proper disposal.

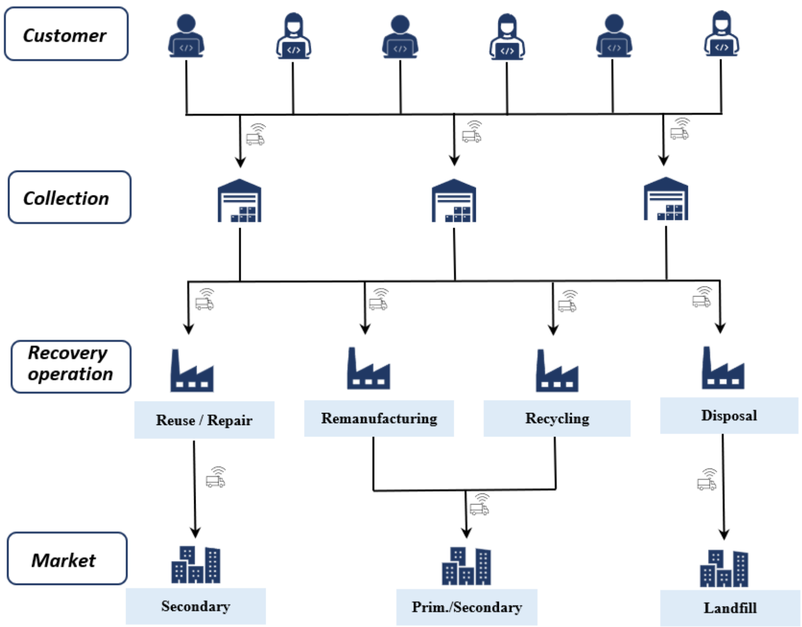

Figure 3-3 A smart multi-echelon reverse logistics system.

Today's disruptive technologies in Industry 4.0 pave the way for improving the smartness and sustainability of reverse logistics systems. For example, internet/5G-based connectivity may better connect all the elements and stakeholders in a reverse logistics system, as shown in the figure. However, the technological impacts on various reverse logistics operations and decision-making, e.g., network design, have not been well investigated and clearly understood, so the research questions are defined accordingly to provide better knowledge on:

1. How will disruptive technologies affect smart and sustainable reverse logistics?
2. What may happen in a smart paradigm transition of reverse logistics?
3. How to design a smart reverse logistics network for improving sustainability?
4. How can a smart digital reverse logistics twin be developed?

3.2.2 Research Goals

The research goals of this Ph.D. project are to properly answer these four research questions. The first goal is to better understand the impacts of using disruptive technologies in Industry 4.0 on smart logistics services and operations, especially, on the smart paradigm transition of reverse logistics. Based on this, an improved decision-support framework is to be developed to better capture the nature of smart reverse logistics transformation and its impact on the decision-making of sustainable reverse logistics network design. Finally, this Ph.D. project is to investigate a conceptual framework for the digital twin reverse logistics twin, which may potentially help to achieve a highly connected and automatic decision-support system for smart and sustainable reverse logistics management.

3.2.3 Conceptual Framework

To answer the research questions and achieve the research goals, a conceptual framework plays a vital role at the beginning stage, which can help to better guide and direct the further methodological development of the Ph.D. project. First, based on a comprehensive analysis of the existing literature and reported case studies, the conceptual development of the smart and sustainable reverse logistics transformation in *Reverse Logistics 4.0* is designed. In the course of this project, I've developed a conceptual framework of Reverse Logistics 4.0 [76]. As shown in **Figure 3-4**, this framework links the technological enablers of Industry 4.0, reverse logistics activities, smart reverse logistics service and operation transformations, and the targeted sustainability goals. Essentially, it reveals the technology-enabled smart transformation occurs across all reverse logistics stages and activities, i.e., collection, sorting and processing, remanufacturing and recycling, transportation, and disposal, which lead to improved services and operations in order to better meet the sustainability goals in economic, environmental, and social dimensions.

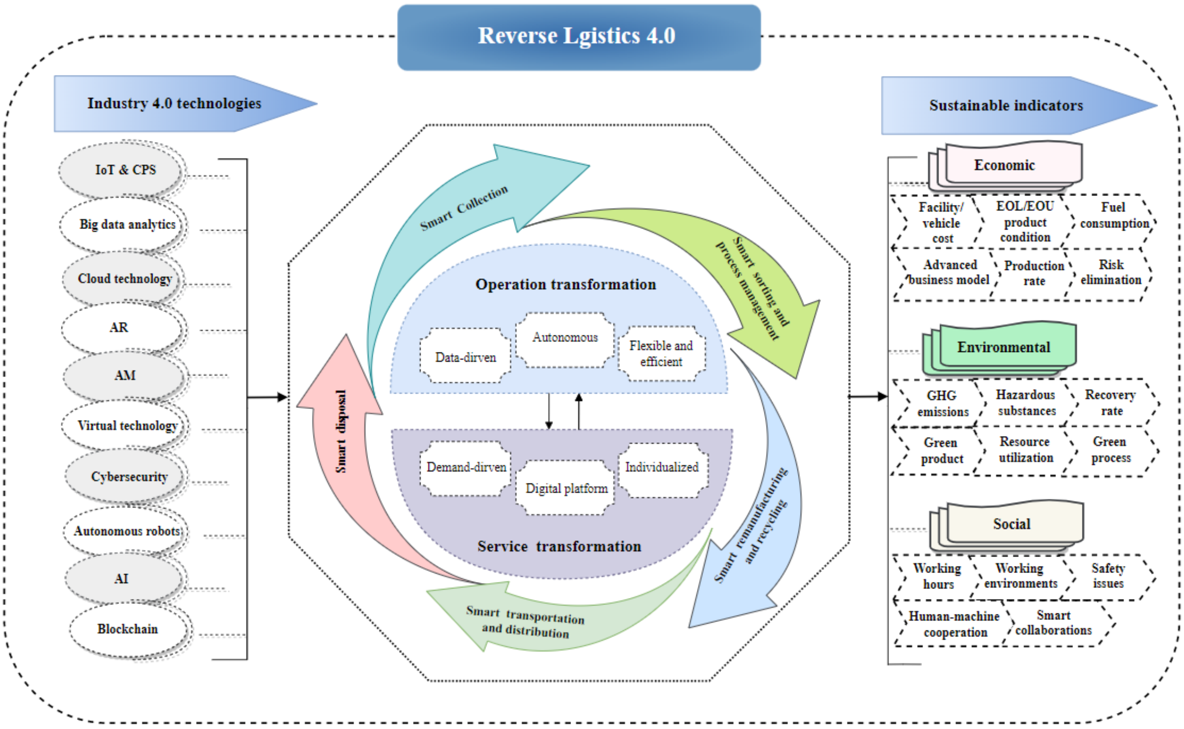

Figure 3-4 A conceptual framework of smart and sustainable reverse logistics transformation in *Reverse Logistics 4.0* [76].

This conceptual framework explicitly shows the interconnection between technology, paradigm transition, and sustainability in the context of reverse logistics. Notably, the adoption of the various enabling technologies in Industry 4.0 is not the goal but rather the means to improve the services and operations in the smart reverse logistics transformation. In addition, technology itself may not be able to achieve a better performance, but the redesign and reform of the reverse logistics services and operations may help to improve sustainability. In this regard, the conceptual development of *Reverse Logistics 4.0* and smart and sustainable reverse logistics transformation is of essential importance, which helps to thoroughly understand how disruptive technologies may affect the service, operation, and performance at different nodes and flows of a reverse logistics network. These form the basis for the development of a decision-support framework for sustainable reverse logistics design under smart transformation. For example, it provides a better understanding of the system and environment under which key decisions are to be made and the decision-support tool is to be developed. In addition, based on the conceptual development, the assumptions, parameter adjustments, and scenario setups can also be properly given in the modeling process so that more comprehensive insights can be obtained for answering the research questions.

3.2.4 Methods

Based on the conceptual framework, improved decision-support methods and systems need to be developed for smart and sustainable reverse logistics network design to properly answer the proposed research questions and achieve the defined goals. In this phase, it is crucial to understand the decision environment and assumptions, develop proper models and methods, and effectively use them with different data sources and the other elements in the decision-support framework.

3.2.4.1 Development Environment and Assumptions

The decision-support framework for smart and sustainable reverse logistics network design needs to be developed under a comprehensive environment that can reflect the key features of the real-life problem. Thus, understanding the development environment is of essential importance, which can be described by six categories of influencing factors as follows:

1) Performance measures
    - Economic performance
    - Environmental performance
    - Social performance
2) Logistics structure
    - Product flow
    - Network structure
    - Transportation links
3) Planning horizon
    - Dynamic
    - Static
4) Parameters
    - Deterministic
    - Uncertain
5) Operations
    - Inventory control
    - Production
    - Sourcing
    - Transportation
6) Configuration
    - Rigid and unchanged
    - Dynamically evolving

These factors can thoroughly depict the features of a reverse logistics system and the development environment, under which the decision-support models and framework are formulated. The first category measures the sustainable performances in different dimensions for a reverse logistics system. Then, the logistics structure is depicted with the type of the reverse product flow, the number of echelons in the network, and the links between each echelon. The third and fourth categories specify the features of the planning horizon and parameters. The fifth category focuses on the operations of the reverse logistics system, while the last category shows the configurational changes over the planning horizon. In this Ph.D. project, considering the smart transformation and the operational policies over the planning horizon, **Table 3-1** explicitly shows the development environment for the decision-support framework.

Table 3-1 Development environment of the decision-support framework for smart and sustainable reverse logistics network design.

Category	Influencing factors	Description
Performance measures	• Economic performance	Total costs of operating the reverse logistics system
	• Environmental performance	Total carbon emissions from reverse logistics activities
Logistics structure	• Product flow	Multiple types of EOL products
	• Network structure	Multi-echelon reverse logistics network
	• Transportation link	Transshipment via regional collection center
Planning horizon	• Dynamic	Dynamic and realistic planning horizon
Parameters	• Uncertain	Parametric uncertainty related to the demand, generation, value recovery operations
Operations	• Inventory	Different inventory control policies used
	• Production	Simple manufacturing strategy
	• Sourcing	Various sourcing policies
	• Transportation	Partial shipment policy and two types of vehicles
Configuration	• Dynamically evolving	Scenario analyses of smart and gradual transformation of facilities and transportation

As shown, a multi-product multi-echelon dynamic and sustainable reverse logistics network design problem is focused on in this Ph.D. project, which considers the trade-off between total costs and total carbon emissions. The parametric uncertainties are taken into account due to the heterogeneous quality and quantity of the reverse product flows. To better formulate the features of a reverse logistics system, various operational strategies and policies are considered at both facility and transpiration levels. Furthermore, the configurational changes within the planning horizon are also considered through scenario analyses.

Several assumptions are made for the development of respective analytical models in the decision support framework:

- The location of the generation points and markets are known.
- The candidate locations for respective facilities can be pre-determined.
- The relevant parameters are known or can be properly estimated.
- Different facilities may implement different operational policies.
- The smart transformation will, in general, yield positive impacts on reverse logistics

3.2.4.2 Methodological Development

Smart and sustainable reverse logistics network design is to make important decisions under a highly dynamic, realistic, and uncertain environment, which requires methodological development combining different analytical tools, e.g., optimization, simulation, etc. While mathematical models have been extensively formulated and used in reverse logistics, the combination with comprehensive simulation analysis remains under-exploited, even in the forward logistics [164]. Due to the complementary of optimization and simulation, they can be combined in the decision-making cycle. On the one hand, a simulation analysis can be used to provide valuable input parameters for the optimization model. For example, Costa, Duarte [167] investigated a simulation-optimization decisional framework for sustainable biodiesel supply chain design, where process simulation was used to estimate the key parameters of the system. On the other hand, the optimization results obtained can be better tested and validated with a comprehensive simulation analysis [168].

However, combining both optimization models and comprehensive simulation analysis in smart and sustainable reverse logistics network design faces several challenges:

- The complexity of building respective models
- The requirement of different software packages and/or coding language
- The unclear linkage between different models
- The data conversion with different levels of aggregation
- The setting up of realistic operational policies

Thus, in this Ph.D. project, a two-level decision-support framework is under investigation, in which the methodological development focuses, by tackling these challenges above, on the combination of mathematical optimization and dynamic simulation. By combining both analytical methods, the features of smart transformation can be better captured and modeled, and its impacts on sustainable reverse logistics network design can be comprehensively and holistically analyzed to support robust and reliable decisions.

3.2.4.3 System Integration

While the proposed decision-support framework can be used as an ad-hoc process for smart and sustainable reverse logistics network design, high-level system integration can help to seamlessly link different elements in a CPS, which forms the foundation for smart digital reverse logistics twin for sustainable reverse logistics management. **Figure 3-5** shows the architecture of a high-level CPS, which includes five important layers:

1. Smart connection
2. Data conversion
3. Cyber-physical system
4. Cognition
5. Configuration

The first three layers emphasize the internet/4G/5G-based connectivity between physical equipment and the cyber environment, where data can be effectively collected, stored, and converted to relevant information for predictive analytics and further decision-making. The fourth layer is located in the cyber system and emphases the computational intelligence and smartness for supporting different decisions in a manufacturing or a logistics process. The fifth layer is considered the highest level of CPS in Industry 4.0, in which the autonomy of a smart system can be achieved through a high level of system integration that enables both connectivity and intelligence through effective connection and interaction between different physical and cyber elements.

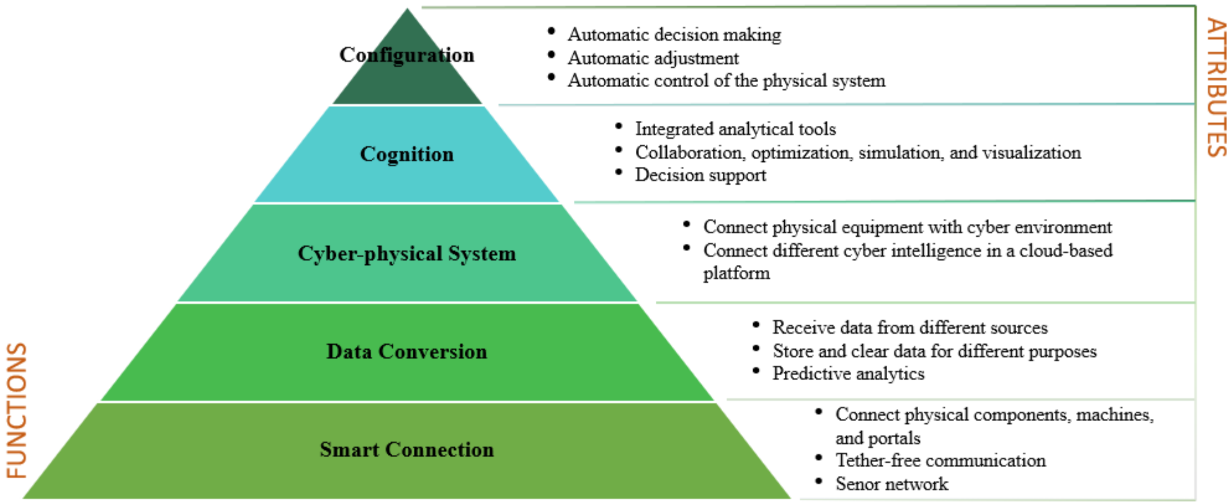

Figure 3-5 The architecture for a high-level CPS, adapted from [169, 170].

This Ph.D. project focuses primarily on the smart decision-support framework in the cognition layer for smart and sustainable reverse logistics management. Furthermore, considering the architecture given in the figure, a conceptual framework of a smart digital reverse logistics twin is given, which specifies the key elements, enablers, and data flows to achieve a high level of system integration for sustainable reverse logistics management. Moreover, the criteria for measuring the maturity level of system integration are also defined to guide future software development in this field.

3.2.5 Validity

The validity of the proposed decision-support framework is to examine the functionality, behavior, and results through different processes. As an important step, the developed models and methods need to be verified and validated before they can be used to support real-life decision-making of smart and sustainable reverse logistics network design. The validity process aims at answering two important questions. The first one is whether the methodological development process is properly performed to obtain the required results, while the second question is if the method formulated is a proper representation of the real-life problem under investigation.

Verification is the process that targets the first question. Verification checks are different depending on the complexity and scope of the methodological development, which may include three phases, e.g., requirement verification, design verification, and code verification. Verification may take place at every stage of the methodological development in order to eliminate defects and save time [171]. In this Ph.D. project, several small-scale numerical experiments under real-life settings are performed to test both the mathematical optimization model and the dynamic simulation in the methodological development phase. With small-scale numerical experiments, whose results are easily obtained, the performance of both the optimization process and the simulation process in the decision-support framework can be verified against the design objectives, the correctness of the model building and coding, and the reliability of the analytical results obtained. Furthermore, these models are evaluated with several sets of parameters with various data structures through several rounds of tests to eliminate errors or defects. In addition, the proposed conceptual framework for system integration and digital reverse logistics twin is also verified by an integrated process, which connects the optimization model and the dynamic simulation with the automatic data flow.

Validation aims, on the other hand, at answering the second question, and it evaluates the final performance, functionality, and usability of the proposed method and checks whether it fulfills all the needs [171]. Validation usually takes place in the later stage of the methodological development, which ensures a high level of compliance between the real-life problem and the method developed, say, the method can be used to reflect the features and effectively solve the modeled problem. In this Ph.D. project, the proposed decision-support framework is validated through a case study of sustainable WEEE management in Norway and comparative analyses. The analytical results given by the decision-support framework are compared with that obtained from a pure mathematical optimization model, which shows the proposed method outperforms a purely mathematical model in capturing the real-life features and providing more reliable decision support for sustainable reverse logistics network design under a dynamic, realistic, and uncertain environment.

Both verification and validation are important steps for the validity of methodological development, which are integral parts to ensure robust and reliable decisions and analyses can be reached in smart and sustainable reverse logistics network design.

3.3 Research Methods

This section provides a brief introduction of the research methods in this Ph.D. project, including the two-level decision-support framework, multi-objective optimization, dynamic simulation, and system integration and digital twin.

3.3.1 Two-Level Decision-Support Framework

Reverse logistics network design is about making important decisions at two stages. In the first stage, the strategic facility location decisions are made to establish and configure a reverse logistics system. In the second stage, the reverse logistics network is utilized through a set of decision-making at both tactical and operational levels, e.g., demand allocation, inventory control, vehicle routing, operational planning, etc. While the strategic facility location decisions are to be *robust*, the tactical and operational decisions are, however, much more flexible to be adjusted for better use of the reverse logistics network. From the decision-making perspective, the uncertainty related to the reverse material flows and the opportunities for smart transformation within the planning horizon have brought more challenges to the initial network design of a reverse logistics system. Thus, in order to solve this challenge, a two-level decision-support framework is proposed in **Figure 3-6** to better support strategic decision-making of smart and sustainable reverse logistics network design in the Industry 4.0 era.

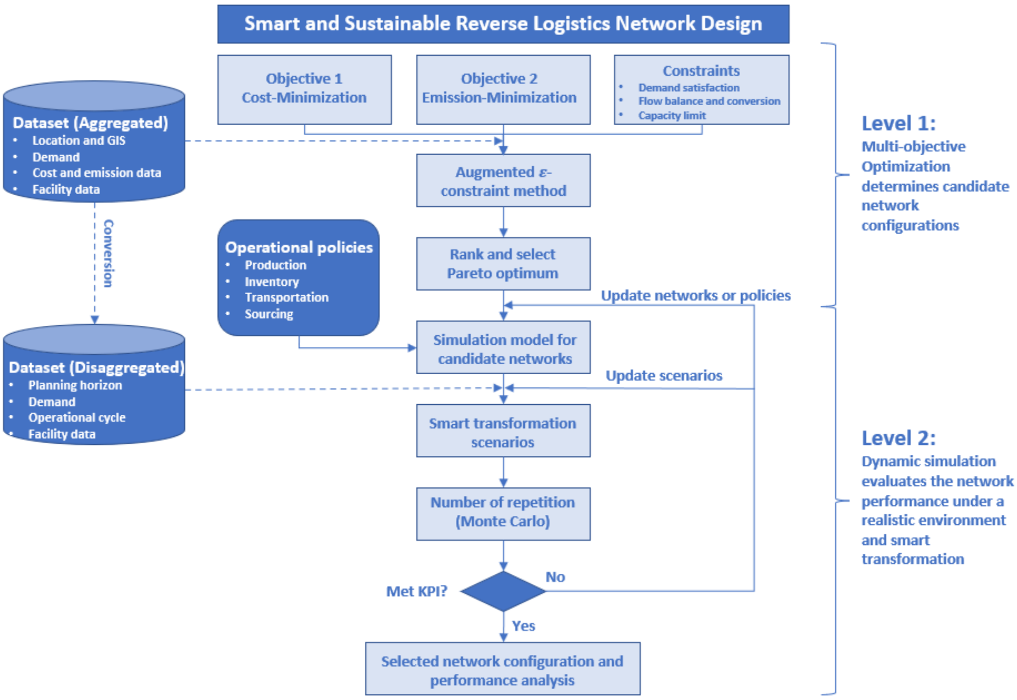

Figure 3-6 The two-level decision-support framework [75].

The proposed framework aims, through methodological integration, at providing a more close-to real-life modeling environment to better capture the features of smart and sustainable reverse logistics network design, in which the strengths of both mathematical optimization and dynamic simulation can be effectively used. Despite optimization and simulation being two extensively focused analytical methods, they are fundamentally different with targets for solving different types of problems. Even if modeling the same problem, they may provide different levels of details and real-life features. As prescriptive analytics, optimization is to formulate the reverse logistics network design problem with a mathematical model, which can help with decision-making at a highly aggregate level. The previous literature has clearly shown the advantage of using a mathematical optimization model lies in the effectiveness of selecting the optimal solutions under various objectives and constraints from a large number of alternative combinations. Both the first-stage and second-stage decisions can be simultaneously made for reverse logistics network design in a holistic fashion. However, a mathematical optimization model suffers from several limitations. For instance, many assumptions need to be made so that the problem can be properly accommodated in the mathematical structure, e.g., linearized transportation flow, highly aggregate amount, etc. Meanwhile, the analysis given by a mathematical optimization model is relatively static, which is, however, ineffective in modeling and analyzing time-dependent system operations and interactions. Furthermore, a more realistic optimization model for the real-life problem may exponentially increase the complexity of solving it.

Simulation is descriptive analytics, which aims at modeling most of the real-life features of a system with minimum assumptions. Modern computer-based simulation software may include and combine different simulation methods, e.g., discrete-event simulation, system dynamics, etc., to provide powerful analytical capabilities for comprehensively evaluating the performance of a system under various scenarios. Meanwhile, the physical elements in a system can be better visualized in the simulation environment, which allows a better understanding of the operations of the system and the interactions among different elements in a real planning horizon. However, there are also several limitations of simulation. First, building and running a highly detailed simulation model of a complex reverse logistics system is extremely time-consuming and require high computational power of the hardware. Thus, simulation models can only be used for performance evaluation, but it is ineffective or impossible to select the optimal solution from a large number of alternative combinations. Second, the input data of a simulation model need to be given at a much more detailed level. Besides, more comprehensive knowledge about the reverse logistics system needs to be provided so that realistic operational policies can be formulated to test the system in a close-to real-life environment. **Table 3-2** shows the comparison between optimization and simulation.

Table 3-2 Comparison between optimization and simulation, adapted from [168].

	Optimization	Simulation
Strengths	• Solving complex decision-making problems • Finding optimal solutions from a large alternative combinations	• Comprehensive performance evaluation in a close-to real-life environment • High-quality system visualization
Weaknesses	• Restricted mathematical structure • Many assumptions and simplifications • Result presentation issues	• The incapability of solving complex decision-making problem • Time-consuming • Requirement of expensive computational power and hardware • Comprehensive data and details of the system

Figure 3-6 illustrates how the mathematical optimization model and the dynamic simulation model are linked by proper data conversion and model set ups in the two-stage decision-support system for smart and sustainable reverse logistics network design. In the first level, a multi-objective optimization model is developed to solve the revere logistics network design problem under sustainability in different dimensions. The model can determine a set of Pareto optimal solutions and simultaneously make both first-stage and second-stage decisions. However, only the first-stage strategic facility location decisions are focused on at this level. Based on the evaluation of the Pareto optimal solutions by the decision-maker, a set of candidate network configurations can be chosen. Then, in the second level, the respective simulation models are built for the selected network configurations, which provide further performance evaluation in a dynamic, realistic, and complex environment. In this Ph.D. project, the dynamic simulation model is established by combining both discrete-event simulation and Monte Carlo simulation in order to appropriately model the dynamic features, parametric uncertainties, logistics operations, and upgrades of facilities and transportation over the planning horizon. The performance of the chosen reverse logistics network configurations is compared with respect to the pre-determined indicators, and new networks, operational policies, and update strategies may be tested if needed.

3.3.2 Multi-Objective Mixed-Integer Optimization

Integer program and mixed-integer program are among the most important optimization techniques to model and solve many real-life problems, where all (integer program) or some (mixed-integer program) of the variables does not belong to real numbers but to integers. For example, a service provider for cold-chain COVID-19 vaccine delivery may purchase several drones to shorten the delivery time, improve service levels, and reduce the risk of infection during the vaccine delivery. An optimization model may thus be formulated to minimize the number of drones required to maintain a certain level of delivery service. In this case, it is apparent to see a non-integer optimal solution is unrealistic, so an integer constraint needs to be incorporated to find the optimal decisions on the number of drones that should be purchased. Mixed-integer programming optimization has been extensively used to formulate and solve reverse logistics network design problems [172]. Considering the two-stage nature of the decision-making, binary decision variables are used to model and determine the strategic facility location decisions at the first stage [125] of reverse logistics network design. While, on the other hand, continuous variables, integer variables, or both of them may be used to model the second-stage decisions related to, for example, demand allocation, vehicle routing, inventory control, and so forth.

The early modeling efforts focus on single-objective mixed-integer optimization with primary consideration of either cost-effectiveness or economic feasibility of EOL and EOU recovery. However, taking into account the environmental footprints and social impacts of reverse logistics activities, increasing research attention has been paid to the management of the environmental and social sustainability through better decision support for reverse logistics systems. For instance, different carbon emission policies have been incorporated in the optimization models for sustainable reverse logistics network design in order to minimize the environmental impact, where the carbon tax can be modeled as an additional cost component in the objective function [85] to penalize the excessive carbon emissions. On the other hand, a carbon cap constraint can be used to set a maximum level of carbon emission for a reverse logistics system. Nonetheless, increasing modeling efforts have tackled the sustainability issues related to reverse logistics network design with multi-objective optimization models.

Multi-objective optimization is another most important modeling technique that can be used to solve a wide range of problems with conflicting objectives, and it has been widely used in economics, logistics and supply chain management, and various engineering disciplines [173]. Many real-life problems cannot be modeled with a single-objective optimization model due to the fact that the conflicting interests, usually among different stakeholders, need to be simultaneously considered in the decision-making. In this regard, a multi-objective optimization model needs to be developed to manage the trade-off among different objectives. In a multi-objective optimization problem, it is usually impossible to find a solution that optimizes all the objectives and fulfills all the constraints at the same time. Instead, the problem is solved by finding a Pareto optimal solution or a set of Pareto optimal solutions. As defined by Censor [174], a Pareto optimal solution is an extreme point within the feasible solution area of a multi-objective optimization problem, at which the value of one objective function cannot be improved without the degradation or compromise of the values of the other objectives.

For solving sustainable reverse logistics network design problems, multi-objective mixed-integer optimization models have been well developed and extensively used to support the two-stage decision-making taking into account conflicting objectives [58, 175]. When using different sustainability indicators to measure the performance of a reverse logistics system, the optimal decisions obtained are by no means identical. For example, the economic objective may, on the one hand, leads to a more compact network configuration to minimize the cost of a reverse logistics system, particularly the expensive facility operating cost. While, on the other hand, an emission reduction objective may lead to a dispersed network structure with more facilities opened to minimize the carbon emissions associated with transportation on links. Furthermore, a social sustainability objective may lead to more employment, which consequently increases the cost of operating the reverse logistics system. In this regard, a Pareto optimal solution needs to be achieved to balance the trade-off among different sustainability indicators through appropriate decisions on both stages of the reverse logistics network design.

$$\begin{gathered} \text{Minimize } g_1(\boldsymbol{x},\boldsymbol{y}) = \boldsymbol{u_1}\boldsymbol{x} + \boldsymbol{f_1}\boldsymbol{y} \\ \text{Minimize } g_2(\boldsymbol{x},\boldsymbol{y}) = \boldsymbol{u_2}\boldsymbol{x} + \boldsymbol{f_2}\boldsymbol{y} \\ \dots \\ \text{Minimize } g_n(\boldsymbol{x},\boldsymbol{y}) = \boldsymbol{u_n}\boldsymbol{x} + \boldsymbol{f_n}\boldsymbol{y} \end{gathered} \tag{1a}$$

Subject to:

$$\boldsymbol{Ax} \geq \boldsymbol{b} \tag{1b}$$

$$\boldsymbol{Cx} \leq \boldsymbol{dy} \tag{1c}$$

$$\boldsymbol{Ex} = \boldsymbol{Hx} \tag{1d}$$

$$\boldsymbol{x} \geq 0 \tag{1e}$$

$$\boldsymbol{y} \in \{0, 1\} \tag{1f}$$

The general form of a multi-objective mixed-integer optimization model for sustainable reverse logistics network design is given in Model (1). The objection functions are given in Eq. (1a), where all objectives are minimized. The model is subjected to three sets of constraints, namely, demand satisfaction (1b), capacity (1c), and flow balance (1d). There are two types of decision variables, i.e., binary integer variables and continuous variables, whose domains are given by constraints (1e) and (1f), respectively.

$$\boldsymbol{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_i \end{bmatrix} \qquad \boldsymbol{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_j \end{bmatrix}$$

As shown above, $\boldsymbol{x}$ and $\boldsymbol{y}$ are the vectors of the continuous variables and the binary variables, and $\boldsymbol{u}$ and $\boldsymbol{f}$ are their corresponding coefficient vectors. Besides, $\boldsymbol{A}$, $\mathbf{C}$, $\boldsymbol{E}$, and $\boldsymbol{H}$ are the coefficient matrixes, and $\boldsymbol{b}$ and $\boldsymbol{d}$ are the right-hand-side vectors for the respective constraints. The expanded forms of $\boldsymbol{A}$ and $\boldsymbol{b}$ are given below.

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1i} \\ a_{21} & a_{22} & & a_{2i} \\ \vdots & & \ddots & \vdots \\ a_{k1} & a_{k2} & \cdots & a_{ki} \end{bmatrix} \qquad \boldsymbol{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_j \end{bmatrix}$$

When all the objectives converge toward the same direction either minimization or maximization, the general multi-objective mixed-integer optimization model can be re-written to a more compact form, as illustrated in Model (2).

$$\text{Minimize/Maximize } g(\boldsymbol{x},\boldsymbol{y}) = (g_1(\boldsymbol{x},\boldsymbol{y}), g_2(\boldsymbol{x},\boldsymbol{y}), \dots, g_n(\boldsymbol{x},\boldsymbol{y}))^T$$

Subject to: (2)

$$\boldsymbol{x},\boldsymbol{y} \in S$$

Herein, $g(\boldsymbol{x},\boldsymbol{y}) = (g_1(\boldsymbol{x},\boldsymbol{y}), g_2(\boldsymbol{x},\boldsymbol{y}), \dots, g_n(\boldsymbol{x},\boldsymbol{y}))^T$ is a n-dimensional vector of the objective functions, whose feasible solution domain is given as follows:

$$S = \{\boldsymbol{x} \in \mathbb{R}^n, \boldsymbol{y} \in \{0,1\} | \boldsymbol{Ax} \geq \boldsymbol{b}, \boldsymbol{Cx} \leq \boldsymbol{dy}, \boldsymbol{Ex} = \boldsymbol{Hx}, \boldsymbol{x} \geq 0\}$$

Solving a multi-objective mixed-integer optimization model for sustainable reverse logistics network design is to find a solution within the feasible domain, which can optimally balance the trade-off among the objective functions under certain conditions. Due to the lack of continuity in the decision variables, a mixed-integer program is much more computationally expensive than a linear program. Several well-known exact solution methods, i.e., branch-and-bound, cutting plane, and branch-and-cut, continuously search the feasible solution area by solving a large number of linear relaxation problems in certain directions. While for large-scale integer or mixed-integer optimization problems, some advanced reformation methods, e.g., Bender's decomposition, Lagrangian relaxation, etc., need to be used to accelerate the solution speed. For more information related to solving an integer or mixed-integer programming model, Conforti, Cornuéjols [176] can be referred to.

The multi-objective optimization problem is solved by converting it into a single-objective optimization problem. There are several well-known scalarization methods, i.e., goal programming, weighting method, and constraint method [177]. By the normalization of the objective functions with a benchmarking value, e.g., the individually optimized value of each objective function, the multiple objective functions can be combined into a single objective function with their respective weights in a weighting method, e.g., weighted-sum and weighted Tchebycheff approach. A goal programming takes a similar idea, and the (weighted) measures of all objective values from their individual optimal solutions are evaluated to determine the Pareto optimal solution of the multi-objective optimization problem. On the other hand, a constraint method, e.g., ε-constraint method, first selects one objective function to be optimized and then converts the other objective functions into constraints of the model. With this method, a set of Pareto optimal solutions can be determined by solving these single-objective optimization problems with changing values of ε. Unlike the weighting methods, in which a set of weight combinations need to be determined first by the decision-makers before solving the optimization model, decisions can be made after the optimization model is solved with the constraint method, so it is more attractive in many ways when determining the objective weights in advance is difficult. However, since more constraints are added on, the constraint method for solving a multi-objective optimization problem is more computationally expensive.

The recent research has enhanced the traditional solution methods for solving multi-objective mixed-integer optimization models in reverse logistics management, e.g., augmented weighted Tchebycheff approach and augmented ε-constraint method [178]. For instance, by employing a lexicographic approach at the initial stage, the quality of the payoff matrix used in the augmented ε-constraint method can be significantly improved by reducing the dominated solutions, which consequently improves the setup of the ε value and the quality of the Pareto optimal frontier obtained [179]. In addition, several metaheuristics, e.g., non-dominated sorting genetic algorithm II (NSGA-II), particle swarm optimization (PSO), etc., have been used to improve the computational efficiency in finding the near-optimal solutions for large-scale problems. In this Ph.D. project, the augmented ε-constraint method [178] is used to provide a set of efficient Pareto optimal solutions and candidate network configurations for smart and sustainable reverse logistics network design.

3.3.3 Dynamic Simulation

Simulation has been increasingly focused on in logistics and supply chain management since it is a powerful tool and can be used for various planning purposes, e.g., system design, performance evaluation, the test of operation policies, analysis of system behaviors understanding, and prediction and estimation of parameters. Today, computer-based high-quality simulation models are capable of providing powerful virtual representations of a process or system over a dynamic horizon and of performing comprehensive scenario analyses in a close-to real-life environment. In general, there are four types of simulation, namely, Monte Carlo simulation, discrete-event simulation, system dynamics, and agent-based simulation.

- ***Monte Carlo simulation*:** is a simple and static simulation method that models a process or a system with a series of probability density functions (PDFs). Based on the repeatedly sampling from the given PDFs, it computes the statistical value of interest [180]. Monte Carlo simulation uses random numbers and probabilities to find approximate values for quantities that are usually difficult to be calculated analytically. For example, based on a given PDF, Monte Carlo simulation can be used to generate randomized custom demands in a supply chain.
- ***Discrete-event simulation*:** is a comprehensive simulation method that, based on queueing theory, models the changes of a process or a system with a sequential set of discrete events [181]. It can be either a deterministic or a stochastic method. The progress of the modeled system is driven by the changing states of discrete events over time. Due to its powerfulness

and applicability in analyzing the behavior of complex systems, discrete event simulation is considered one of the most important modeling tools for manufacturing and service systems as well as supply chains [182]. For example, discrete event simulation can be used to analyze a manufacturing or a remanufacturing system, where parts are processed in various sequences at different stations before leaving the system [182]. It can also provide a holistic analysis of an inventory system, in which different products are replenished at various supply chain stages before being purchased at the store.

- ***System dynamics*****:** is a continuous modeling technique that depicts the change and progress of a process or system with differential questions, and it is specifically designed for long-term, chronic, dynamic management problems [183]. The structure of the system dynamics method is described by causal-loop or influence diagrams, and it represents the system as a set of flows and accumulations [184]. A causal-loop diagram describes the key feedback loop (either negative feedback or positive feedback loops) [185]. It is an effective method to analyze and assess the continued dynamic nature of large-scale complex systems. For example, system dynamics models have widely been used to predict the development of an epidemic disease [186].
- ***Agent-based simulation*****:** is a relatively novel modeling technique that can be used to simulate autonomous decision-making individuals (agents)' activities and communications, behaviors, influences, and interactions in order to analyze their effects on the system as a whole [187, 188]. Different from the other traditional simulation techniques, which model and analyze the whole system's behaviors, agent-based simulation primarily focuses on the autonomous agents and provides valuable information about a process or a system based on the collective analysis of their behaviors and interactions. The agents can represent a variety of real-life entities, e.g., people, animals, vehicles, etc., and their behaviors need to be first defined in a dynamic simulation environment. Agent-based simulation has been extensively used in biological sciences and social sciences. For instance, agent-based models can be used for analysis and decision-support of disaster response and emergency management [189].

Based on the introduction above, a comparison of different simulation methods is shown in **Table 3-3**.

Table 3-3 Comparison of the four simulation methods.

Simulation methods	**Model classification criteria**	
	Static / Dynamic	Deterministic / Stochastic
Monte Carlo simulation	Static	Stochastic
Discrete-event simulation	Dynamic (discrete)	Mostly stochastic
System dynamics	Dynamic (continuous)	Mostly deterministic
Agent-based simulation	Dynamic (discrete)	Mostly stochastic

Despite system dynamics and agent-based simulation can be used in several areas, e.g., prediction of epidemic development for temporary reverse logistics network design under the pandemic [190], etc., Monte Carlo simulation and discrete-event simulation are the most widely used modeling tools in logistics planning and supply chain management due to their effectiveness and applicability. Monte Carlo simulation is primarily used for parameter generation and performance evaluation under stochasticity. On the other hand, computer-based discrete-event simulation models are powerful tools to holistically and dynamically re-create the logistics systems and various operations in the virtual environment, which allows comprehensive performance analyses under different scenarios and real-life environments.

In smart and sustainable reverse logistics network design, the term “dynamic simulation” refers to the combination of both discrete-event simulation and Monte Carlo simulation. Discrete-event simulation is used to model the reverse logistics flow logic, facility operational policies, souring and transportation strategies, and dynamic transformation of facilities and transportation in the real planning horizon. Monte Carlo simulation is to deal with the stochasticity related to input parameters, which, through repetitively running the simulation model, ensures high confidence in the simulation result under uncertain environments.

3.3.4 System Integration and Digital Twin

The proposed decision-support framework allows a high level of methodological integration with different analytical tools and various sources of data. However, the effective utilization of these analytical methods and data by decision-makers, practitioners, as well as other non-expert users requires a user-friendly interface with a highly integrated system and environment. Therefore, system integration of different physical elements, data, analytical models, and algorithms for reverse logistics management plays a vital role. In this Ph.D. thesis, the conceptual framework of a digital reverse logistics twin is proposed from the system perspective, which potentially helps to achieve a highly connected and automatic decision-support for various reverse logistics activities. Digital twin is not a new concept in reverse logistics related operations and activities. For example, a product-based digital twin can provide valuable information and data throughout the entire product lifecycle. At the EOL stage, the data provided by a digital twin can help to better organize the collection and value recovery activities [27].

From the system perspective, **Figure 3-7** illustrates the key elements and their connections in a smart digital twin for sustainable reverse logistics management. The product-based digital twin can also be incorporated, as well as the other IoT-enabled smart devices, to provide key data of the reverse logistics system, e.g., product data, vehicle data, facility data, real-time traffic and weather data, etc. Through highly integrated data flow, the physical assets can be collected with the cyber layer that provides intelligence for smart and sustainable reverse logistics management. At the cyber layer, data needs to be properly cleaned and processed, and several analytical tools, i.e., predictive analytics, prescriptive analytics, and descriptive analytics, are needed for supporting various decision-making at strategic, tactical, and operational levels in an interactive way [191].

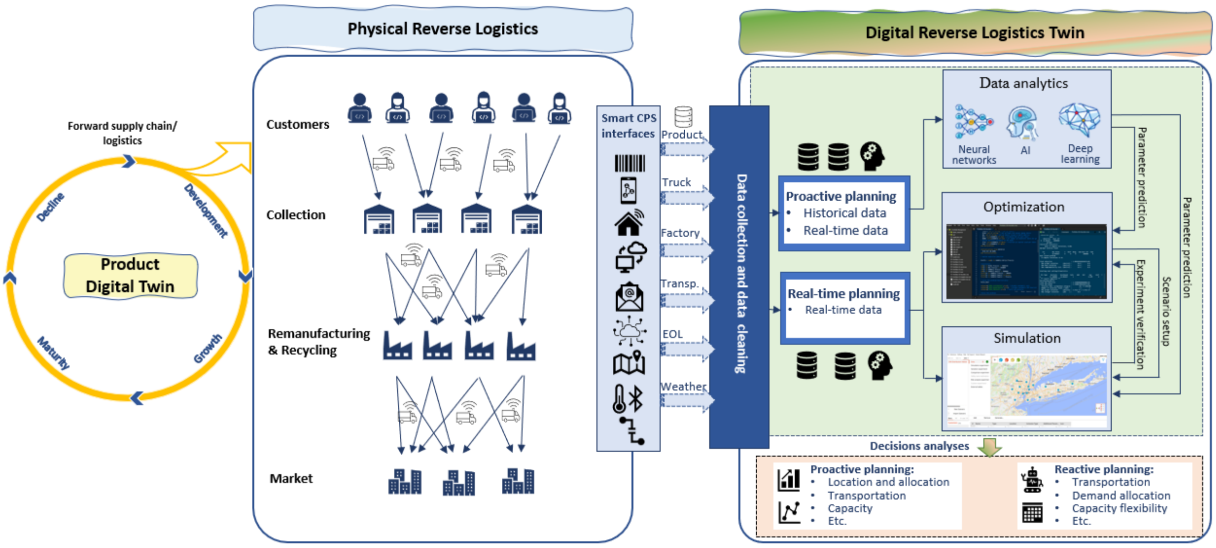

Figure 3-7 Digital reverse logistics twin [192].

A digital reverse logistics twin is an integrated information platform, where the potential of different elements, e.g., AI, GIS, analytical models, simulation, etc., can be effectively utilized to support different decisions for reverse logistics management. To develop a smart twin for sustainable reverse logistics management, seven criteria are defined to measure the level of maturity of system integration, which can be used to evaluate the existing software solutions and also to guide future software development.

These criteria are discussed as follows [50]:

- ***Cyber-physical structure*** is considered the fundamental level of system integration, which enables the collection of various data from both physical and cyber elements of a reverse logistics system. Data is the most important component that links the physical system and the virtual system, through which different analytical models in the cyber layer can also be seamlessly connected for different decision-support purposes.
- ***Cloud-based system*** is to provide a cloud-based platform for both data and analytical tools in the cyber layer, which enables effective connection and distributed access to the data and analytical models.
- ***Shared database and data conversion*** ensure the same dataset is used and can effectively be converted for different analytical models that may require different input structures and the level of aggregation. This is important to guarantee the consistency and reliability of the analysis.
- ***Flexible network structure*** requires that the digital twin needs to be flexible enough to adapt to the structural change of actors, facilities, material flows, operational policies, as well as other factors in a reverse logistics system, for example, by adding or subtracting relevant elements in the system.

- ***Large model database*** ensures that several decision-support models need to be included in the digital twin to tackle a wide range of reverse logistics planning problems at different levels, e.g., facility location, vehicle routing, inventory control, etc.
- ***Flexible model modification*** refers to the flexibility related to the model building, which means the model can be easily modified based on the changing environments and specific problems. For example, new objectives and/or new constraints can be added to model the new features in the digital reverse logistics twin.
- ***User-friendly interface*** can provide an easier way for users without professional modeling background. Furthermore, it can provide better visualization of result analysis, which can help with better decision support.

The ultimate goal of a digital reverse logistics twin is to link different physical and cyber elements in a highly integrated way through data, in which the value of data in decision support can be better exploited for smart and sustainable reverse logistics management.

4 CONCLUSION AND FUTURE WORKS

4.1 Summary of the Ph.D. Project

This Ph.D. thesis consists of five papers, of which three are published and/or submitted to peer-reviewed international journals and two are conference papers. **Figure 4-1** shows the structure of the selected papers with respect to the progress of this Ph.D. project. As shown, these five selected papers can explicitly reflect the objectives of this Ph.D. project from the beginning to the completion in a linear and clear manner. At the beginning stage of the Ph.D. project, a systematic literature review was first conducted to illustrate and explore the current and future research trends and opportunities of sustainable logistics in Industry 4.0. Based on the targeted research directions from **Paper 1**, a holistic and systematic conceptual development of *Reverse Logistics 4.0* is given in **Paper 2**, which presents a roadmap and several possible challenges for achieving the smart and sustainable transformation of reverse logistic systems. Besides, it also explains why smart reverse logistics should be better studied in the context of digitalization and technological innovations. Next, based on one of the major challenges of *Reverse Logistics 4.0* identified in **Paper 2**, **Paper 3** focuses on the methodological development of a two-level decision-support framework combining both mathematical optimization and dynamic simulation for designing a dynamic, smart, and sustainable reverse logistics network. The proposed decision-support framework can better capture the nature of smart reverse logistics transformation and provide effective decision support and visual representation of the system. Last, a conceptual framework from the system integration and digital twin's perspectives was proposed in **Paper 4** and **Paper 5**, which formulated the system structure and the key components required for automatic decision-supports through the digital reverse logistics twin. These two papers help to guide the development of next-generation methodological and system integration for smart reverse logistics management.

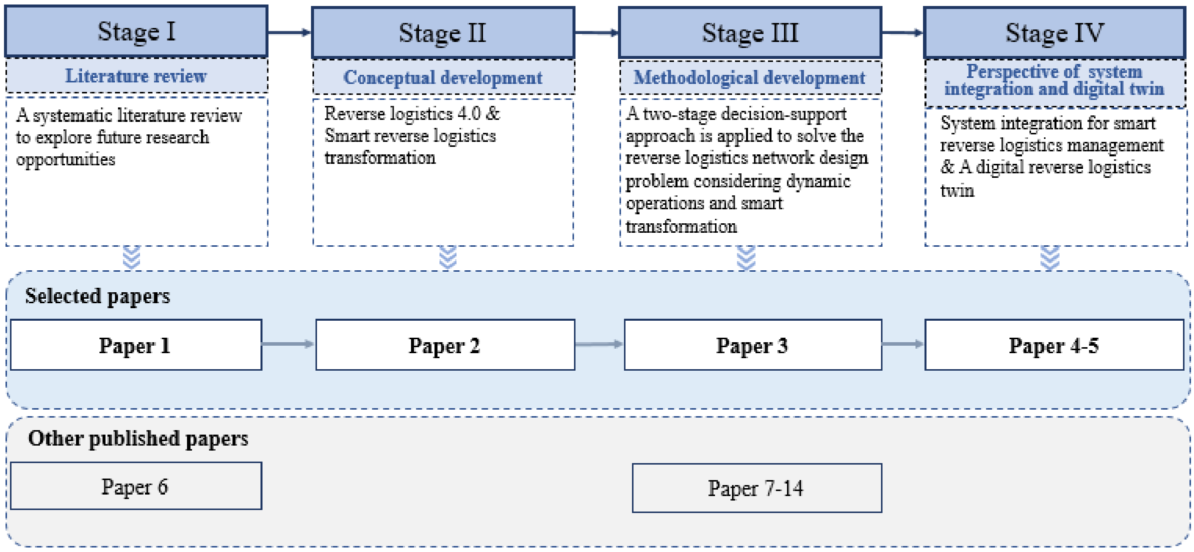

Figure 4-1 Schematic view of the structure of the selected papers and other published papers in this Ph.D. project.

In addition, the other published papers (**Papers 6-14**) have also contributed to both theoretical and methodological developments of this project. For instance, **Paper 6** discussed the opportunities for improving sustainable supply chain management with the key enabling technologies of Industry 4.0. In **Paper 8**, a system dynamic simulation was used at the first stage to yield the estimation of infections at the early stage of the COVID-19 outbreak in Wuhan, China, whose results were then used as the inputs to a multi-objective mixed integer programming model to optimize the locations of temporary waste incinerators during the pandemic. Besides, a combined two-stage optimization-simulation analysis was performed for route optimization and evaluation of different transportation strategies for cold chain vaccine distributions in the COVID-19 outbreak in **Paper 7**. The research results of these papers may also be applicable, to some extent, for solving specified reverse logistics challenges.

For the papers that are essential for the subject specified for this Ph.D. project, a brief summary is as follows:

Paper 1 *The Application of Industry 4.0 Technologies in Sustainable Logistics: A Systematic Literature Review (2012—2020) to Explore Future Research Opportunities*

Through a systematic literature analysis of 115 papers published in peer-reviewed international journals between 2012 and 2020, **Paper 1** presents a comprehensive understanding of the impacts of disruptive technologies on sustainable logistics operations and management in Industry 4.0. A bibliometric analysis was first given to show the quantitative insights into several key metrics, i.e., publication trend, influential research, co-citation networks, and important keywords. A detailed content analysis was then given to show an overview of the current research landscape related to the impacts of Industry 4.0 technologies on the performance and sustainability of four main logistics activities including production and purchasing, warehousing, transportation, and general system integration. The results of **Paper 1** show the opportunities brought by Industry 4.0 technologies to improve sustainable logistics in economic, environmental, and social dimensions. However, the technology-driven paradigm shift also brings several challenges for sustainable logistics, e.g., the trade-offs among conflicting sustainability measures, unclear evaluation of overall benefits and lifecycle impacts, etc. Besides, there is also a lack of general guidelines for enterprises to achieve sustainability through uptaking of Industry 4.0 technologies. To better guide the future research, nine research directions are proposed:

1. Human-centric smart logistics transformation
2. Multi-objective balanced system design for sustainable logistics operations
3. Lifecycle environmental impact
4. Analytical optimization for smart implementation of Industry 4.0 technologies
5. Digital twin of sustainable logistics systems
6. Semi-autonomous sustainable transportation solutions
7. Broad and diversified technology focus
8. Sustainable reverse logistics
9. The smart and sustainable logistics solutions for the pandemic

These research directions have clearly guided the further development of this Ph.D. project. **Paper 2** focuses on smart and sustainable reverse logistics (7, 8). **Paper 3** develops analytical methods and multi-objective models for smart and sustainable reverse logistics design (2, 3, 8). **Paper 4** and **Paper 5** emphasize the methodological and system integration in a digital reverse logistics twin (5, 8). In addition, the logistical challenges brought by the pandemic are tackled by **Paper 7** and **Paper 8** (2, 4, 9).

Paper 2 *Towards the Smart and Sustainable Transformation of Reverse Logistics 4.0: A Conceptualization and Research Agenda*

The increasing adoption of new technologies provides opportunities to allow a high level of system integration enabled by intelligent devices and smart portals, autonomous robots, and data and model-based analytical tools, where the value of technological innovations can be exploited to solve various reverse logistics problems. Several studies have been conducted to improve the smartness, connectivity, and autonomy of isolated reverse logistics operations, e.g., collection, sorting, etc. Based on the findings from the literature and reported case studies, **Paper 2** presents a holistic and systematic conceptual development of *Reverse Logistics 4.0* to guide the smart reverse logistics transformation by adopting Industry 4.0 technologies. The conceptual development of *Reverse Logistics 4.0* is given based on the comparison with the four Industrial Revolutions in history. The technology-enabled smartness and service innovation, i.e., *individualization*, are explicitly explained in the reverse logistics context. Furthermore, to explicitly reveal the connection between the technological enablers and the smart service and operational transformation, the potential impacts of the five main reverse logistics activities are analyzed:

- Smart collection
- Smart sorting and process management
- Smart remanufacturing and recycling
- Smart transportation and distribution
- Smart disposal

To show a clear roadmap toward *Reverse Logistics 4.0* through a smart and sustainable transformation, **Paper 2** specifies a research agenda with a focus on smart reverse logistics network management, service innovation, integration, and digital twin.

Paper 3 *A Two-Level Decision-Support Framework for Smart and Sustainable Reverse Logistics Network Design*

Based on the findings from the literature review and conceptual development, **Paper 3** focuses on the methodological development for smart and sustainable reverse logistics network design. A novel two-level decision-support framework is proposed considering the trade-off between multiple objective functions, smart and dynamic system transformation, parametric uncertainty, real-world GIS, and practical operational policies. The first-level multi-objective mixed integer programming model and the second-level dynamic simulation model are connected via a shared database, which converts the inputs to the appropriate aggregation levels for respective models. This decision-support framework uses the strengths of both optimization and simulation, which enables robust decision-making and comprehensive performance analysis of smart and sustainable reverse logistics network design:

- **Stage I** (*Multi-objective optimization solved with the augmented ε-constraint method*): is to determine a set of Pareto optimal solutions for reverse logistics network configurations considering both economic and environmental objectives. Based on this, a set of candidate solutions is selected.
- **Stage II** (*Dynamic simulation combined with both discrete event simulation and Monte Carlo simulation*): is to run and evaluate the system performance of each candidate solution under a dynamic and realistic environment. The impact of the smart transformation within the planning horizon is also evaluated under different scenarios.

Paper 3 is the first research that combines a mathematical optimization model, discrete event simulation, and Monte Carlo simulation in supporting the strategic decision-making of reverse logistics network design. The proposed two-level decision-support framework is validated through a case study in Norway. The results show that the future smart transformation may affect the strategic decisions of reverse logistics network design at the initial stage. Besides, incorporating a dynamic simulation model can effectively complement the shortcomings of the mathematical optimization model and help to yield robust strategic decisions and comprehensive performance analyses.

Paper 4 *System Integration for Smart Reverse Logistics Management*

Based on the methodological development in **Paper 3** and from the end users' perspective, **Paper 4** discusses the requirements for system integration in smart reverse logistics management. The effective management of a reverse logistics system may require a wide range of analytical tools, i.e., predictive analytics, prescriptive analytics, and descriptive analytics, in order to support decision-making at strategic, tactical, and operational levels. However, using these analytical tools may require different software packages, different coding languages, different data structures, and so forth. **Paper 4** presents a comprehensive framework for system integration in a smart reverse logistics decision-support system, and seven criteria are defined to evaluate the level of maturity of the system integration:

1. Cyber-physical structure
2. Cloud-based system
3. Shared databased and data conversion
4. Flexible network structure
5. Large model database
6. Flexible model modification
7. User-friendly interface

These seven criteria are explained based on the case study performed in **Paper 3**. Three existing software packages in today's market, i.e., SAP, Optimity, and AnyLogistix, are compared against these seven criteria for smart reverse logistics management. **Paper 4** identifies a clear roadmap to guide the next-generation system integration for smart reverse logistics management, and it also defines the criteria for evaluating the level of maturity of system integration.

Paper 5 *A Digital Reverse Logistics Twin for Improving Sustainability in Industry 5.0*

Based on the results from **Paper 3** and **Paper 4**, **Paper 5** further develops the concept and method of digital reverse logistics twin. As one of the most promising concepts and enablers of Industry 4.0/5.0, the digital twin has been defined in reverse logistics, primarily from the product- or process-based perspectives, but not from the system-based perspective. To fill this gap, **Paper 5** investigates the concept and structure of digital reverse logistics twin from the system perspective:

Digital Reverse Logistics Twin is a data-based digital representation of a real-world reverse logistics system, which forms a multi-architecture and high-level integrated information platform by integrating different stakeholders, data, and analytical tools to support various proactive and/or reactive decisions.

The digital reverse logistics twin is considered a high level of CPS that enables effective system visualization and data-driven decision-making with better proactive planning and real-time reactive adjustments. **Paper 5** shows the structure of the digital reverse logistics twin and partially illustrates its application with a remanufacturing network planning problem. Compared with the method in **Paper 3**, the optimization results and the simulation models in **Paper 5** can be better and seamlessly connected via the automatic data conversion in the shared database. **Paper 5** is considered a further development of **Paper 3** and **Paper 4**, which shows the future trend in the development of smart and sustainable reverse logistics management systems.

From the theoretical and methodological development perspective, **Figure 4-2** explicitly illustrates the connection among the papers in this Ph.D. project.

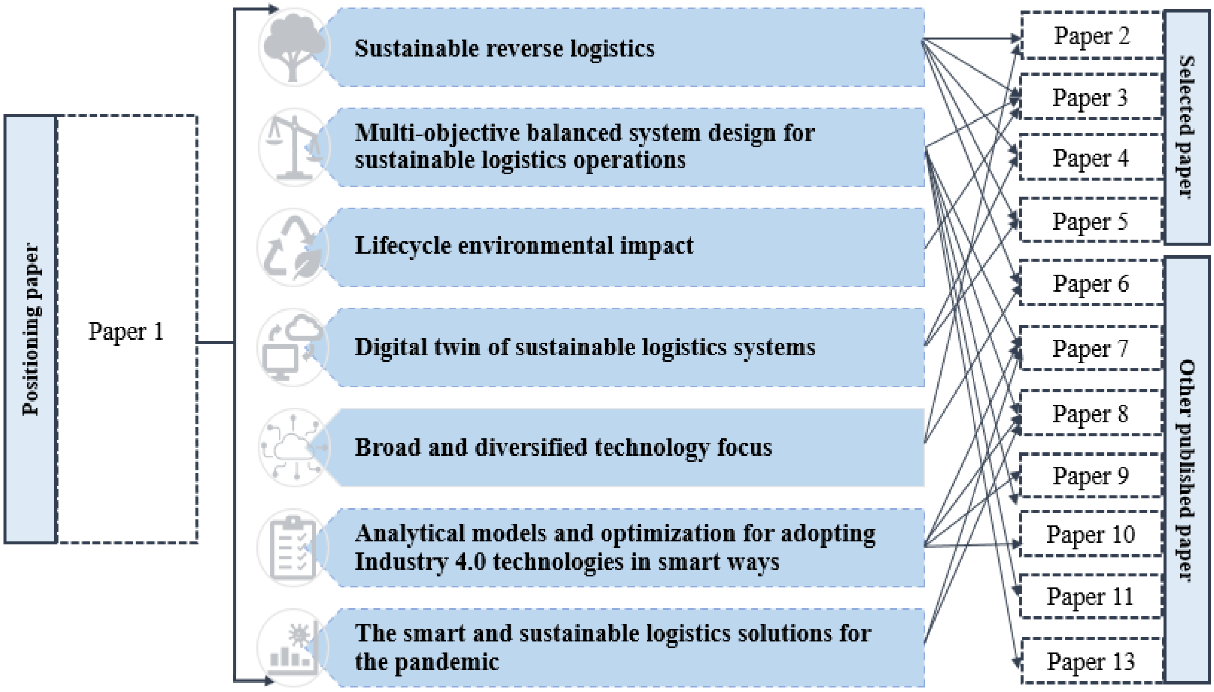

Figure 4-2 Illustration of the connection among the papers in this Ph.D. project.

4.2 Conclusions

Reverse logistics is gaining increasing momentum and has become a strategic emphasis for worldwide companies to attain sustainable competitiveness in today's market. The rapid and accelerated pace of technological advancements has opened up new opportunities for a smart and sustainable reverse logistics transformation in *Reverse Logistics 4.0*. The literature review shows a lack of a systematic analysis of the impacts of disruptive technologies in Industry 4.0 on smart and sustainable reverse logistics management. Furthermore, the current mathematical and simulation models cannot sufficiently support the reverse logistics network design considering smart transformation, dynamicity, uncertainty, and practical operational conditions. Due to these reasons, the robustness and reliability of these models may be significantly compromised in the strategic decision-making of a smart and sustainable reverse logistics system.

Table 4-1 The answers to the research questions of the Ph.D. project.

Research questions	Papers	Conceptual/Methodological development

RQ1: What are the impacts of disruptive technologies on smart and sustainable logistics/reverse logistics operations?	**Paper 1:** Bibliometric analysis and systematic literature review	Providing a comprehensive overview of the recent development and application of the key enabling Industry 4.0 technologies in sustainable logistics at both intra- and inter-company levels to provide a better understanding of the challenges and opportunities of the digital transformation for sustainable logistics. The results identify several research directions to guide future research.
RQ2: What is the potential smart reverse logistics transformation in Industry 4.0?	**Paper 2:** Conceptual development	Providing a systematic conceptual development of *Reverse Logistics 4.0* and analyzing the opportunities for smart and sustainable reverse logistics transformation concerning: • Smart collection • Smart sorting and process management • Smart remanufacturing and recycling • Smart transportation and distribution • Smart disposal
RQ3: How to design and configure a smart and sustainable reverse logistics network?	**Paper 3:** An improved decision-support framework	Developing an improved two-level decision-support system for smart and sustainable reverse logistics network design, where the multi-objective optimization and dynamic simulation models are connected with a shared database to better model the practical features and analyze the dynamic system behaviour of the reverse logistics system.
RQ4: How to develop a smart digital reverse logistics twin?	**Paper 4** and **Paper 5**: System integration and digital reverse logistics twin	Proposing a highly integrated and automatic structure with the purpose of guiding the next-generation system integration and the development of a fully functional digital twin for smart reverse logistics management

In this Ph.D. project, the aforementioned literature gaps are filled with both conceptual and methodological developments. The technological impacts of Industry 4.0 on smart logistics are first analyzed to provide several promising research directions in this field. Based on the proposed directions, research efforts are given accordingly to the conceptual development of smart transformation in *Reverse Logistics 4.0*, the methodological development of the decision-support system for smart and sustainable reverse logistic network design, and the system integration and digital twin for smart reverse logistics management. **Table 4.1** illustrates how the research questions can be answered with the results of the Ph.D. project. The research contributions and industrial contributions are discussed in **Section 4.2.1** and **Section 4.2.2**, respectively.

4.2.1 Research Contributions

By answering the proposed research questions, this Ph.D. project has made the following contributions to the research community related to smart and sustainable reverse logistics management:

1. This project provides a comprehensive analysis of the impacts of Industry 4.0 on both forward and reverse logistics. Nine research directions are suggested to show a clear roadmap toward technology-enabled smart and sustainable logistics systems.
2. This project provides a holistic and systematic conceptualization and definition of *Reverse Logistics 4.0*. It also identifies the key enablers for the smart and sustainable reverse logistics transformation.
3. A novel decision-support framework that integrates multi-objective optimization and dynamic simulation is designed for smart and sustainable reverse logistics network design, which is validated with a case study.
4. From the system configuration perspective, the impacts of smart transformation and technological upgrades on reverse logistics systems are investigated by using a quantitative method.
5. From the methodological perspective, this project demonstrates the benefits of combining advanced optimization with dynamic simulation in the decision support of reverse logistics network design under a highly dynamic, uncertain, and closer to a real-life environment.
6. This project presents a comprehensive discussion on the requirements of system integration and defines the structure of the digital reverse logistics twin for smart and sustainable reverse logistics management. The data flows and conversion among different elements and analytical models are also clearly specified.

4.2.2 Industrial and Managerial Contributions

The industrial and managerial contributions are discussed as follows:

1. The theoretical and conceptual study of Industry 4.0 enabled sustainable logistics provides the logistics companies and practitioners with a clear understanding and roadmap to increase the chance of success of adopting new technologies in the smart logistics transformation. In this regard, one should bear in mind that the benefits should never be overestimated, and the challenges and commitments required should never be underestimated.
2. For government, supply chain and logistics managers, and practitioners, this project provides a hands-on decision-support framework to optimize the strategic network decisions and evaluate new technologies and new operational policies holistically.
3. This project illustrates the application of the proposed decision-support framework with a case study and discusses several managerial implications. For example, the technological upgrade may be carefully planned due to its potential impacts on the costs, carbon emissions, and service level. From the practical perspective, these discussions may also provide other companies with implications for guiding their logistics transformations in the Industry 4.0 era.
4. From the software development perspective, this project defines the structure and key elements for a system-based digital reverse logistics twin. Seven key criteria are also defined for evaluating the maturity level of the system integration in a digital reverse logistics twin, which can be used for better guiding future software development toward smart and sustainable reverse logistics management.

4.3 Limitations and Future Works

The Ph.D. project has proposed new concepts and methods for supporting the decision-making for smart and sustainable reverse logistics network design in *Reverse logistics 4.0*. However, there are still several limitations that need to be improved in future research:

1. First, the parametric uncertainty is not considered in the first-stage multi-objective optimization model of the decision-support framework but is evaluated by dynamic simulation. Since the uncertainties may influence strategic location decisions to a large extent, future research is thus suggested to improve the optimization model to better manage uncertainty.
2. In this Ph.D. project, the economic and environmental indicators are mainly considered in the decision-making of smart and sustainable reverse logistics network design. Future research is needed to better incorporate the social performance in the decision-support framework.
3. In the validation stage of the proposed decision-support framework, several assumptions are used due to data unavailability, i.e., lack of quantitative data related to smart transformation. For future improvement, more quantitative data needs to be acquired for achieving more accurate analytical results.
4. The designed decision-support framework is validated with a case study, which may be inadequate to show an overall picture of the impacts of smart transformation and technological adoption on reverse logistics network design. Therefore, future works may be performed to implement the decision-support framework in other regions, which may yield different insights.
5. In this Ph.D. project, a conceptual framework of a digital reverse logistics twin was designed for methodological and system integration. However, only the combination of prescriptive analytics and descriptive analytics is focused on. Future research is thus suggested to also combine predictive analytics and real-time data in smart and sustainable reverse logistics management.
6. Last but not the least, this Ph.D. project focuses primarily on the technology-driven paradigm transition of *Reverse Logistics 4.0*. However, increasing discussions have been given to the human centricity, resilience, and sustainability of smart logistics transformation in Industry 5.0 [193], so future research is invited to investigate the impact of Industry 5.0 on reverse logistics.

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PAPER 1

The Application of Industry 4.0 Technologies in Sustainable Logistics: A Systematic Literature Review (2012—2020) to Explore Future Research Opportunities

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Author's Contribution

Xu Sun is the main contribution of conceptualization, methodology, data curation, formal analysis, writhing-original draft, and writing-review and editing of the paper.

The Application of Industry 4.0 Technologies in Sustainable Logistics: A Systematic Literature Review (2012—2020) to Explore Future Research Opportunities

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Abstract: Nowadays, the market competition becomes increasingly fierce due to diversified customer needs, stringent environmental requirements, and global competitors. One of the most important factors for companies to not only survive but also thrive in today's competitive market is their logistics performance. This paper aims, through a systematic literature analysis of 115 papers from 2012 to 2020, at presenting quantitative insights and comprehensive overviews of the current and future research landscapes of sustainable logistics in the Industry 4.0 era. The results show that Industry 4.0 technologies provide opportunities for improving the economic efficiency, environmental performance, and social impact of logistics sectors. However, several challenges arise with this technological transformation, i.e., trade-offs among different sustainability indicators, unclear benefits, lifecycle environmental impact, inequity issues, technology maturity, etc. Thus, to better tackle the current research gaps, future suggestions are given to focus on the balance among different sustainability indicators through the entire lifecycle, human-centric technological transformation, system integration and digital twin, semi-autonomous transportation solutions, smart reverse logistics, and so forth.

Keywords: sustainable logistics; green logistics; Industry 4.0; smart technology; literature review; bibliometric analysis

1 Introduction

With the increasing concerns on environmental pollution, resource depletion, and climate change from the whole society, enterprises must transform their businesses and operations into more sustainable ways [1]. Recent studies have shown that more focus and investments on enterprises' sustainable practices not only help them to build up a socially responsible image but also improve their overall sustainable performance in economic and environmental dimensions [2]. Logistics links different operations and players within a supply chain and is a vital part that largely determines a company's overall effectiveness and resource efficiency [3]. Managing a logistics system involves several related activities, i.e., warehousing, inventory handling, information services, and transportation, and any decisions may influence a large number of stakeholders in either positive or negative ways [4]. The effectiveness and sustainability of a logistics system determine the long-term competitiveness and the success of an enterprise. Therefore, new methods are investigated by both academia and industrial practitioners to improve the economic, environmental, and social sustainability of logistics activities.

The recent technological advancement and innovation of Industry 4.0 have provided new opportunities for enterprises to achieve value creation and proposition through satisfying individualized customer demands responsively and cost-effectively [5]. This has not only led to a shift of the manufacturing paradigm but also drastically affected the way of logistics operations toward a high level of digitalization, connectivity, intelligence, integration, and responsiveness [6]. Even though Industry 4.0 provides new opportunities for enterprises to enhance their sustainable logistics practices, the operational transformation by adopting these new technologies has, however, never been a painless endeavor, which may also encounter structural resistance at both intra- and inter-enterprise levels [7]. Thus, a systematic literature analysis is important to provide useful implications into the advantages and challenges of adopting new technologies in sustainable logistics, which can help with a successful transformation of a company in the coming digital era.

Previous literature reviews have provided comprehensive insights into sustainable logistics planning [3, 8], green and sustainable logistics practices [9-11], sustainable freight transport [12, 13], and knowledge management in sustainable logistics [14]. To improve the intelligence, agility, and efficiency of logistics activities, recent studies have put predominant emphasis on the adoption of new technologies, e.g., big data analytics [15], blockchain [16], artificial intelligence (AI) [17, 18], internet of things (IoT) [19], and additive manufacturing (AM) [20]. This trend has led to the new architecture of Logistics 4.0 [21]. Besides, several recent reviews have discussed the connection between Industry 4.0 and general sustainable practices [22].

Table 1 shows the comparison of recent literature reviews related to Industry 4.0, sustainability, and logistics. As shown, the research focus has been predominantly given to the general sustainability and supply chain issues related to Industry 4.0. However, there is still a lack of systematic analyses focusing on linking sustainable logistics practices with different Industry 4.0 technologies. Logistics is traditionally a labor-intensive industry, which experiences significant changes in this digital transformation, and both positive and negative impacts on the economic, environmental, and social sustainability need thus to be better understood. Besides, the use of both bibliometric analysis and content analysis has not been fully exploited. Bibliometric analysis is a quantitative method that shows the network data visualization of the inter-connections of different literature in several dimensions, but it has been rarely used in the literature reviews of Industry 4.0 and sustainability, particularly in combination with content analysis.

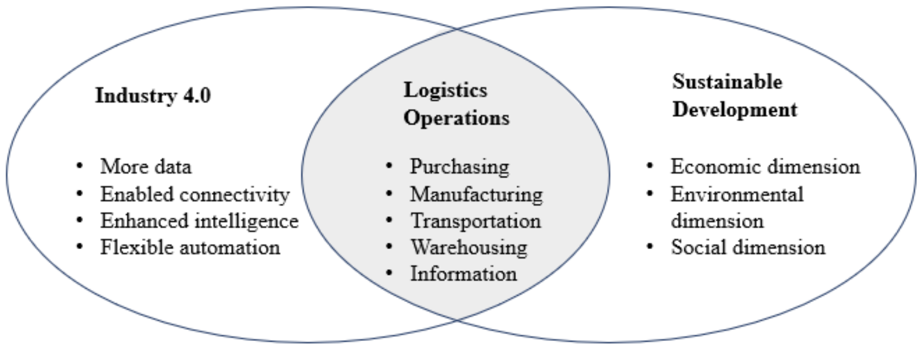

Figure 1 Schematic of the research focus of this paper.

Therefore, as shown in Figure 1, this paper aims at filling the literature gap by conducting a systematic literature review to illustrate the current and future research landscapes of sustainable logistics in the Industry 4.0 era. The contributions are summarized as follows:

1. Using both bibliometric analysis and content analysis, we thoroughly explore the current research landscape that links sustainable logistics practices with various Industry 4.0 technologies.
2. We analyze both opportunities and challenges of adopting Industry 4.0 technologies in logistics sectors related to economic, environmental, and social sustainability.
3. We suggest nine future research directions to fill the current research gaps.
4. From the practical perspective, the discussions provide some successful examples of Industry 4.0 enabled transformation of logistics systems.

Following the introduction, Section 2 gives the theoretical background of sustainable logistics and Industry 4.0. Section 3 presents the research method. Sections 4 and 5 provide the bibliometric analysis and the content analysis. The opportunities, challenges, and future research suggestions are discussed in Section 6. Finally, Section 7 concludes the paper.

Table 1 Relevant literature reviews related to Industry 4.0, sustainability, and logistics.

Papers	Research Method		Sample selection		Research focus and perspectives	Keywords			
	Bibliometric analysis	Content analysis	Horizon	Sample size		Industry 4.0	Sustainability	Logistics	Supply chain
Davarzani, Fahimnia [23]	√		1975- 2014	338	Green and sustainable maritime logistics		√	√	
Bag, Telukdarie [24]		√	1998-2017	53	Industry 4.0 enablers of supply chain sustainability	√	√		√
Ranieri, Digiesi [25]		√	2012-2016	24	Innovative last-mile delivery systems			√	
Kazemi, Modak [26]	√	√	2000-2017	94	Reverse logistics and closed-loop supply chain			√	√
Nenni, Sforza [12]		√	1997-2018	93	Sustainability of urban freight transport		√		
Tijan, Aksentijević [19]		√	Until 2018	--	Blockchain technology in logistics			√	
Manavalan and Jayakrishna [27]		√	2009-2018	--	IoT embedded sustainable supply chain	√			√
Martins, Anholon [11]		√	Until 2019	45	Sustainable logistics considering TBL		√	√	
Ren, Hu [9]	√	√	1999-2019	306	Green and sustainable logistics		√	√	√
Chalmeta and Santos-deLeon [15]	√		2009-2019	87	Industry 4.0 and big data in sustainable supply chain practices	√	√		√

Winkelhaus and Grosse [6]		√	2005-2018	114	Industry 4.0 and logistics	√		√	
Roblek, Thorpe [22]		√	2010-2020	173	Industry 4.0 and sustainability	√	√		
Ejsmont, Gladysz [28]	√		2011-2020	162	Sustainability and Industry 4.0	√	√		
Ghobakhloo [29]		√	2012-2019	72	Industry 4.0 and sustainability	√	√		
Furstenau, Sott [30]	√		2010-2019	894	Industry 4.0 and sustainability	√	√		
Birkel and Müller [31]		√	2011-2019	55	Industry 4.0 for sustainable supply chain management	√	√		√
Margherita and Braccini [32]		√	2009-2019	18	Industry 4.0 organizational impacts on sustainability	√	√		
Beier, Ullrich [33]		√	2013-2021	51	Industry 4.0 and socio-technical sustainability	√	√		
Grzybowska and Awasthi [34]	√		1991–2018	892	Sustainable production and logistics		√	√	
Abdirad and Krishnan [35]		√	2014-2018	56	Industry 4.0 in supply chain management	√		√	√
Jahani, Sepehri [36]		√	2015-2020	70	Industry 4.0 in the procurement processes of supply chains	√	√		√
Beltrami, Orzes [37]		√	2011-2020	117	Industry 4.0 and sustainability	√	√		
This paper	√	√	2011-2020	115	Sustainable logistics enabled by Industry 4.0	√	√	√	

2 Theoretical Background

2.1 Sustainable logistics

The word logistics appeared more than a century ago and was originally associated with the movement of troops and military supplies [38]. Over time, this word has been widely used to broadly describe the movement of physical goods among different locations [39]. Logistics deals with the entire cycle including pre-production, in-production, and post-production activities [40]. To fulfill customer needs at a satisfactory level, logistics aims at implementing a set of decisions including the purchase of raw materials, parts, and components, the handling and storage of inventories, and the transportation of goods from one location to another. The effectiveness and efficiency of the logistics system largely determine an enterprise's performance in cost, customer satisfaction, and profitability. Recently, a concept called supply chain management has been used interchangeably to depict several logistics activities, but the scopes of the two words are not overlapped with each other [41]. Several researchers suggest that supply chain management focuses more on forming strategies to manage the relationships and coordination among different partners [6, 42], while logistics, on the other hand, emphasizes the implementation of these strategies to connect different companies with physical flows [39]. In this regard, logistics can be considered a subset of supply chain management [6], which focuses on the physical movement of goods and the relevant information flow.

Sustainable development has been focused on due to the concerns of increasingly severe environmental and social challenges. The widely accepted definition of sustainable development is "*to meet the needs of the present without compromising the ability of future generations to meet their own needs*" [43]. Sustainable development is driven by three dimensions, namely, economic prosperity, environmental friendliness, and social fairness and equity, which are also known as the triple bottom line. The objective of a sustainable development society is to achieve harmony among these three dimensions. For tackling the global challenges related to hunger and poverty, health and well-being, environmental pollution, climate change, and global warming, the United Nations (UN) has recently set up 17 sustainable development goals, which are the call for actions to achieve a better future for all human beings by 2030 [44].

A drastic increase of companies has started to incorporate sustainability into logistics operations to enhance their social image and competitive advantage [45]. Sustainable logistics was initially focused on from the environmental perspective of lowering the ecological footprint related to logistics activities [46]. The concept of green logistics was first proposed to reduce environmental impacts, e.g., GHG emissions [47], energy consumption [48], etc., through better strategic designs and operational planning. Reverse logistics and closed-loop supply chain (CLSC) have been increasingly focused to achieve sustainable value re-creation from end-of-life (EOL) products [49] and minimizing the environmental pollution from waste management [50, 51]. However, improper disposal activities lead to risk exposure to both humans and the environment [52, 53]. Thus, recent research efforts have been given to minimize the ecological footprint of both forward and reverse logistics [54]. Furthermore, not only the economic and environmental dimensions but also the social sustainability indicators, i.e., job creation and working environments, have been holistically considered in sustainable logistics. Therefore, sustainable logistics aims at balancing the socio-economic performance of a logistics system with its eco-environmental robustness in managing system activities. This balance embodies in making decisions by considering the interplay of different logistics functions, i.e., network configuration, transportation, purchasing, demand allocation, and resource management. The optimization of a sustainable logistics system is highly dependent on the ability to balance the trade-offs among the three dimensions of sustainability.

2.2 Industry 4.0

Industry 4.0, or the fourth industrial revolution, was put forward at the Hannover Fair of Industrial Technologies in 2011 to enhance the competitiveness of the German manufacturing industry [55]. At the global level, several countries have also launched their strategies, e.g., United States's *National Network for Manufacturing Innovation*, Japan's *New Robot Strategy,* and China's *Made in China 2025,* to strengthen their manufacturing industries by taking advantage of technological innovations [56]. While the past three industrial revolutions in history were the major results of mechanization, mass-production, and automated production [55], Industry 4.0 puts predominant focus on combining Internet-based communication technologies, digitalization, and future-oriented intelligent manufacturing technologies to build smart machines and systems, implement smart processes, and provide smart products and services [56]. Empowered by Industry 4.0 technologies, a smart production network can achieve real-time monitoring, responsive communications, autonomous operations, and smooth material flows. Technological advancement has provided opportunities and new business models for value creation and proposition from individualized customizations and service innovations [57]. Based on previous studies [58-60], the 12 most important Industry 4.0 technologies are introduced as follows:

- ***Internet of Things (IoT)***: IoT refers to the network interconnection that possibly connects millions of physical objects with the Internet [61]. It allows different smart devices can be interconnected, monitored, communicated, and controlled based on standard communication protocols to facilitate the transition of goods, services, and information [60].
- ***Cyber-Physical System (CPS)***: CPS is the system integration of computational intelligence and physical elements, which enables effective interactions between the system and humans [62]. CPS aims at achieving a high level of connectivity, intelligence, and automation by integrating both cyber and physical components [63]. Thus, the level of CPS largely determines the successful implementation of Industry 4.0 [64].
- ***Big Data Analytics***: Big data analytics is the state-of-the-art analytical capability to process a large volume of dynamic data with high velocity, high complexity, and high variety. The strategies and operations of a company or a system can be continuously evaluated through massive data analytics to obtain critical insights for better business planning and decision making [65].
- ***Artificial Intelligence (AI)***: AI refers to the computer systems and applications that perform tasks needing human intelligence [66], and it also has the capacity of learning and improving the thinking, perception, and action through training from data and algorithms [67]. AI algorithms are widely used in many areas, e.g., routing, traffic management, maintenance, and security [68].
- ***Cloud Technologies***: Cloud technologies provide a central platform for the storage and integration of configurable information technology (IT) resources, which enable the accessibility of data and resources from decentralized locations. Cloud technologies form the

service-oriented architecture that links the concepts of Platform-as-a-Service (PaaS), Software-as-a-Service (SaaS), and Information-as-a-Service (IaaS) [69].

- ***Blockchain:*** Blockchain is an innovative way for implementing distributed ledger technologies that can be programmed to record and track any data by anyone without a central authority, and it is a peer-to-peer network and a nondestructive way to track data changes over time [70].
- ***Autonomous Robots***: Autonomous robots are highly intelligent and capable of self-organization, self-evaluation, and decision making for executing several tasks without human instructions [71]. An autonomous robot can be in various sizes and shapes, and with different levels of autonomy, mobility, and intelligence [71].
- ***Unmanned Aerial Vehicle (UAV)***: UAV, or commonly referred to as drone, is a flying device that does not require a human pilot onboard. It is typically piloted by remote control or by a combined control with computer programming [72].
- ***Additive Manufacturing (AM)***: AM, or 3D printing, is a layer-wised production or generative manufacturing. By adding material layer upon layer, it provides opportunities for the accurate production of items at the required size, shape, and material without any wastes [73]. With technological maturity and the growing awareness of sustainability, AM has been increasingly used as the main element in both production and logistics processes.
- ***Augmented Reality (AR)***: AR in the overlaying of computer-generated digital information, e.g., texts, images, and effects, in the real world, which can interact with users and give real-time instructions in a user-friendly way [74].
- ***Virtual technologies and simulation:*** Virtual technologies are powerful tools, which can mimic, evaluate, optimize, and control a real-world entity or a system in its digital representation under a risk-free and cost-efficient environment.
- ***Cybersecurity*:** Cybersecurity refers to the protection and defense of critical data, servers and computers, software, and other IT resources from cyber-attacks [75].

3 Research Method

A systematic literature review aims at identifying, evaluating, interpreting, and categorizing all relevant articles engaging one or more research questions and topics [25, 76]. Compared with a narrative literature study whose results mainly focus on the descriptive findings of a specific domain of knowledge and may suffer from selection bias, a systematic literature review can present a comprehensive overview of the research landscapes [14]. Based on Kazemi, Modak [26] and Ren, Hu [9], a systematic literature review consists of the following steps:

1. *Identification of Research questions*: Formulating the research questions to be answered.
2. *Literature search and selection*: Developing a document search strategy with a broad combination of keywords to have a comprehensive overview of the area under investigation. Then, proper filters are set up so that the most relevant sample of articles is solicited.
3. *Bibliometric analysis*: Presenting a quantitative analysis and data visualization of the selected sample of articles to understand the key characteristics of the topic, e.g., publication trend, journals and citations, collaborations, keyword focus, etc.

4. *Content analysis*: Performing a detailed content analysis of the selected articles to summarize the contributions of several related topical areas. Based on this, the current research landscape can be understood, and future research opportunities can be identified.

The research questions are formulated to reflect the aim and scope. This paper links two concepts: sustainable logistics and Industry 4.0, and their interactions in literature are thus focused on. Concerning these concepts, the following three research questions are proposed to understand the state of knowledge of adopting Industry 4.0 technologies in sustainable logistics:

- *RQ1*: What literatures exist on sustainable logistics enabled by Industry 4.0 and how can they be categorized?
- *RQ2*: What are the implications of sustainable logistics in the Industry 4.0 era?
- *RQ3*: What are the future research directions to fill the gaps?

Based on the research questions above, Figure 2 formulates the document search strategy, which includes five steps: 1) keyword search, 2) setting of the filters, 3) investigation of the titles and abstracts, 4) investigation of the full text, and 5) result analysis, respectively.

1. ***Keyword search***: In this paper, we performed a keyword search using two electronic databases: Scopus and Web of Science core collection. The literature search was conducted in November 2020, and two main sets of keywords related to sustainable logistics and Industry 4.0 were used. The first set of keywords is associated with sustainable and smart logistics, which consist of "sustainable logistics", "smart logistics", and "logistics 4.0". Besides, since many logistics issues were discussed in the context of supply chains, "sustainable supply chain" was added to this group. The other set of keywords related to Industry 4.0 includes "Industry 4.0", "I4.0", "smart manufacturing", "smart production", "the fourth industrial revolution", "IoT", "CPS", "big data analytics", "augmented reality", "cloud computing", "additive manufacturing", "autonomous robots", "smart robot", "simulation", "cybersecurity", "virtual technology", "artificial intelligence", "unmanned aerial vehicle", and "blockchain". The Boolean operator "OR" was used to combine the keywords within the same group, and "AND" was used to combine the two main groups of keywords related to both sustainable logistics and Industry 4.0. The initial search yielded 512 results in Scopus and 245 in Web of Science.

2. ***The setting of the filters:*** The second step is to set up several filters to select the most relevant articles, and the papers are excluded if they are not within the research scope or are irrelevant for answering the research questions. First, since the concept of Industry 4.0 was originally presented at the Hannover fair in 2011 [55], the search horizon was re-set to 2011—present. Considering the quality and rigor of selected papers, the search results were also limited to journal articles that had passed the peer-review stage. The publishing language was restricted to English. Thus, conference proceedings, book chapters, pre-prints, and papers published in another language were excluded in this study. After implementing these new filters, the search resulted in 211 and 126 qualified articles in Scopus and Web of Science, respectively. We combined the search results from the two databases and removed the duplicated ones, which resulted in 229 articles.

3. ***Investigation of the titles and abstracts***: First, we investigated the type of paper in the filtered sample, 8 bibliometric analysis papers, editorial and review articles were excluded. Then, we investigated the thematic relevance of these articles, papers that have little relevance of using Industry 4.0 and smart technologies in sustainable logistics were excluded. Besides, papers dealing with behavior supply chain issues, e.g., customer relations management, but without a logistics focus, were also excluded. In total, 101 papers were excluded in this stage.

4. ***Investigation of the full text***: In the next step, we conducted a full-text reading in the second-round paper selection. In this stage, special emphasis was paid to the papers that lack direct implications for the proposed research questions. Even though these papers have both keywords of Industry 4.0 and logistics or sustainability, the application of Industry 4.0 technologies in sustainable logistics is not thoroughly discussed, so these papers are considered irrelevant to answer the research questions. In this stage, another 13 papers were considered not to fit well with the topic and were thus removed. Then, a total of 115 papers were selected.

5. ***Result analysis:*** Based on the selected sample, the bibliometric analysis was conducted to provide the results of publication trend, source distribution, co-authorship analysis, citation analysis, and keyword co-occurrence analysis. Next, the content analysis was performed to discuss how different logistics operations can be improved by Industry 4.0 technologies and present the opportunities, challenges, and future research directions.

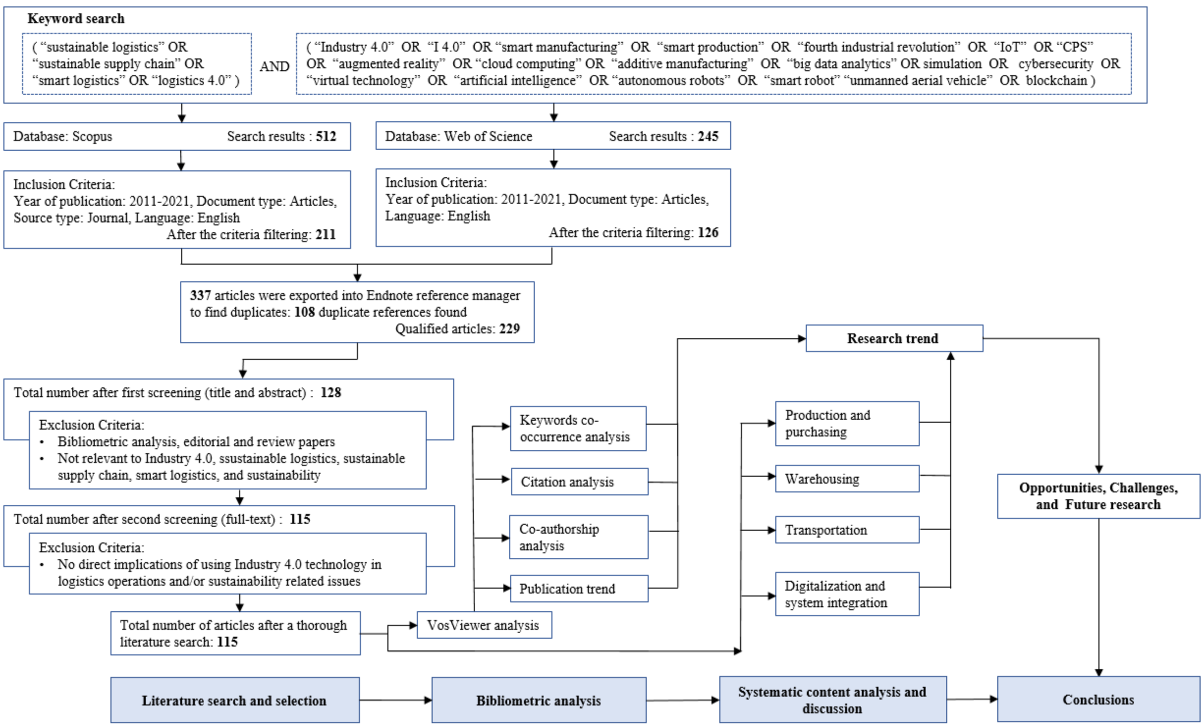

Figure 2 Research method.

4 Bibliometric Analysis

4.1 Publication trend

Figure 3 illustrates the number of articles published between 2012 and 2020. It can be seen that increasing focuses have been given to adopting Industry 4.0 technologies in sustainable logistics planning and operations, and this trend has experienced a significant acceleration since 2017. In 2020 alone, 48 papers have been published in international journals, which amounts for 41.7% of the total publications in the last decade. The publication trend shows that the recent rise of Industry 4.0 related research has presented new opportunities for achieving sustainable value creation, environmental friendliness, and improved social responsibility in logistics activities, which have been noted by both industry professionals and academia.

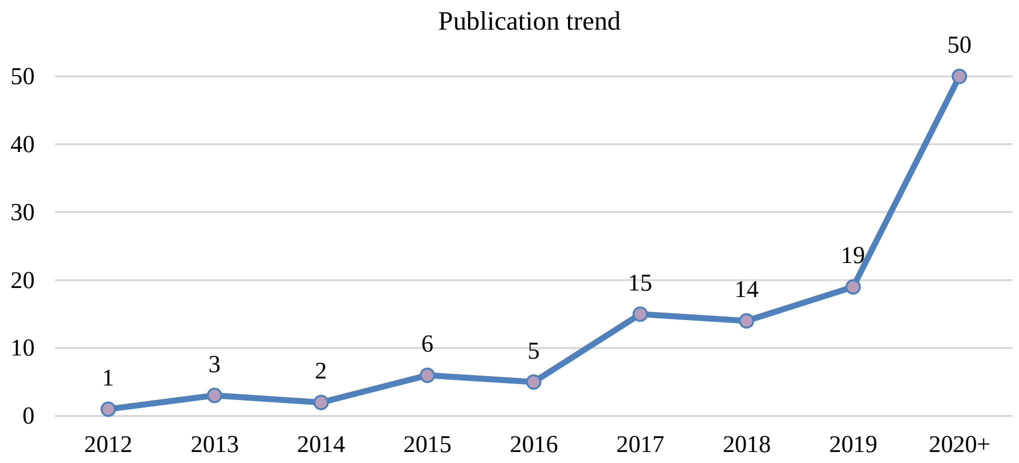

Figure 3 Publication trend of sustainable logistics enabled by Industry 4.0.

4.2 Source distribution, influences, and interactions

Table 2 presents the source distribution of the selected 115 articles, which are published in 73 journals. The most popular 15 journals in this field published 57 articles, accounting for nearly 50% of the total amount. With 9 papers published, Journal of Cleaner Production has the highest number of publications, and it is followed by Sustainability with 8 papers. Both are multidisciplinary with the primary focus on theoretical advancements and practices in sustainable development and circular economy. The next three most popular journals are International Journal of Production Research, Resources Conservation and Recycling, and IEEE Access, contributing to 7, 5, and 5 papers, respectively. Followed by Industrial Management and Data Systems, International Journal of Production Economics, and Journal of Self Governance and Management Economics with 3 articles each. Among the most popular 15 journals, Sustainability, IEEE Access, and Applied Sciences are open access journals, while the others are hybrid journals with both subscriptions only and paid open access options. These 15 journals cover various topics, i.e., sustainable development, production and economics, engineering, computer and data sciences, and logistics and transportation, which shows the cross-disciplinary nature of combining Industry 4.0 and sustainable logistics.

Table 2 Source distribution.

Publication source (Journal)	Number of papers
Journal of Cleaner Production	9
Sustainability Switzerland	8
International Journal of Production Research	7
Resources Conservation and Recycling	5
IEEE Access	5
Industrial Management and Data Systems	3
International Journal of Production Economics	3
Journal of Self Governance and Management Economics	3
Applied Sciences Switzerland	2
Chemical Engineering Transactions	2
Computers and Electronics in Agriculture	2
Economics Management and Financial Markets	2
International Journal of Logistics Management	2
International Journal of Logistics Research and Applications	2
Transportation Research Part E Logistics and Transportation Review	2
Others (1 per Journal)	58

We conducted a co-citation analysis to understand the interactions among the most influential journals in this field. The minimum number of citations per journal was set to 20 in VOSviewer, which led to 16 qualified sources for the co-citation analysis. Compared with the list of journals in Table 2, six new journals were selected including Computers & Industrial Engineering, Expert Systems and Applications, Omega, Journal of Operations Management, International Journal of Physical Distribution & Logistics Management, and Procedia CIRP. The result is shown in Figure 4. The size of each node shows the number of citations received by the relevant papers published in each journal, and the arc linking two journals illustrates the co-citation strength between them.

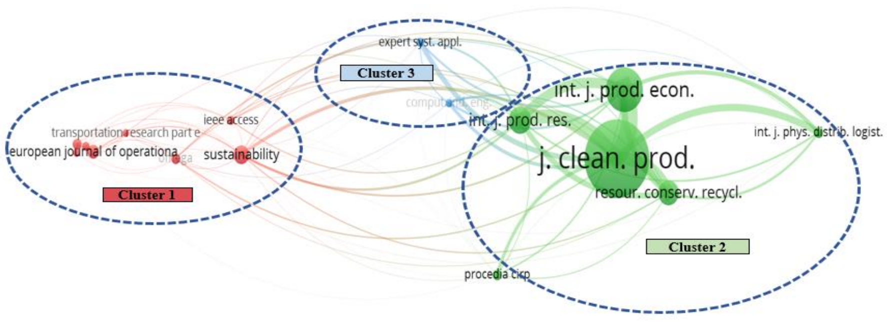

Figure 4 The journal co-citation network.

Three general clusters of journals are identified based on their co-citation activities. The first cluster focuses on operations research and operations management. Besides, two inter-disciplinary journals (Sustainability and IEEE Access) are also assigned to this cluster. The second cluster relates to production technologies and management, while the third cluster emphasizes industrial applications.

The journals in the second cluster, particularly Journal of Cleaner Production, International Journal of Production Economics, and International Journal of Production Research, have yielded the most significant impact and the most active interactions with others in the contemporary research associated with sustainable logistics and Industry 4.0. In addition, the active interactions between clusters 1 and 2, and between clusters 2 and 3 indicate that production-related journals become a bridge to connect the theoretically focused operations research and management methods with real-world industrial applications.

4.3 Influential research, co-authorship network, and co-citation map

Table 3 presents the authors, technologies, applications, and the number of citations of the top ten most influential papers by the time of this research. The most cited article is given by Saberi, Kouhizadeh [77], in which the relationship between blockchain and sustainable logistics is thoroughly investigated. Followed by Barreto, Amaral [60] and Luthra and Mangla [45], the implications and challenges of Industry 4.0 on logistics activities are discussed. The fourth and fifth highly cited papers are from Prause [78] and Prause and Atari [79], which focus on Industry 4.0 enabled architectures of sustainable business models and sustainable manufacturing networks related to logistics operations. In addition, the other papers give comprehensive discussions on the use of several emerging technologies to achieve smart and sustainable logistics, i.e., cloud-enabled product-service system [80], IoT-based smart warehouse management [81, 82], smart technology-enabled innovative and sustainable business models [59], smart decision making of sustainable logistics [83], and sustainable logistics practices [84, 85]. The results show that, in sustainable logistics systems, the application of several Industry 4.0 technologies, i.e., blockchain, IoT, and cloud-based technologies, has enjoyed tremendous popularity among recent research.

Table 3 The top 10 highly cited articles.

Papers	Technological keywords	Application focuses	Citations
Saberi, Kouhizadeh [77]	Blockchain	Sustainable logistics and supply chain	225
Barreto, Amaral [60]	Industry 4.0	Logistics operations	132
Luthra and Mangla [45]	Industry 4.0	Sustainable logistics and supply chain challenges in developing countries	106
Prause [78]	Industry 4.0	Sustainable business models	60
Prause and Atari [79]	Industry 4.0	Sustainable production networks and logistics	52
Zhang, Liu [80]	Cloud technology	Product-service oriented cloud logistics	52
Lee, Lv [81]	IoT	Smart warehouse management	47
Strandhagen, Vallandingham [59]	Industry 4.0	Sustainable business innovations for Logistics 4.0	43
Cole, Stevenson [86]	Blockchain	Logistics and supply chain	40
Li, Fang [83]	Cloud technology	Sustainable logistics and supply chain	34

To identify the most fruitful collaborations and active interactions among different researchers in this field, co-authorship mapping and co-citation mapping are given in Figures 5 and 6. With the help of VOSviewer, a comprehensive co-authorship network analysis of 363 authors was performed, whose result illustrated the 16 most collaborative authors and their collaborations on the time horizon. The nodes are identified by the authors' names, whose sizes show the levels of collaborations of different authors. The arcs link these authors with the number of co-authored papers and the time of publications, which are represented by the width and the color of an arc. The total link strength (TLS) of an author is determined by both the number of connecting links and the number of co-authored documents. As shown in Figure 5, these 16 authors are divided into five clusters with a different number of co-authored papers and citations. The co-citation map in Figure 6 evaluates the influence of the key researchers and the impacts of their papers on other researchers' works in sustainable logistics enabled by Industry 4.0. In this analysis, the minimum number of citations per author was set to 20 to identify the most influential researchers who drove the advancement of this field. The results have shown the 21 most influential researchers and their co-citation networks.

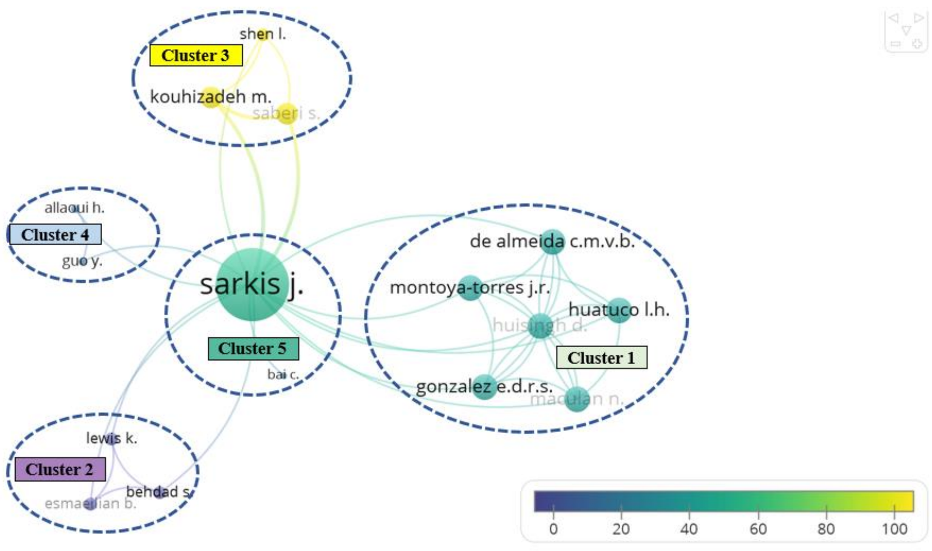

Figure 5 Co-authorship mapping of collaboration.

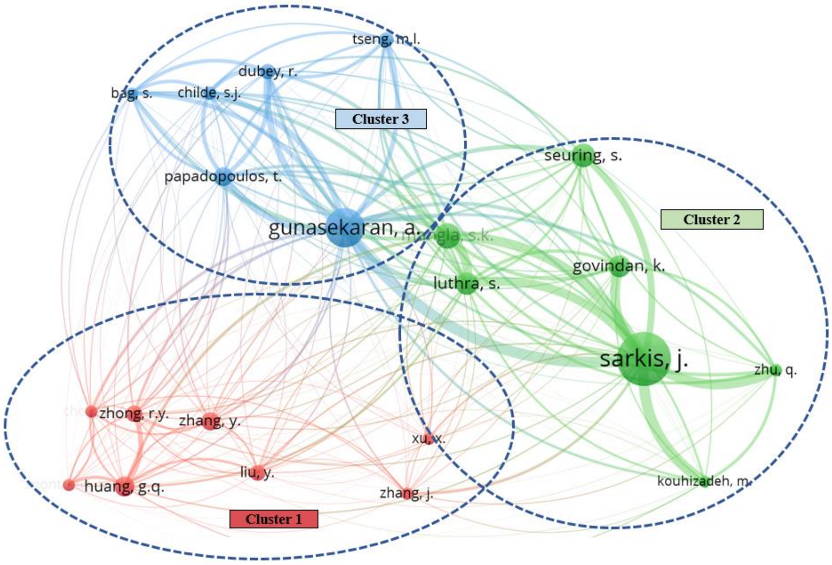

Figure 6 Co-citation map.

Through the comparison between the co-authorship map and the co-citation map, two interesting findings are obtained. First, even though the combination between sustainable logistics and Industry 4.0 has been extensively focused on by worldwide researchers, the collaboration network has not become extensive compared with other well-established fields. This is because this emerging and cross-disciplinary research topic is still at its initial stage. Another reason may be explained by the time from cooperation to publication is usually very long, which may also significantly affect the results of the co-authorship analysis. The second finding is that, even if the collaboration potential has not been fully exploited, several influential researchers and works have led the research and drastically push forward the knowledge accumulation, which forms the foundation to promote fruitful collaboration in the future.

4.4 Research highlights and keywords

To identify the research highlights, a co-occurrence analysis of the highly used keywords related to Industry 4.0 and sustainable logistics was performed. For presenting a complete overview of the current research landscape, we used “all keywords” and “full counting” options to enumerate all the keywords that appeared in previous studies and calculate the total co-occurrence. With the minimum threshold of three times of co-occurrence, Figure 7 shows the mapping and interactions of the 78 qualified ones out of the total 1006 keywords. The clusters, occurrences, and TLSs of these keywords are given in Appendix A.

The 10 mostly used keywords in the selected literatures consist of supply chain management (Occurrence = 39, TSL = 264), Industry 4.0 (Occurrence = 34, TSL = 151), sustainability (Occurrence = 29, TSL = 191), sustainable development (Occurrence = 28, TSL = 220), sustainable supply chains (Occurrence = 28, TSL = 235), internet of things (Occurrence = 21, TSL = 117), decision making (Occurrence = 19, TSL = 115), smart logistics (Occurrence = 17, TSL = 52), logistics (Occurrence = 14, TSL = 59), and supply chains (Occurrence = 13, TSL = 94). Clearly, these mostly used keywords have critical impact and define the general nature of smart and sustainable logistics systems. Besides, it is noted that even if supply chain management and logistics are two concepts, they are not mutually exclusive. Since logistics is considered an important element of supply chain, many relevant studies discuss the sustainable logistics enabled by Industry 4.0 in the context of supply chain management and sustainable supply chain.

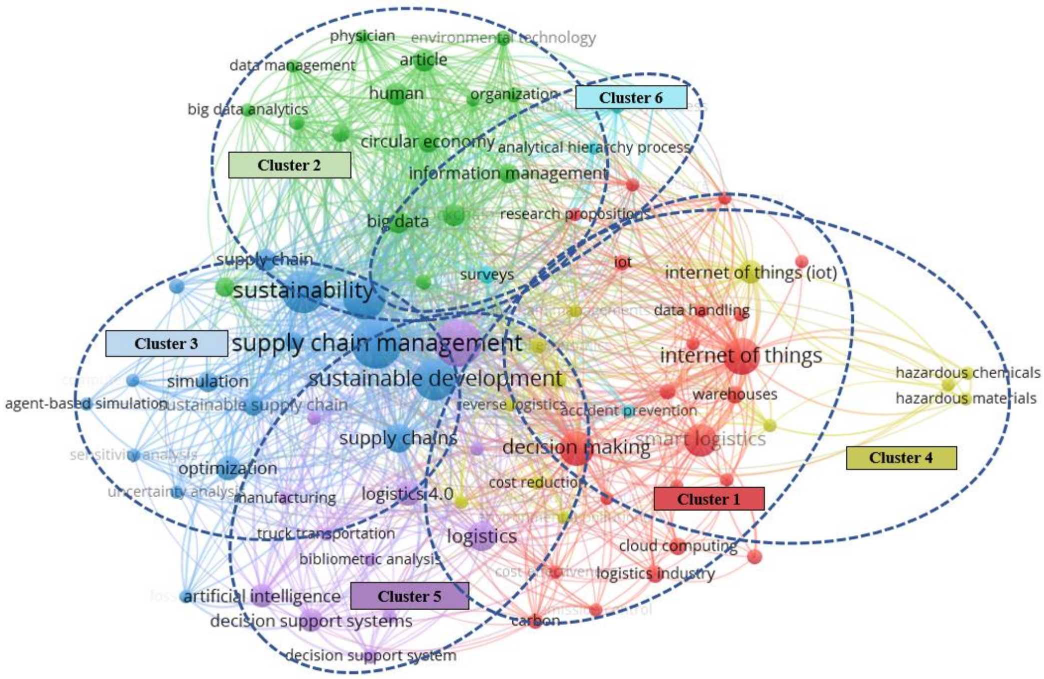

Figure 7 Keyword co-occurrence map.

The 78 frequently appeared keywords are grouped into six clusters, with which the mainstream research directions on Industry 4.0 enabled sustainable logistics can be pinpointed. The six keywords clusters have identified the different research focuses. Cluster 1 comprises 23 keywords focusing mainly on the application of new technologies, e.g., IoT, cloud computing, etc., in smart warehousing, smart information systems, and other logistics operations. Cluster 2 contains 16 items that predominantly emphasize the use of big data analytics and blockchain to improve sustainable logistics and circular economy. Cluster 3 covers 16 nodes focusing on sustainable logistics operations with optimization and simulation methods. Cluster 4 consists of 11 keywords, which engage in the economic, environmental, and social sustainability of hazardous material management. Cluster 5 includes 8 nodes that focus on improved decision making with AI and other smart technologies. Cluster 6 consists of 4 keywords related to literature studies, which show efforts have been spent to summarize the recent research results.

5 Content Analysis

The keyword co-occurrence analysis has shown the importance of technology and data in sustainable logistics, and the content analysis is performed to understand how smart technologies and data analytics will affect the paradigm of logistics operations and the system’s sustainability. Content analysis is an important step to systematically analyze the research development of several topical areas [26]. In this section, we present a detailed content analysis of four main topics related to sustainable logistics operations throughout the pre-production, in-production, and post-production stages. First, smart production drives new demand patterns and changes the way of how demands are satisfied, and it consequently changes the demands of purchasing and logistics services. Thus, Industry 4.0 enabled sustainable production and purchasing was first discussed. The smart solutions for the two most important logistics operations, namely, warehousing and transportation, were then introduced. Last but not least, the general digitalization and system integration issues for streamlining different operations within a sustainable logistics system were given. Figure 8 shows the article distribution over the four topics, and it is noted 22.6% of papers focus on two or more topical areas. A summary of relevant papers, technologies, and sustainability dimensions (environmental or social) of logistics systems in each topic is given in Appendix B.

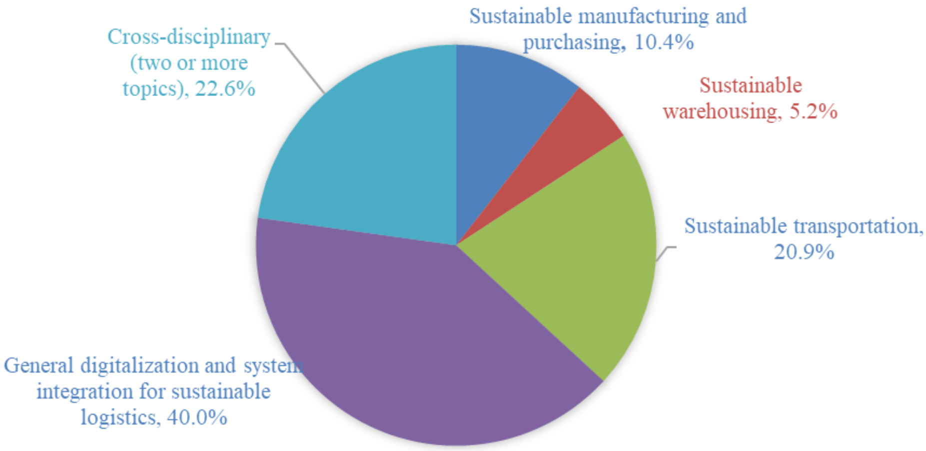

Figure 8 Article distribution over different topical areas.

5.1 Industry 4.0 enabled sustainable production and purchasing

In an increasingly globalized and dynamic market, Industry 4.0 technologies play vital roles in improving the sustainability of production operations, purchasing decisions, and resource planning. These technologies can enable efficient commodity flow and information flow from raw material purchasing to product delivery through an open, dynamic, smart, and sustainable production-logistics network [79]. Besides, they can affect the capabilities of dynamic remanufacturing, green production, waste reduction, and recycling in a sustainable logistics system [87, 88].

IoT and autonomous robots are the fundamental parts of a smart production system, which allow for a high level of connectivity and automation. IoT-embedded systems can provide better tracking and traceability, which help products move faster and provide customers with real-time information about the deliveries [89]. The integration of IoT-enabled devices, autonomous robots, cloud-based data analytics form a connected, digitalized, and smart production CPS. This smart networking of both physical devices and cyber intelligence enables effective machine-to-machine communications and human-machine interactions [57], which pave the way for an autonomous production system with high flexibility and agility.

Big data analysis has gained increasing focus in production and logistics. Advanced analytical tools, i.e., AI and machine learning, have been used to treat a large amount of complex data collected from different sources [65]. The results can be used to analyze market trends, purchasing patterns, potential risks, equipment maintenance cycles [90], delivery reliability and responsiveness [89], and other important performance indicators [65], based on which production activities can be planned more sustainably.

AM can be used for on-demand and decentralized production, which allows customers to be actively involved in product design. AM can help to reduce size-related resource constraints [91], to minimize waste of materials, and to support low-volume and highly customized production, e.g., spare parts [73]. The open design architecture of AM facilitates market growth, promotes localized production, generates value-differentiated consumer demands, changes the market leaders' practices, and supports and diffuses social sustainability in their daily activities [91].

Cloud technologies provide a platform for centralized storage and decentralized access of various data analytics and computing tools to fulfill the growing demands of mass individualization, improve the responsiveness to customers and market change, and enable broader global cooperation [59]. The maturity of supplier selection and purchasing strategy can be affected by the effectiveness and timeliness of data exchange with partners [92]. In this regard, Ma, Wang [93] presented a sustainable make-to-order apparel supply chain model with a collaborative cloud service platform. The key information, i.e., the order queue of the supplier, the raw material status, and the production capacity can be accessed in real-time, which are used for making sustainable production and purchasing decisions in the apparel industry.

With the high reliability and transparency, blockchain is another highly focused Industry 4.0 technology for the effective integration of information flow and material flow [77]. Blockchain can change the way of obtaining, managing, and using the critical product data through the entire product lifecycle, which enables a better product design, more effective production and sales planning, and responsible recovery at the EOL stage [57]. From the environmental perspective, blockchain can help to reduce waste and promote recycling. In addition, blockchain traceability can improve social sustainability through a better assurance of human rights, equity, and safety aspects [77]. For example, the traceable record of product history allows buyers and producers to trade with high confidence.

5.2 Industry 4.0 enabled sustainable warehousing

Warehouses are the important storage and hub facilities in a logistics network, which provide protection of goods and bridge the gap between different logistics activities, e.g., purchasing and production. Warehouse management consists of four operations, namely, receiving and recording of goods from different suppliers, storing goods at appropriate locations, retrieving and picking goods when they are needed, and shipment to customers [94]. Industry 4.0 technologies have brought opportunities for smart and sustainable warehousing solutions with enhanced capability of information and communication-based decision making [95]. The use of IoT, CPS, AI, and autonomous robots has been investigated in various operations [81], e.g., product receiving, identification, storing and allocation [96], and product picking [97] and shipping with autonomous robots [95, 98].

IoT-enabled devices have been widely used in smart warehouse management by several large companies, i.e., DHL, Amazon, and JD.com. The combination of both IoT and CPS provides a quick interconnection of smart assets in a warehouse, e.g., pallets, forklifts, machines, and robots. This enables real-time data collection and system monitoring of goods, equipment, and personnel, which improves warehousing operations, decision making, safety, and resource utilization [99, 100]. Besides, by using IoT, cloud technologies, and blockchain [101], traceability and transparency can be facilitated, and the errors and delays of warehousing operations can be minimized [81].

Combining cloud-based data collection, analytics, and optimization enables better communication and positioning of transport vehicles and more accurate prediction of their arrival time in order to optimize the docking slot and achieve just-in-sequence delivery [60, 102], through which good handing costs, greenhouse gas (GHG) emissions, and truck drivers' working hours can be reduced. Lv, Xiang [103] investigated a data-driven optimization framework for improving the operational efficiency of yard management in steel logistics parks. With the help of smart sensors, AI-supported optimization can adjust the allocations and e-routes of goods and optimize the work assignments with real-time information of available spaces and resources [104]. Besides, these technologies can provide better visibility of inventory levels, enhanced inventory accuracy and space usage [81], reduced inventory costs, improved process management and safety [95], and better customer services.

Smart robots consist of various sensors and powerful processors that allow them to sense extensively, decide intelligently, and behave precisely [105]. Smart robots have been increasingly used to replace manual operations, minimize errors, and improve effectiveness and safety. The use of UAVs for picking, data collection, and process monitoring has also been discussed [106]. AM is another emerging technology that has been increasingly used in warehouse management, and it provides an inexpensive solution for holding digital inventory of a large variety of products with low and irregular demands.

Virtual technologies have been extensively adopted to improve the effectiveness and training of warehousing operations. For instance, virtual reality (VR) can be used for the training of new employees without interrupting warehouse operations [105], and under minimum risks, it can also be used for providing the training of some dangerous operations, e.g., hazardous materials handling. Simulation has been widely used for visualization, testing, and performance evaluation of new technologies and processes [107]. Several logistics companies, e.g., DHL, use AR to manage and control the warehousing processes [98], where real-time instructions and task visualizations can be given to the operators in order to provide better assistance and maximize their effectiveness.

5.3 Industry 4.0 enabled sustainable transportation

The transportation of goods among different locations largely determines the sustainability of a logistics system, and Industry 4.0 technologies can be used for improving sustainability in different transportation activities [108], e.g., intelligent transportation systems [109], vehicle routing, emission reduction [110], green-fleet management [90], and pick-up and delivery services [111]. The integration of IoT and AI in a cloud-based platform enables real-time data processing and analysis of traffic conditions, vehicle information, dynamic demands, and recourse availability and usage. Combining advanced optimization algorithms, e.g., genetic algorithm, simulated annealing algorithm [63], etc., the real-time information can be used for better transportation planning and timely decision making to minimize transport delays

[112], increase accident responses, reduce fuel consumption and costs, and minimize GHG emissions, noise [109] and the population exposure to risks and hazards [113].

Big data analytics and AI provide computational powers for processing a large amount of multi-sourced data collected from IoT sensors and selecting the right quality and quantity of data for different decision-support tools, and this has led to an increasing focus on data-driven sustainable transportation planning and logistics optimization. Su and Fan [114] investigated a green vehicle routing system embedded with big data analytics and AI for better transportation of a smart logistics system, where the performances of costs, energy consumption, GHG emissions, and customer services were improved. Data-driven optimization has also been used in the sustainable planning of multimodal transportation [115]. Through the data-driven capacity balancing and optimization of different transportation modes, the use of low-carbon and environmentally friendly transportation modes has been drastically increased, e.g., a shift from road to rail transport [116], without a significant compromise on cost-effectiveness.

Virtual technologies provide powerful modules to include sustainability in the modeling and analysis of real-world logistics systems [117]. Sun, Zhang [115] presented a simulation-based analysis for the planning, decision making, and control of a CPS-enabled logistics network. By minimizing the number of trucks with low or empty loads, the simulation improves transportation strategies with reduced fuel consumption, costs, GHG emissions, and truck drivers' working hours. Simulation models have also been used to show the benefits of resource sharing in sustainable logistics systems [117]. Besides, combined optimization and simulation have been increasingly used in sustainable logistics, e.g., infrastructure design [118] and network optimization [119], to take advantage of the strengths of both methods.

Industry 4.0 technologies have changed the ways of the goods delivery. The focus on smart and self-driving vehicles, i.e., autonomous trucks and lorries, has shown the potential to reduce the costs, accident rates, and CO_2 emissions [120]. Another game-changing technology is the UAV, which has been used in many countries for the delivery of parcels, foods, medicines, vaccines, and blood samples [72]. The UAV or combined vehicle-and-drone system becomes appealing for highly agile last-mile delivery services, which has been practiced by several large companies, e.g., Amazon and Walmart [121]. Besides, it also provides a cost-effective solution for the delivery of low-quantity and emergency goods, e.g., medical supplies, to remote areas [122].

Blockchain-based platforms have been used for helping companies track and measure carbon emissions related to their logistics activities [77]. Deep learning and AI technologies have shown the value of using digital voice assistance and intelligent information support system in transportation and logistics services, which improve the deliverymen's working experiences, service levels, and operational efficiency [123].

5.4 Digitalization and system integration for sustainable logistics

In general, digitalization is the most important characteristic of an Industry 4.0 enabled logistics system, which aims at the transformation toward fully data-driven operations [124]. This digital transformation requires a high-level integration of different smart technologies and systems, which will promote operational excellence and create sustainable value-added opportunities [125]. In this regard, many studies have been conducted for enhancing the digitalization and system integration of the entire logistics system.

Many believe IoT-based platforms, which establish the connection between the physical world and the digital world [100], are the initial step to achieve a high-level digitalization and system integration of different logistics operations. Big data analytics and AI are digital elements for trend analysis, facility control, risk management, and other logistics operations [126]. The cloud-based integration of IoT and AI enables real-time data analytics and optimal decision support. Besides, advanced controlling and autonomous technologies improve the operational efficiency, accuracy, and safety of various logistics activities. Trappey, Trappey [82] investigated an IoT- and AI-enabled intelligent logistics system, which improved logistics services by integrating several operations, i.e., machine-loading control, production flow monitoring, vehicle routing, delivery schedules, and vehicle movement tracking.

The multi-sourced real-time information flow not only improves the operations within the border of a company but also paves the way for better resource sharing and demand matching among different companies. Gebresenbet, Bosona [127] developed a web-based smart platform for quality control, traceability, and demand matching and optimization of farmers, transporters, and customers in a reverse logistics system for biomass recovery and trading. Liu [128] investigated a data-driven logistics information system for smart collaborations among different stakeholders, e.g., governments, banks, facilities, service providers, and customers, to achieve rapid decision making, cost reduction, and high-quality services. To evaluate the effectiveness of Industry 4.0 enabled sustainable logistics systems, simulation models can be used to provide quantitative insights. By using simulation models, Zissis, Aktas [129] analyzed the cost reduction and service level of the smart collaborations for the home delivery of online groceries.

Considering both economic and environmental sustainability, Mastos, Nizamis [130] proposed an Industry 4.0 enabled forward-reverse logistics system for effective treatment of hazardous chemicals. At the intra-company level, this system enables effective logistics operations including the data-driven collection of hazardous chemicals, proactive maintenance of equipment, vehicle monitoring, data visualization, and decision optimization. At the inter-company level, a cloud-based collaborative ecosystem is established for effective demand matching and cooperation. From the corporate social sustainability perspective, Daú, Scavarda [131] discussed the application of IoT and other smart technologies to improve the sustainable practices of healthcare logistics.

Blockchain is another important technology for the digitalization of a logistics system and the integration of smart devices and platforms for data sharing and virtual currency transactions. It improves transparency, traceability, and security at every stage of logistics operations [132] through the tracking of information, physical components, transactions, and participants' actions and behaviors [133], which facilitates the capability of conflict management [134] and risk mitigation [135] in the entire logistics system. This also paves the way for sustainable collaboration among different stakeholders in a trustworthy business environment [86]. Besides, the opportunities for using blockchain-based digital systems to improve the environmental performance of logistics operations through life cycle assessment have also been discussed [136].

6 Discussions

In this section, the opportunities and challenges for sustainable logistics in the Industry 4.0 era are first discussed, and the suggestions for future research are then given.

6.1 Opportunities

Increasing attention has been paid to improve the sustainability of logistics systems with Industry 4.0 technologies, and worldwide efforts have been spent to advance theoretical development, technology transfer, business model innovation, and industrial applications. Based on the content analysis, Figure 9 summarizes the impacts of Industry 4.0 technologies on the economic, environmental, and social dimensions of sustainable logistics. The technological revolution provides companies with opportunities to transform their logistics operations to become more responsive to external market changes, while simultaneously being efficient with internal operations. On the one hand, through small-scale localized production with AM and autonomous robots, new business opportunities arise with increasing demands of individualized customizations and product-related services [137], and this requires service innovation and improvement of logistics operations. Furthermore, the web-based information-sharing systems improve service level and customers' experiences by a high level of customer involvement throughout the design, production, and delivery processes. On the other hand, the integration of IoT, big data analytics, and AI algorithms via cloud-based platforms provides computing power to handle multi-sourced large volume data, which can be used for better visualization and analysis of some key parameters [138, 139], i.e., demand trends, maintenance requirements [140], etc. Furthermore, using better data as inputs to optimization and simulation models, important logistics decisions [118], e.g., production planning, inventory management, routing, delivery schedules, etc., can be made in a timely and more accurate manner [63].

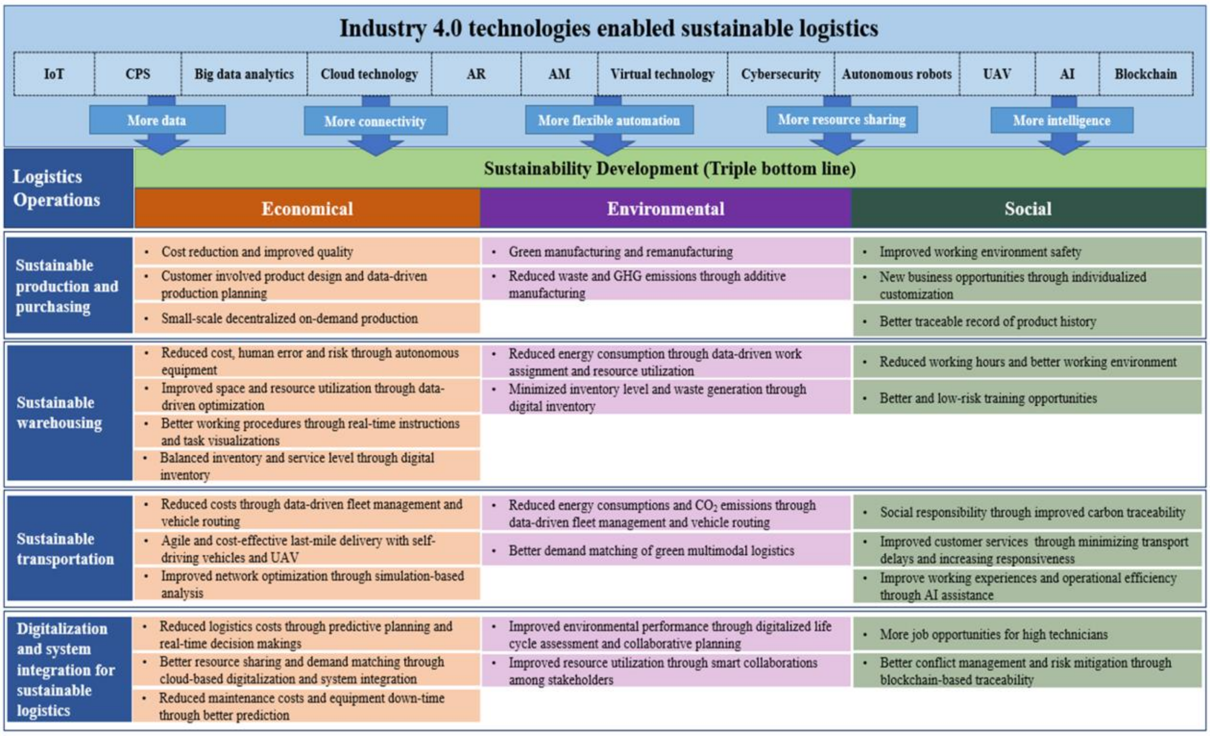

Figure 9 Sustainable logistics enabled by Industry 4.0 technologies.

The most important characteristic of an Industry 4.0 enabled sustainable logistics system is data-driven proactive planning, real-time decision making, and autonomous operations. This high-level digitalization and system integration have led to the conceptual architecture of the digital twin of logistics systems [141]. The digital twin of a logistics system is fully driven by the data collected from both cyber and physical sources [142], e.g., smart sensors, enterprise resource planning [143], etc., and it is capable of proactive planning with better analytics of historical data and reactive decision making and scenario analysis with real-time data. From the socio-economic perspective, information sharing among companies in a logistics system and the use of data analytics provide opportunities for better demand matching, resource sharing, and facility usage. The use of autonomous robots and UAV minimizes errors, risks, and labor costs of production, warehousing, and transportation while, simultaneously, provides innovative and environmentally friendly ways of goods delivery [109]. For instance, logistics information sharing and autonomous equipment are particularly important during the COVID-19 outbreak, which can help to minimize the shortage of emergency medical supplies and to effectively allocate and deliver them to the demand regions.

Better resource planning reduces waste generation and environmental footprints at different stages of a logistics system. Besides, the cloud-based information system provides opportunities to monitor the entire product life cycle and promote effective cloud-based remanufacturing and recycling when they become EOL products [142]. From the social sustainability perspective, the adoption of blockchain technologies provides better traceability and more trustworthy business environments in logistics systems. The increased use of autonomous devices improves the safety and working environment of various logistics operations. AI-enabled virtual technologies and AR provide logistics operators with risk-free training, virtual assistance, and real-time task instructions and visualization to improve their working experiences and effectiveness [125, 144]. In addition, with the requirements of increased digitalization, hardware and software development, and system integration, new job opportunities can be created in the logistics sector as well as in the other related industries.

6.2 Challenges and gaps

Most articles focus on how Industry 4.0 supports sustainable logistics, but less effort has been paid to understand the challenges of this digital transformation. Even though the new technologies have provided many opportunities, it also brings several challenges for sustainable logistics. One example is shown by China's rapidly developing express delivery and food delivery systems due to the booming of e-commerce. On the one hand, thanks to the better demand allocation and order tracking system empowered by AI, IoT, and advanced optimization, customers can now enjoy cheaper and faster delivery services of their foods and merchandise ordered online. However, on the other hand, these responsive logistics services require much more frequent last-mile deliveries, which lead to more traffic congestions and carbon emissions. Furthermore, the online platform assigns strict requirements to ensure on-time delivery, which raises concerns about the safety issues and job satisfaction of the deliverymen. Thus, we discuss several main challenges and gaps of sustainable logistics in the Industry 4.0 era:

- ***Lack of a holistic consideration of multiple sustainable indicators***: A sustainable logistics system balances the trade-off among the economic, environmental, and social dimensions. However, this has not been holistically considered in the adoption of Industry 4.0. For instance, the delivery allocation algorithm of the online food ordering platforms is designed to maximize the service level so that customer satisfaction and economic sustainability can be enhanced, but more environmental and safety issues are not considered holistically.

- ***Unclear economic benefits and the impacts of other sustainability indicators:*** Compared with the development of technologies, less effort has been spent on the development of quantitative and analytical methods [145] to evaluate the economic benefits and the impacts of other sustainability indicators by adopting Industry 4.0 in logistics systems. For example, using robots to replace manual operations in a warehouse not only affects a single activity but also largely influences other operations and the performance of the whole logistics system. Several studies show that the lack of concrete evidence on performance improvement has become a major hindrance to confirming companies to adopt Industry 4.0 in their logistics operations [45].

- ***Lifecycle energy consumption and environmental footprint:*** Even if Industry 4.0 shows the potential to reduce waste generation and improve resource utilization, from the lifecycle analysis perspective, the use of a large number of sensors, robots, and other smart devices in various logistics operations has inevitably lead to higher energy consumption and potential environmental footprints. For example, UAV is believed an environmentally friendly way to provide responsive and low-carbon delivery service. However, the recent research by Stolaroff, Samaras [146] has shown that the environmental footprints of UAV delivery may be higher than the traditional road delivery due to its limited capacity.

- ***Job loss and difficulties for workers:*** Logistics is a labor-intensive industry, and there is not a high requirement of knowledge and education for first-line operators. On the one hand, the human-centered technological revolution improves logistics operations, efficiency, agility, safety, and working environment. However, on the other hand, from the social sustainability perspective, it will inevitably cause job losses, the anxiety of employees who worry about their careers, and difficulties especially for aging workers both technically and psychologically to adapt to this new transformation.

- ***Inequity issues:*** the paradigm change of sustainable logistics is led by the market leaders like DHL, Amazon, JD.COM, etc., who spent large investments for developing smart and autonomous logistics solutions [147]. However, the lack of financial and technological resources of small and medium-sized enterprises (SMEs) significantly hinder the adoption of smart technologies and sustainable practices in their logistics systems, which results in an unequal position in the competition with large companies. In addition, studies also reveal that some Industry 4.0 technologies, e.g., big data analytics, can be used for unfair price discrimination and dynamic pricing throughout different players in a logistics system [148].

- ***Lack of a general guideline:*** The current research focuses on the adoption of an individual or several Industry 4.0 technologies in sustainable logistics. However, the practices are ad-hoc endeavors, and there is a lack of systematic guidelines to link different Industry 4.0 technologies and sustainable logistics operations at various stages.

- ***System integration and interoperability:*** The meaning of interoperability is that different smart devices and systems can independently communicate and access each other's functions [149]. Implementing Industry 4.0 in a sustainable logistics system that has many devices for different operations requires not only technological upgrades but also system integration with existing equipment. The communication protocols and control methods of the existing equipment and the new devices or system are by no means identical, so large efforts and upfront costs are required to make the existing logistics system more autonomous, smart, and sustainable.

- ***Data quality and cybersecurity concerns:*** Industry 4.0 requires effective data sharing horizontally among different facilities and companies in a logistics system and vertically throughout different functions and operations within a company [150]. However, the maturity and quality of data processing at different companies may not be at the same level, so this technological transformation requires collaborative efforts from various stakeholders in a logistics network. Besides, the concerns of cybersecurity and data safety also hinder the adoption of Industry 4.0 in logistics operations [149].

In addition, there exist knowledge siloing of current research. Industry 4.0 enabled sustainable logistics is a topic related to several subjects, e.g., computer and data sciences, automation and control, robotics, operations research, and social science. However, from the bibliometric analysis, it is evident that there is still a lack of effective research cooperation among researchers and groups with different backgrounds and geographical locations. This limits the generation of a general guideline and solution that can be widely applicable in different regions.

6.3 Future research suggestions

Several research directions are recommended to fill the literature gaps and better support this smart transformation of sustainable logistics:

1. ***Human-centric smart logistics transformation*** needs to be focused on. The latest concept of Industry 5.0 extends the technology-centric transformation of Industry 4.0 to a more socially sustainable human-centric transformation, and future research is thus needed to understand how human-centric smart transformation can be achieved in logistics sectors. Besides, several social impacts such as the demographic change and the impacts to aging workers for adopting these smart technologies in logistics sectors need to be better understood.

2. ***Multi-objective balanced system design*** for sustainable logistics operations. This requires new algorithms and systems that are designed to help with decision making considering multiple objectives. For example, in the order allocation algorithm for food delivery assignment, a balance needs to be achieved among the service level, the environmental footprints, and the deliverymen's safety issues in the real-time traffic condition.

3. ***The lifecycle environmental impact*** of Industry 4.0 enabled logistics systems needs to be better analyzed. Future studies are needed to provide deeper insights into the environmental footprints through lifecycle analysis. For instance, the system boundary of the analysis should be extended to the energy consumption and resource usage related to the production and recycling of the smart devices used in sustainable logistics.

4. ***Analytical models and optimization*** for adopting Industry 4.0 technologies in smart ways in different logistics operations and for providing quantitative implications of the cost benefits, different sustainability indicators, and overall system performance. Besides, in the Industry 4.0 era, the logistics system's effectiveness, efficiency, flexibility, agility, and environmental footprints need probably to be re-balanced [147], which requires better-designed analytical tools and optimization algorithms.

5. ***The digital twin*** of sustainable logistics systems needs to be focused to provide end-to-end solutions to various logistics operations. Via a cloud-based system, the predictive analytics with AI and the real-time data from IoT sensors as well as other cyber and physical portals need to be seamlessly connected with analytical optimization and simulation tools to improve both proactive and real-time decision making in sustainable logistics operations. Besides, future research is also suggested to develop the bi-directional control architecture to achieve highly autonomous logistics operations, e.g., warehousing.

6. ***Semi-autonomous sustainable transportation solutions:*** Even if autonomous driving vehicles have been extensively focused on in recent years, the realization of a fully autonomous transportation system faces many challenges and uncertainties, i.e., legal restrictions, technological maturity, and safety issues. Thus, the use of semi-autonomous solutions is an attractive alternative for sustainable logistics solutions. For example, truck platooning is a semi-

autonomous system that has several benefits, e.g., improved efficiency, reduced labor costs, and reduced fuel consumption and carbon emissions due to the reduction of the aerodynamic resistance of the following trucks.

7. ***Broad and diversified technology focus*** should be given not only to IoT, CPS, AI, and autonomous robots but also to others, e.g., AR and AM, which receive much less attention in the literature related to sustainable logistics. Thus, future research is needed to provide a better understanding of how those Industry 4.0 can be used to enhance sustainable logistics operations.

8. ***Sustainable reverse logistics*** enabled by Industry 4.0 is another opportunity for future research. Less focus has been given to the smart transformation of reverse logistics, which faces challenges related to the uncertainty of the market demands and the quantity and quality of the returned products. Smart technologies provide opportunities for minimizing the impact of uncertainty with better prediction and for more effective resource sharing among different companies. Besides, the use of AI-enabled autonomous robots has shown potentials to replace human workers from harsh working environments, e.g., manual sorting of waste. In addition, the terms “demand individualization” and “individualized customization” need to be redefined in reverse logistics.

9. ***The smart and sustainable logistics solutions for the COVID-19*** need to be focused on. Due to the rapidly increased demand, strict border control and city lockdown, and reduced transportation capacity, the COVID-19 pandemic has hindered the flows of goods, increased logistics costs, and imposed a higher risk on vulnerable groups related to the shortage of medical supplies, foods, and other necessities. In this regard, the role of Industry 4.0 technologies needs to be highlighted to tackle the logistics challenges during the pandemic. For example, the use of robots to collect infectious waste at healthcare facilities may reduce the infection risks.

7 Conclusions

The concepts of sustainable logistics and Industry 4.0 have been focused on by many researchers due to the increasing need for technology-driven smart and sustainable logistics. This paper provides a systematic literature review focusing on the recent development and adoption of various Industry 4.0 technologies in sustainable logistics at both intra- and inter-company levels. First, a bibliometric analysis was conducted to identify the publication trend, the most influential journals and research, the co-citation networks, and the most frequently used keywords. Then, a content analysis was performed to understand the current research landscape on how Industry 4.0 technologies can be used to improve sustainable logistics activities, namely, production and purchasing, warehousing, transportation, and general system integration. Finally, current research developments were summarized, and the challenges, literature gaps, and future research opportunities were discussed. To answer the proposed research questions:

- *RQ1*, we systematically analyze the state-of-the-knowledge of Industry 4.0 and sustainable logistics with both bibliometric analysis and content analysis in Sections 4 and 5.

- *RQ2*, we thoroughly discuss both the opportunities and the challenges of sustainable logistics in the Industry 4.0 era in sections 6.1 and 6.2.

- *RQ3*, we identify 9 future research directions in section 6.3.

From the research perspective, the results show an increasing focus has been given to Industry 4.0 enabled sustainable logistics, which is an area attracting worldwide researchers and practitioners. The results suggest that cooperation among researchers should be enhanced in the future. In addition, the paper analyses the current research landscape and how the paradigm shift of various logistics activities is driven by technological advancements, and their implications on improving economic, environmental, and social sustainability are discussed. Based on this, the gaps and opportunities are identified to guide future research.

From the practical perspective, the results provide insights for the potential application of Industry 4.0 technologies to enhance sustainable logistics practices, which will promote knowledge transfer from academic research to industrial applications. In particular, the use of data-driven decision-support platforms may provide cost-effective, safe, and reliable tools for a better understanding and analysis of the effectiveness and challenges of adopting new technologies, digital solutions, and business models in sustainable logistics systems. From a broader perspective, these discussions also provide other companies with implications and some successful examples for guiding their logistics transformations in the Industry 4.0 era. Besides, the challenges of Industry 4.0 to sustainable logistics systems need to be noticed in this technological and operational transformation. One should bear in mind that the benefits should never be overestimated, and the challenges and commitments required should never be underestimated.

The paper inevitably has several limitations regarding the filters used in the sample selection, which only account for the journal articles published in English with respect to the selected keywords, the two databases, and the time of the search. Sustainable logistics and Industry 4.0 are extensively focused by worldwide researchers, and some important publications may be published in different languages. Besides, both concepts are currently getting fast-growing attention, and relevant papers may be published in different forms, i.e., conference papers, book chapters, magazines, industrial reports, or under the peer-review stage as pre-prints. Therefore, the results presented in this paper are not exhaustive, and future improvements are needed to present a more comprehensive analysis with an extended sample selection.

Appendix I

Table A1 The clusters, the occurrences, and the TLSs of the highly used keywords (The maximum number of keywords included from each cluster is 10).

Clusters	Keywords	Occurrences	TLS
Cluster 1	Internet of things	21	117
	Decision making	19	115
	Smart logistics	17	52
	Cloud computing	5	18
	Logistics industry	5	18
	Warehouses	5	21
	Carbon	4	24
	Embedded systems	4	29
	Information platform	4	8
	IoT	4	21
Cluster 2	Article	8	100
	Big data	8	61
	Blockchain	8	75
	Human	8	100
	Circular economy	7	68
	Information management	6	50
	Sustainable supply chain management	6	36
	Economic aspect	5	58
	Data analytics	4	50
	Environmental sustainability	4	46
Cluster 3	Supply chain management	39	264
	Sustainability	29	191
	Sustainable development	28	220
	Sustainable supply chains	28	235
	Supply chains	13	94
	Optimization	10	51
	Supply chain	8	56
	Simulation	7	32
	Sustainable supply chain	7	46
	Environmental impact	5	43
Cluster 4	Cost reduction	3	16
	Design/methodology/approach	4	32
	Economic and social effects	3	28
	Environmental pollutions	3	20
	Hazardous chemicals	3	13

	Hazardous materials	3	13
	Hazards	3	13
	Industrial economics	4	35
	Industrial research	3	21
	Internet of things (iot)	9	68
Cluster 5	Industry 4.0	34	151
	Logistics	14	59
	Logistics 4.0	10	18
	Artificial intelligence	9	53
	Decision support systems	9	57
	Decision support system	4	29
	Bibliometric analysis	3	16
	Food supply	3	17
	Industrial revolutions	3	14
	Manufacturing	3	14
Cluster 6	Surveys	5	37
	Analytic hierarchy process	3	27
	Analytical hierarchy process	3	27
	Analytic hierarchy process (ahp)	3	21
	Accident prevention	3	16

Appendix B

Table B1 Industry 4.0 enabled sustainable manufacturing and purchasing.

Author/Year	Industry 4.0 technology												Sustainable logistics dimension	
	IoT	CPS	Big data	Cloud tech.	AR	AM	Virtual tech.	Cyber-security	Autonomous robots	UAV	AI	Block-chain	Environmental	Social
Strandhagen, Vallandingham [59]	√	√	√	√	√	√			√		√		√	√
Barreto, Amaral [60]	√	√	√	√									√	√
Facchini, Oleśków-Szłapka [92]	√	√	√	√	√				√					
Chong, Low [151]	√	√												
Sutawijaya and Nawangsari [58]	√		√						√		√		√	
Motevalli-Taher, Paydar [152]							√						√	√
Saberi, Kouhizadeh [77]												√	√	√
Bag, Yadav [89]	√		√								√		√	√
Beltagui, Kunz [91]						√								√
Esmaeilian, Sarkis [57]	√	√		√	√	√		√	√		√	√	√	√
Prause and Atari [79]		√												
Samir, Abdelsamad [90]	√		√	√		√						√		
Isasi-Sanchez, Morcillo-Bellido [73]		√				√							√	√
Wang, Gunasekaran [65]													√	√
Björklund and Forslund [88]													√	√

Tuffnell, Kral [153]	√	√	√	√	√						√	
Sheares [154]	√	√	√		√	√		√	√	√		√
Nica [155]	√	√							√			√
Felstead [144]	√	√							√			
Li, Fang [83]											√	√
Bourke [138]	√								√			√
Gonzalez, Sarkis [87]											√	√
Ma, Wang [93]							√					

Table B2 Industry4.0 enabled sustainable warehousing.

Author/Year	Industry 4.0 technology												Sustainable logistics dimension	
	IoT	CPS	Big data	Cloud tech.	AR	AM	Virtual tech.	Cyber-security	Autonomous robots	UAV	AI	Block-chain	Environmental	Social
Barreto, Amaral [60]	√	√	√	√									√	√
Ding, Jin [102]	√		√	√							√			
Abbas and Marwat [139]	√	√					√							
Yavas and Ozkan-Ozen [98]	√	√			√								√	
Munsamy, Telukdarie [104]	√	√	√	√	√	√	√	√	√	√			√	
Issaoui, Khiat [121]	√	√	√	√							√	√	√	√
Lv, Xiang [103]	√		√											√
Shoaib, Lim [101]	√											√		√
Rakyta, Fusko [97]			√										√	√
Sciortino, Micale [156]			√										√	
Wen, He [109]	√		√						√	√	√		√	√
Trab, Bajic [95]	√													
Jabbar, Khan [99]	√													
Lee, Lv [81]	√	√												
Samir, Abdelsamad [90]	√		√	√		√						√		
Wang, Gunasekaran [65]													√	√
Zhou, Piramuthu [96]														
Cui [157]	√								√					
Tang, Liu [100]							√						√	√

Table B3 Industry 4.0 enabled sustainable transportation.

Author/Year	Industry 4.0 technology												Sustainable logistics dimension	
	IoT	CPS	Big data	Cloud tech.	AR	AM	Virtual tech.	Cyber-security	Autonomous robots	UAV	AI	Block-chain	Environ mental	Social
Barreto, Amaral [60]	√	√	√	√									√	√
Facchini, Oléśków-Szłapka [92]	√	√	√	√	√				√					
Ding, Jin [102]	√		√	√							√			
Liu [128]			√											√
Yavas and Ozkan-Ozen [98]	√	√											√	
Munsamy, Telukdarie [104]	√	√	√	√	√	√	√	√	√	√			√	
Issaoui, Khiat [121]	√	√	√	√							√	√	√	√
Sutawijaya and Nawangsari [58]	√		√						√		√		√	
Su and Fan [114]			√								√		√	√
Mehmann and Teuteberg [158]							√						√	√
Saberi, Kouhizadeh [77]												√	√	√
Pan, Li [110]													√	√
Zhao, Zhang [112]	√												√	
Greif, Stein [159]	√						√							
Yang, Guizani [72]									√	√	√		√	√
Frontoni, Rosetti [111]														
Hoffa-Dabrowska and Grzybowska [117]													√	
Dong and Boute [116]													√	
Esmaeilian, Sarkis [57]	√	√		√	√	√		√	√		√	√	√	√

da Silva, Rangel [118]						√					√	
Hilpert, Kranz [85]											√	
Sciortino, Micale [156]			√								√	
Sivamani, Kwak [160]	√											√
Zhang [63]	√	√	√	√								
Wen, He [109]	√		√				√	√	√		√	√
Teucke, Broda [161]	√					√						
Hong, Alzaman [119]						√					√	√
Sundarakani, Lai [162]												√
Luo and Fu [163]											√	√
Anandhi, Anitha [113]	√											√
Hsiao and Chang [123]									√			√
Samir, Abdelsamad [90]	√		√	√	√					√		
Wang, Gunasekaran [65]											√	√
Yu, Jung [164]												
Björklund and Forslund [88]											√	√
Cho and Kim [165]	√											√
Benotmane, Belalem [69]				√								
Tatham, Stadler [122]								√				√
Gružauskas, Baskutis [120]	√	√	√	√		√					√	
Sun, Zhang [115]						√					√	√
Lin, Shi [166]	√					√						
Wanke, Correa [167]						√					√	
Tang, Liu [100]						√					√	√

Table B4 Industry 4.0 enabled digitalization and system integration for sustainable logistics.

Author/Year	Industry 4.0 technology												Sustainable logistics dimension	
	IoT	CPS	Big data	Cloud tech.	AR	AM	Virtual tech.	Cyber-security	Autonomous robots	UAV	AI	Block-chain	Environ mental	Social
Strandhagen, Vallandingham [59]	√	√	√	√	√	√			√		√		√	√
Barreto, Amaral [60]	√	√	√	√									√	√
Kucukaltan, Saatcioglu [168]			√	√		√			√	√				√
Abbas and Marwat [139]	√	√					√							
Liu [128]			√											√
Luthra and Mangla [45]	√	√	√										√	√
Yavas and Ozkan-Ozen [98]	√	√											√	
Allaoui, Guo [2]													√	√
Tseng, Wu [169]			√										√	√
Kumar, Singh [170]	√	√		√		√							√	√
Sutawijaya and Nawangsari [58]	√		√						√		√		√	
Motevalli-Taher, Paydar [152]							√						√	√
Cole, Stevenson [86]												√		√
Zhang, Liu [80]	√	√		√									√	
Tang [171]	√		√	√										
Greif, Stein [159]	√						√							
Correa, Sampaio [172]	√		√											√
Kodym, Kubáč [135]	√	√	√	√		√		√				√	√	√
Bag, Yadav [89]	√		√								√		√	√
Cui, Gao [173]	√													

Ebinger and Omondi [125]	√		√	√						√	√	√	√
Mastos, Nizamis [130]	√	√	√		√							√	
Chiappetta Jabbour, Fiorini [174]			√									√	√
Morella, Lambán [175]	√	√	√	√	√	√	√	√	√			√	
Bag, Wood [126]			√										√
Yadav and Singh [176]											√		√
Esmaeilian, Sarkis [57]	√	√		√	√	√		√	√	√	√	√	√
Yadav, Luthra [177]												√	√
Manupati, Schoenherr [134]											√	√	
Shoaib, Lim [101]	√										√		√
Bai and Sarkis [133]											√		√
Rejeb and Rejeb [178]											√	√	√
Rakyta, Fusko [97]			√									√	√
Daú, Scavarda [131]	√											√	√
Krykavskyy, Pokhylchenko [124]													√
Hasan, Jiang [179]													
Xie [180]	√												√
Trappey, Trappey [82]	√		√	√									
Anandhi, Anitha [113]	√												√
Gebresenbet, Bosona [127]													
Bosona, Gebresenbet [181]													
Liu, Zhang [182]	√		√									√	
Bag, Gupta [183]	√	√	√	√									
Liu, Wei [184]			√									√	√
Lee, Kang [185]												√	

Sahay and Ierapetritou [186]						√				
Byun, Nasridinov [187]	√									√
La Scalia, Nasca [188]						√			√	
Zhang, Zhong [136]	√		√					√	√	√
Ma, Wang [189]									√	
Bricher and Müller [190]							√			√
Cimini, Lagorio [191]	√	√	√	√						√
Prause [78]	√	√	√		√				√	√
Dai [192]	√		√							√
Dominguez, Cannella [193]						√			√	
Gružauskas, Baskutis [120]	√	√	√	√		√			√	
Tseng, Wee [194]									√	
Xu, Jiao [195]	√		√							
Bukowski [196]	√		√	√						
Ma, Wang [93]						√				
Zissis, Aktas [129]						√			√	√

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PAPER 2

Towards the smart and sustainable transformation of Reverse Logistics 4.0: a conceptualization and research agenda

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Submitted manuscript

Author's Contribution

Xu Sun is the main contribution of conceptualization, methodology, data curation, formal analysis, writhing-original draft of the paper, and writing-review and editing of the paper.

Towards the smart and sustainable transformation of Reverse Logistics 4.0: a conceptualization and research agenda

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Abstract: The recent advancement of digitalization and information and communication technology (ICT) has not only shifted the manufacturing paradigm towards the Fourth Industrial Revolution, namely Industry 4.0, but also provided opportunities for a smart logistics transformation. Despite studies have focused on improving the smartness, connectivity, and autonomy of isolated logistics operations with a primary focus on the forward channels, there is still a lack of a systematic conceptualization to guide the coming paradigm shift of reverse logistics, for instance, how "individualization" and "service innovation" should be interpreted in a smart reverse logistics context? To fill this gap, Reverse logistics 4.0 is defined, from a holistic perspective, in this paper to offer a systematic analysis of the technological impact of Industry 4.0 on reverse logistics. Based on the reported research and case studies from the literature, the conceptual framework of smart reverse logistics transformation is proposed to link Industry 4.0 enablers, smart service and operation transformation, and targeted sustainability goals. A smart reverse logistics architecture is also given to allow a high level of system integration enabled by intelligent devices and smart portals, autonomous robots, and advanced analytical tools, where the value of technological innovations can be exploited to solve various reverse logistics problems. Thus, the contribution of this research lies, through conceptual development, in presenting a clear roadmap and research agenda for the reverse logistics transformation in Industry 4.0.

Keywords: Industry 4.0; technological transformation; smart technologies; reverse supply chain; waste management; sustainability

1 Introduction

Recently, the increasing focus on sustainable development and circular economy from the whole society and the more stringent environmental regulations have required companies to take responsibility for the entire lifecycle of their products. The primary aim of reverse logistics is to maximize the recovery of the remaining value from end-of-life (EOL) products through the proper design, operating, controlling, and maintaining effective and economic-efficient flows starting from customers towards initial suppliers and manufacturers [1], and the non-recyclables should be appropriately disposed of. Designing and operating a reverse logistics system need to balance the trade-off between economic, environmental, and social sustainability [2]. However, this is not an easy endeavor due to the complexity of effectively managing several stakeholders to perform various operations including collection, sorting, distribution, disassembling, repair, reuse, remanufacturing, recycling, energy recovery, and proper waste disposal [3]. Furthermore, the increased system operating costs [4], the high uncertainty related to the quantity and the quality of EOL products in the reverse flows [5], the lack of relevant and real-time information for decision making [6, 7], and the lack of coordination among different partners [4] have become some major obstacles for sustainable reverse logistics management.

These challenges may be better tackled today with the emerging concept of Industry 4.0 as well as its enabling technologies, which provide new opportunities for achieving improved internet-based connectivity, smartness, intelligence, and autonomous operations of not only manufacturing processes but also logistics systems [8, 9]. Taking advantage of the technological innovation of the Fourth Industrial Revolution, the concept of Logistics 4.0 has also been proposed in recent years [10, 11]. Combining several cutting-edge technologies, e.g., internet of things (IoT), big data analytics, artificial intelligence (AI), etc., in a cyber-physical system (CPS) that integrates both computational intelligence and smart physical assets, a Logistics 4.0 system can achieve real-time monitoring and decision making, responsive communications, better resource allocation, and smoother material flows. These smart technologies can also be used to improve the economic, environmental, and social sustainability of reverse logistics systems.

The changing demands and the integration of different Industry 4.0 technologies will together lead to a paradigm shift of reverse logistics, where the former is the driver and the latter is the enabler of this smart and sustainable transformation. The increased data availability can improve the prediction and traceability of EOL products, which minimizes the uncertainty of the reverse flows and improves the planning of different operations, e.g., collection [12] and remanufacturing [7, 13]. The high-quality data also improves the outputs of the model-based optimization and simulation approaches for critical decisions [6], i.e., scheduling of collection, routing, inventory management, distribution, etc. In addition, the increased use of AI-enabled smart robots can replace human workers in the harsh working environment, and the enhanced interaction between different partners and stakeholders via a highly connected digital platform may improve inter-company information sharing and resource utilization.

Even though recent studies have been conducted to show the application of several Industry 4.0 technologies in isolated reverse logistics operations, there is still a lack of a systematic conceptual framework to better understand the potential and implications of these technological innovations for the entire reverse logistics system, particularly from the service innovation perspective. For example, how "*individualization*" should be interpreted in a smart reverse logistics context? Furthermore, most studies only emphasize the benefits of implementing Industry 4.0, but much less effort has been paid to discussing the challenges of technological adoption in reverse logistics systems. Therefore, by analyzing the state-of-the-art research and case studies in a comprehensive and cross-disciplinary manner, this paper aims at filling these gaps by answering the following three research questions (RQs):

RQ1: What are the definition and the key features of *Reverse Logistics 4.0*?

RQ2: What is the smart and sustainable transformation of *Reverse Logistics 4.0*?

RQ3: What is the future research agenda of *Reverse Logistics 4.0*?

By answering these questions, we define the concept of *Reverse Logistics 4.0* in comparison with the four Industrial Revolutions in history, where the technology-enabled innovation in both service and operations are systematically analyzed in the reverse logistics context. Moreover, based on the reported research and case studies from the literature, we present a roadmap for both researchers and practitioners in the smart and sustainable reverse logistics transformation. Finally, we also present a research agenda in four directions: 1) smart and innovative reverse logistics services; 2) quantitative models for smart and sustainable reverse logistics management; 3) digital reverse logistics twin, and 4) human-centricity and *Reverse Logistics 5.0*.

The rest of the paper is organized as follows. Section 2 provides state-of-the-art developments in both reverse logistics and Industry 4.0. Section 3 conceptualizes *Reverse Logistics 4.0* and discusses its main features. Section 4 investigates the smart and sustainable reverse logistics transformation enabled by disruptive technologies. Section 5 identifies a future research agenda. Section 6 concludes the paper.

2 State of the Art

2.1 Reverse Logistics

Reverse logistics focuses on the value recovery from EOL products and on the proper treatment of non-recyclables [1]. The reuse and recycling practices can be dated back to a long time ago, for example, after proper cleaning and treatment, the returned bottles can be reused many times by beverage manufacturers for their new products. In the early 1990s, the concept of reverse logistics was first put forward to depict all relevant activities and logistics flows from the end customers to different producers, recyclers as well as other actors [14]. The main operations of a reverse logistics system consist of the collection of EOL products from customers and end-users, the appropriate inspection, sorting, disassembling and/or pre-processing, the distribution of different products, parts and components to respective facilities for proper treatment, and the planning and scheduling of facility operations and transportation [15, 16]. Configuring a reverse logistics system for effective management of these operations requires proper decision-making at strategic, tactical, and operational levels. During the past three decades, extensive research efforts have been spent to improve conceptual development [17, 18], formulate advanced mathematical models and algorithms [19, 20], provide empirical studies and implications [21], and develop other qualitative and quantitative methods for supporting various decisions in reverse logistics [22].

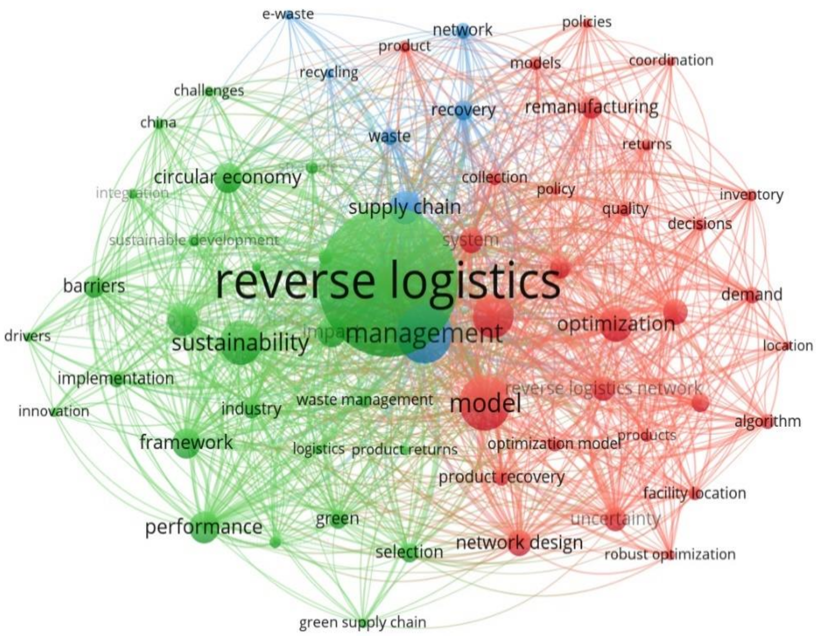

Figure 1 Keyword co-occurrence analysis of reverse logistics.

The motivation of reverse logistics comes initially from two aspects [15]. From the ecological perspective, reverse logistics improves the utilization of different materials and helps thus to solve the global resource depletion problems. Besides, it may provide companies with opportunities to improve their cost reduction and profitability through product recovery. However, in practice, the value recovery through reverse logistics may be drastically hindered by several factors, i.e., the low-profit margin [23], the possible competition with new products or market cannibalization [24], the uncertainty related to market acceptance [25], and the complexity of managing reverse flows. Moreover, even though reverse logistics has been considered a fundamental part of sustainable development and circular economy, improper recycling activities may result in negative environmental and social impacts [26]. For example, the large export volume of waste electrical and electronic equipment (WEEE) from developed countries, i.e., the US, EU, Japan, etc., to the developing countries in southeast Asia not only causes increased greenhouse gas (GHG) emissions related to maritime transportation but also poses significant threats to the workers and the environment due to the primitive and low-tech recycling methods used. Thus, the effective design of a reverse logistics system will help to promote more sustainable practices of different activities.

Figure 1 presents a keyword co-occurrence analysis of the latest publications on reverse logistics. The web of science (WOS) database was used for searching the relevant papers to generate the visualization. The recent research on reverse logistics has focused on managing various types of EOL products through different options considering economic, social, and environmental performances. Several important decisions, i.e., facility location, transportation, vehicle routing, etc., have been predominantly tackled by using advanced quantitative methods, i.e., mathematical models [27], multi-criteria decision support methods [28], and simulation [29-31]. Among these, optimization is the most extensively used technique to solve complex decision-making problems in reverse logistics. Early research focuses on developing deterministic single objective optimization models for either minimizing the system operating cost or maximizing the total profit [27]. However, recent studies emphasize the balance among different sustainable indicators with multi-objective optimization models [19, 32], the proper formulation and treatment of uncertainties [33-35], the improvement of the models' computational efficiency [36, 37], and the management of different stakeholders [38].

2.2 Industry 4.0

Industry 4.0, also known as the Fourth Industrial Revolution, was put forward by German researchers and industrial practitioners in 2011 [39], which presented the blueprint of the next-generation manufacturing systems with the adoption of state-of-the-art manufacturing technologies and ICT. Even if it is a new concept, Industry 4.0 has been widely discussed by worldwide researchers during the last decade due to its potential to dramatically change today's paradigms of almost all industries and businesses through digital transformation. On the one hand, the current change of the industrial paradigm is driven by new demands for increased individualization on both products and services, shortened time-to-market, small-scale decentralized customer segments, and so forth. On the other hand, these new demand patterns can be better addressed with recent technological advancements that have provided companies with opportunities to achieve a highly flexible, agile, responsive, and resource-efficient manufacturing process through digitalization and various smart technologies [40]. Compared with the Third Industry Revolution starting from the early 1970s, where industrial robots, advanced machine tools, computer-aided manufacturing (CAM), and lean production were used to achieve mass customization through increased automation, reconfigurability, and flexibility, Industry 4.0 has several new features. From the technological perspective, an Industry 4.0 manufacturing system emphasizes the internet/5G-based communication and connectivity of different smart devices and cyber elements, which enable real-time data collection, autonomous system control, and effective human-machine interaction [41]. Another significant feature is the computational intelligence brought by AI, big data analytics, and improved optimization and simulation tools, which enables better prediction and real-time data-driven decision making. From the commercial perspective, these Industry 4.0 technologies pave the way for new business models, individualized customization, better resource sharing, and sustainable production [8, 42].

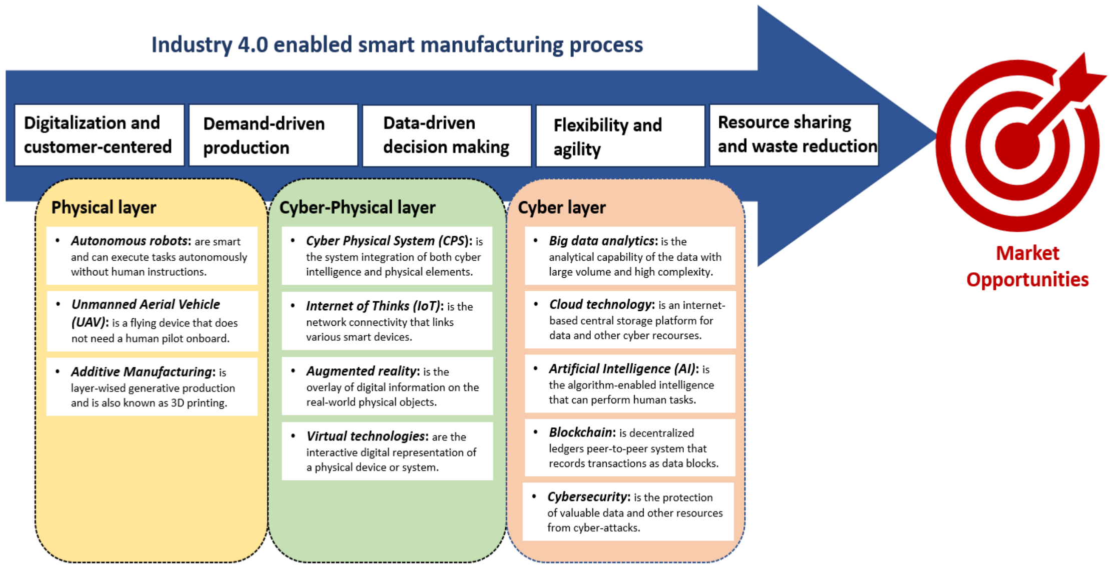

Figure 2 Industry 4.0 enabled smart manufacturing.

Based on Salkin, Oner [41], Bai, Dallasega [8], Frank, Dalenogare [39], and Phuyal, Bista [43], Figure 2 summarizes the key Industry 4.0 technologies into three categories, namely, physical layer, cyber layer, and cyber-physical layer. The drastically increased use of connected devices has driven a rapid digital transformation. Recent research has shown that the total amount of connected devices in the world has increased by nearly 99 times during the past two decades, and the average number of connected devices per person has reached approximately 6.58 in 2020 [43]. An Industry 4.0 enabled manufacturing system comprises a large amount of various smart and connected robots and devices, which are communicated with each other and interacted with cyber intelligence in real-time. The level of integration of both physical elements and cyber technologies within a CPS determines the system's sophistication, connectivity, intelligence, and autonomy. Lee, Bagheri [44] defined five levels of technological integration in a CPS, which are machine-level connection, data transmission and conversion, system-level connectivity, system cognition, and system intelligence and self-configuration. With the highest level of CPS, a smart manufacturing system can make self-decisions based upon individual customer orders, generate production procedures, test different scenarios in virtual environments, and control intelligent robots and machines for an autonomous and highly responsive production process.

Figure 3 illustrates the keyword co-occurrence analysis of the recent research related to Industry 4.0. The research focuses have been predominantly given to the technological development of CPS, IoT, AI, big data analytics, blockchain, additive manufacturing, etc., to achieve predictive maintenance, real-time decision making, smart manufacturing, and better production control and planning. Besides, these technologies are not only used to improve manufacturing processes but are also applied to enhance supply chain management [45], innovation [46], and sustainable development [47]. Particularly, recent research has shown great opportunities to improve sustainability and circular economy with the help of Industry 4.0 [8, 48]. For example, reducing waste generation and improving material utilization by adopting a demand-driven small-scale intelligent production process with additive manufacturing [49].

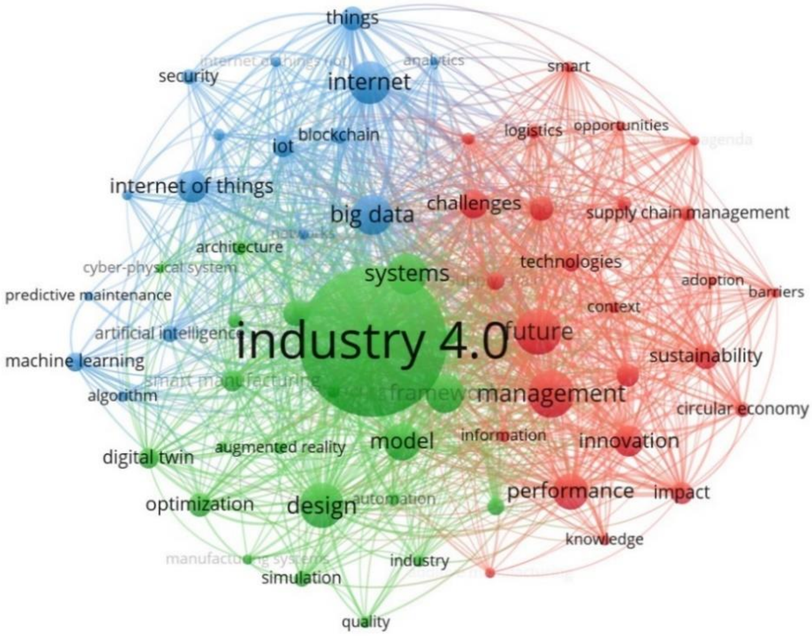

Figure 3 Keyword co-occurrence analysis of Industry 4.0.

2.3 The contributions of this research

Table 1 shows the search information of the top 60 keywords related to reverse logistics and Industry 4.0, and the top keywords related to both reverse logistics and Industry 4.0 are "sustainability", "circular economy", "model", "impact", "challenges", "systems", "design", "sustainable development", respectively. Through a comparison of these keywords, it is noteworthy that even if Industry 4.0 has provided new opportunities for improving decision-making and operations with better use of smart devices, data analytics, and computational intelligence, their adoption in reverse logistics is still in its infancy and has not been widely discussed in the literature. For example, many optimization models have been developed for supporting decision-making in reverse logistics, whose results are heavily dependent on the availability and the quality of input data. The high uncertainty related to the input parameters will make these models computationally expensive to solve within polynomial time. Moreover, the reliability of the models' outputs and the decisions obtained may also be drastically influenced. Due to these, the adoption of Industry 4.0 technologies is well justified for their impacts on improving the data quality, computational intelligence, and operations in reverse logistics.

Table 1 Literation analysis of the recent publications.

Search criteria	Keywords		
	"*Reverse logistics*"	"*Industry 4.0*"	"*Reverse logistics*" AND "*Industry 4.0*"
Database	Web of Science	Web of Science	Web of Science
Source	Journal	Journal	Journal
Language	English	English	English
Total articles	1282	5135	21
Total keywords	4704	16575	174
Co-occurrence threshold	35	70	3
Selected keywords	62	63	16

Based on both theoretical and practical insights related to different reverse logistics activities, this paper aims at providing a systematic conceptual development and research agenda for the smart and sustainable transformation of reverse logistics in Industry 4.0, namely *Reverse Logistics 4.0*. The contributions of this paper can be summarized as follows:

- The concept of *Reverse Logistics 4.0* is defined considering both technological advancement and service innovation.
- The conceptual framework for smart and sustainable *Reverse Logistics 4.0* transformation is formulated.
- The research agenda for smart and sustainable *Reverse Logistics 4.0* transformation is given.

3 Reverse Logistics 4.0

This section first introduces the conceptual development of Logistics 4.0, based on which the concept of *Reverse Logistics 4.0* is defined.

3.1 Logistics 4.0

Today, the phrase “4.0” has been widely used not only in the manufacturing industry but also in many other fields to describe the future paradigm shifts brought by digitalization and advanced ICT. By adopting the technological innovations from Industry 4.0, the concept of Logistics 4.0 was first put forward in 2014 [50], which emphasized the real-time ability, fast decision supports, and convertibility of a new IT system empowered by CPS for supporting logistics decisions. Concerning the four Industrial Revolutions in history, Wang [10] systematically summarized the four logistics evolution stages featured with the mechanization of transportation (Logistics 1.0), the automation of logistics operations (Logistics 2.0), the advancement of logistics management systems (Logistics 3.0), and the smart and autonomous logistics systems (Logistics 4.0), respectively. Several researchers argue that Logistics 4.0 is to digitize and automize the logistics processes and operations with the help of CPS [51], whose technological architecture requires six layers, namely, the physical asset layer, the data acquisition layer with sensors and middleware, the control layer, the database layer, the analytical and decision-support layer, and the management layer [10]. From the business innovation perspective, Logistics 4.0 is viewed as a conceptual extension of Industry 4.0, whose main features are discussed in several studies (e.g., Yu and Solvang [52]):

- ***Demand-driven individualization and personalization***: Value proposition by satisfying highly individualized customer demands with CPS, customer-involved design, additive manufacturing, and pull production and logistics.

- ***Product-service system***: Transforming towards the increased selling of services instead of the selling of products, for example, Rolls-Royce’s TotalCare® program, also known as Powered-by-the-hours, has helped to achieve a win-win solution for both the airlines and the jet engine manufacturer [53].

- ***Digitalization***: Increased digitalization enables effective communication between humans and machines, and it helps to converge the physical and virtual worlds.

- ***Autonomous operations***: Different logistics operations, e.g., material handling, transportation, etc., will become increasingly autonomous with the help of IoT, CPS, AI, UAV, and smart robots.

- ***Resource sharing***: The real-time data collection and analytical power enabled by IoT, AI and advanced optimization improve the level of resource sharing among different stakeholders in a logistics system, which may offset the increased cost and environmental impacts to satisfying small-scale individualized and geographically dispersed customer demands with a high service level.

- ***Green and sustainable logistics***: The waste generation can be reduced with on-demand and additive manufacturing, and the environmental impacts of various logistics operations can be better tracked and minimized with blockchains.

To achieve these goals, increased digitalization and system integration at both intra- and inter-enterprise levels are required to facilitate effective interactions among stakeholders, better use of data, real-time decision making, streamlined operations, and improved resource utilization in a logistics system. Recently, the conceptual development of Logistics 4.0 trends to synchronize business innovations with technological advancements, where business innovations are considered the goals of the next generation of smart logistic systems and technological advancements are believed to be the enablers to realize these goals. As defined by Winkelhaus and Grosse [11], Logistics 4.0 refers to cost-affordable and highly responsive logistics services for individualization and personalization empowered by smart technologies. To further facilitate the adoption of the concept of Logistics 4.0, studies have been conducted to provide implications on the use of different Industry 4.0 technologies in various logistics operations [54], to establish models for measuring the maturity level of Logistics 4.0 [55, 56], and to understand the relevant human factors and learning effects [57].

3.2 Reverse Logistics 4.0

Even though Logistics 4.0 has been increasingly discussed in recent years, not as much research focus has been given to reverse logistics [54]. On the one hand, several Industry 4.0 technologies can benefit reverse logistics operations in the same way as they do in forward logistics. However, on the other hand, there are significant differences between forward logistics and reverse logistics in terms of their purposes and operations. For instance, the business objective of a Logistics 4.0 system is to achieve the value proposition through providing highly individualized products and responsive services, but for a reverse logistics system, the purpose may be different or the meaning of individualization may need to be interpreted in another way, for example, an individualized collection schedule in a smart waste management system. Thus, it is important to provide a thorough understanding of *Reverse Logistics 4.0*.

Recently, increasing efforts have been spent to improve the sustainability and the operations of reverse logistics with Industry 4.0 technologies, for example, through real-time information sharing and diffusion of green products [58, 59]. From the conceptual development perspective, Figure 5 presents a systematic paradigm change of reverse logistics with respect to the four industrial revolutions. Even though reverse logistics was not conceptualized before the early1990s, its activities were widely practiced, e.g., part recycling, waste disposal, etc. The modern industrialization from the early 19 century led to an increase in population and rapid urbanization, which created the market for second-hand products and raised the need for modernized reverse logistics systems. An early organized material recycling and waste management system was established in London, UK, to maintain sanitation and the general quality of urban life [60]. Similar to the impacts in other industries, the first two industrial revolutions changed the means of collection, transportation, and disposal of waste with mass mechanization and the use of steam power and electricity. However, the main destinations of used products were either second-hand markets or dumpsites, and well-organized recycling activities were not widely practiced at that time. With the increased concerns on environmental pollution and resource depletion, the focus of reverse logistics shifted from waste landfill to resource recovery through better source separation and increased reuse, remanufacturing, and recycling activities. The advancements of computers and robotics in Industry 3.0 helped to better support decision making with advanced optimization, simulation, and geographical information system (GIS) and to automize various reverse logistics operations. Besides, the drastically increased reconfigurability and flexibility of manufacturing systems not only realize mass customization but also pave the way for flexible remanufacturing in reverse logistics [61]. In this period, diverting the EOL product flows from landfills to other value recovery alternatives was the focus, and reverse logistics was conceptualized to depict all relevant activities and flows related to the effective management of EOL products [15].

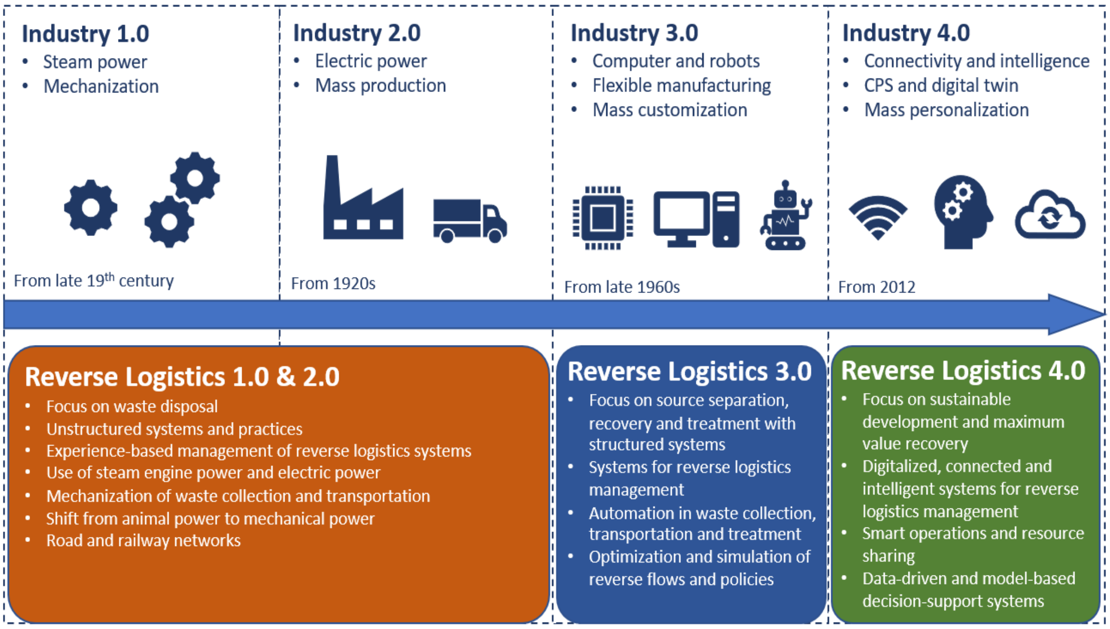

Figure 5 Reverse logistics evolution compared to the four Industrial Revolutions.

During the last decade, not only the economic benefits from product recovery but also the environmental and social performances of the entire reverse logistics system have been increasingly focused on through a holistic trade-off analysis [19]. Besides, the technological advancements have provided digital and smart solutions to change the paradigms of reverse logistics mainly in three ways: data, services, and operations. The value of data has been unprecedently uncovered by adopting IoT, smart devices, AI, and big data analytics, which enable better and real-time planning of different resources and operations. The cloud-based interactive and intelligent digital platform connects different service providers and customers to achieve optimal resource sharing and provide innovative services. Consumers' involvement in reverse logistics has become increasingly important [4], which provides better information on the quality, quantity, and the time and location of return of different EOL products [7, 62]. Furthermore, reverse logistics activities become increasingly autonomous with the use of AI-supported smart robots and vehicles. Thus, based on these characteristics, the concept of *Reverse Logistics 4.0* is defined as follows:

Reverse Logistics 4.0 is the sustainable management of all relevant flows and activities for value recovery and/or proper disposal of EOL products by using data-driven and smart technologies enabled individualization and innovative services.

Compared with the current definitional elements, *Reverse Logistics 4.0* emphasizes the use of data and smart technologies to realize innovative reverse logistics services and to achieve harmony among the three pillars of sustainable development including economic effectiveness, environment friendliness, and social responsibility. In the context of *Reverse Logistics 4.0*, the phrase "*individualization*" represents service smartness and innovations, whose demands are either pulled by customers, e.g., individualized collection [12], or driven by product and data, e.g., data-driven remanufacturing of WEEE [7]. For example, an individual collection and remanufacturing process can be planned and optimized based on the real-time information of the EOL product flows, e.g., type of product, material, structure, and quality level, and the available resources of the company.

4 Smart and Sustainable Reverse Logistics Transformation

Based on the definition of *Reverse Logistics 4.0*, Figure 6 presents a conceptual framework for smart reverse logistics transformation, where the role of Industry 4.0 technologies in shaping the reverse logistics service and operations and the three pillars of sustainable development are focused on. The conceptual framework consists of four fundamental elements that drive the paradigm transition in *Reverse Logistics 4.0*:

1. The key Industry 4.0 technologies, e.g., IoT, CPS, AI, autonomous robots, etc., are enablers to support the smart reverse logistics transformation.

2. The five main reverse logistics processes, i.e., collection of EOL products, sorting and pre-processing, transportation, value recovery through remanufacturing and recycling, and disposal, are affected by adopting disruptive technologies.

3. The improvement in the reverse logistics service and operations is centered on the reverse logistics transformation.

4. The targeted areas in the triple-bottom-line for improving the economic, environmental, and social sustainability in reverse logistics.

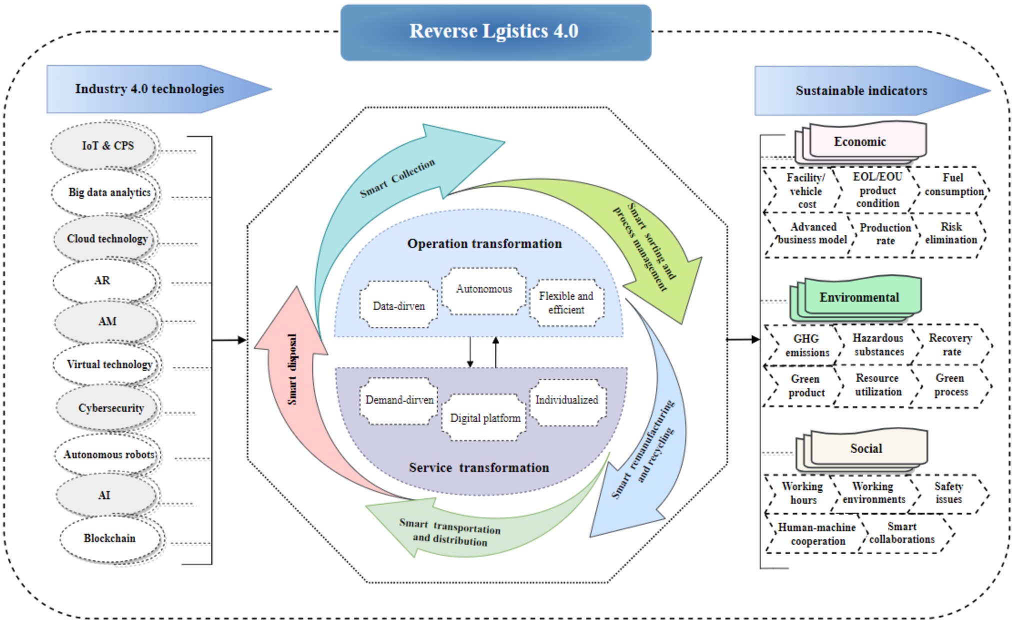

Figure 6 A conceptual framework of smart and sustainable reverse logistics transformation in *Reverse Logistics 4.0*.

This conceptual framework explicitly illustrates the connections between technological enablers, reverse logistics processes and transformations, and sustainability goals. With the increasing adoption of Industry 4.0 technologies, the transformation of reverse logistics service and operations is centered on *Reverse Logistics 4.0*:

- ***Smart service transformation***: Demand-driven and service-oriented transformation is the key driver of *Reverse Logistics 4.0*. For example, individualized collection services of used products can be provided to maximize the customer value and service. However, providing such kind of service in a traditional reverse logistic system is usually expensive and requires much more resource commitments. Thus, a digitalized platform may enhance better communication and information sharing among different stakeholders in real-time, and a data-driven intelligent decision-support system may help to improve resource planning and utilization, based on which individualized services can be performed in an efficient manner.

- ***Smart operation transformation***: Data-driven and autonomous operations are the key enablers of *Reverse Logistics 4.0* to offset the increased costs of providing a high level of individualized service, improve the operational effectiveness and resource efficiency, minimize the downtime, and reduce the risks and harshnesses in the working environment, and so forth. For example, the collection, transportation, and remanufacturing of used products can be better planned with both predictive data and real-time data. Besides, the operations and working environment of various reverse logistics activities can be potentially improved, e.g., autonomous and highly accurate waste sorting with AI-enabled smart robots.

Table 2 Technological framework for supporting smart and sustainable reverse logistics transformation.

Industry 4.0 technology	Smart reverse logistics transformation					References
	Smart collection	Smart sorting and process management	Smart remanufacturing and recycling	Smart transportation and distribution	Smart disposal	
IoT/CPS	• IoT-embedded smart bins • Smart monitoring	• Balanced inventory and process management through smart sorting	• Digitized the entire product life cycle	• Dynamic optimization and data-driven fleet management and vehicle routing • Improved traceability	• Intelligent remote-control operations	[6, 7, 63-68],
Big data	• Smart prediction and monitoring • Real-time routing of collection vehicles		• Predictive planning and real-time decision makings			[69-71]
Cloud technology	• Cloud-based autonomous waste collection system			• Effective collaboration, better resource sharing, and demand matching through cloud-based digitalization	• Cloud-based leachate monitoring and management	[66, 72, 73]
AR			• Effective functionality restoration and individualized maintenance services			[74].
AM			• Flexible product redesign and data-driven remanufacturing planning			[13]
Virtual technology	• Dynamic web data dashboard		• Better working procedures through real-time instructions and task visualizations • Predictive planning and real-time and effective decision makings	• Effective collaboration, better resource sharing, and demand matching through system integration		[66, 68, 75, 76]
Autonomous robots	• Smart robots for autonomous waste collection	• AI-enabled intelligent robot-based autonomous sorting system	• Better working procedures and effective functionality restoration			[77-81]
AI	• Digital and individualized collection services	• Smart sorting multicriteria analysis	•	• Self-driving trucks and automated driving support systems	• Garbage disposal EVs	[12, 79, 82]

The logic of this conceptual framework indicates that, essentially, the smart service and operation transformations across all stages of a reverse logistics system are driven by the better meeting of the targeted sustainability goals, while on the other hand, Industry 4.0 technologies are the most important enablers. It is noteworthy that, in this smart paradigm transition, adopting new and disruptive technologies is not the goal but rather the means to enable responsive services and efficient processes. Meanwhile, technology itself will not lead to the better system performance of a reverse logistics system, but the transformation and redesign of service and operations may potentially improve sustainability in economic, environmental, and social dimensions. In this regard, this conceptual framework helps to better understand the adoption of Industry 4.0 technologies in various smart reverse logistics operations. Based on the analysis of the existing literature and case studies, Table 2 presents a technological framework for supporting smart and sustainable reverse logistics transformation. The subsequent sub-sections discuss the potential paradigm changes with respect to the five main reverse logistics processes: 1) smart collection; 2) smart sorting and process management; 3) smart remanufacturing and recycling; 4) smart transportation and distribution; 5) smart disposal.

4.1 Smart Collection

Even though the routes can be regularly optimized in a traditional collection system of EOL products, the inherent uncertainty may lead to a resource allocation dilemma, which requires a balance between operating costs and service levels. For instance, the collection of EOL products and other types of waste on fixed schedule and routes usually lead to inefficient use of resources, high fuel consumption [84], and low service level. To make it worse, the low service level of biodegrade waste may result in an accumulation of bacteria from bad odors and the spread of diseases [68]. To tackle this problem, smart bins embedded with IoT sensors are increasingly used to monitor and provide real-time information about their fill levels and locations [63], based on which the collection routes can be dynamically optimized and digitally updated. An IoT-driven Kanban system was designed by Thürer, Pan [76] for the collection of EOL products. Another IoT-enabled prediction and monitoring system was proposed by John, Varkey [68], which could be installed in the existing collection bins of different sizes. Empowered by an intelligent neural network, it can learn and predict the waste generation patterns and send timely notifications to appropriate personnel via a firebase cloud messaging system with a dynamic web data dashboard.

Combining with GIS and data-driven optimization models, the routing of collection vehicles can be individualized and dynamically optimized with real-time data [69], based on which the collection service can be drastically improved without an increase in resource needs. To guarantee the real-time capability of data transmission, Cotet, Deac [72] developed a cloud-based automated system for innovative waste collection services. The combination of smart sensors, data, and optimization algorithms forms a smart CPS for EOL product collection in reverse logistics [85]. With increasing customers' involvement via digital platforms, the collection service can be provided based on individualized customer demands [12]. This provides a new business model for improved policy-making and value proposition, e.g., pricing-by-service, and for better interactions among different stakeholders. In addition, the use of smart robots for autonomous waste collection has recently been focused on during the COVID-19 pandemic due to their potential impacts on reducing infection risks of health workers.

4.2 Smart Sorting and Process Management

Due to the complex composition and quality of EOL products in the reverse flows, sorting is traditionally a semi-automated and labor-intensive process, where different recyclables need to be manually picked up and separated by human workers. However, the hazardous substances and the harsh working environment have put significant threats to the health of these workers. The recent developments of AI and vision-based systems have empowered smart robots with the capability of recognizing and automatically separating different types of recyclables [80, 81], which has shown great potential to become the gamechanger in reverse logistics operations [82]. An automated AI-enabled intelligent robot-based sorting system has been investigated for separating hazardous materials from WEEE [77] For some types of EOL products, i.e., aluminum cans and plastic bottles, recent research shows that the separation accuracy by robot-based smart systems can be up to 90% [86]. To support the separate collection of different types of EOL products at the sources, e.g., home and office, etc., a prototype of small-scale automatic sorting bins is developed by Ismail, Jayakumar [87], which used smart sensors and material classification technologies.

Industry 4.0 technologies can also help to better manage different processes and facilities. The end-to-end integration of radio-frequency identification (RFID), Bluetooth low energy (BLE), smart sensors, smart containers, and hybrid gateway in a networked CPS allows real-time information collected from various reverse logistics processes, i.e., returned product identification, classification, local information and global information, which can be used for better inventory control and environmental management of the whole process [88]. Another reverse logistics challenge is caused by the increased generation of infectious waste during the COVID-19 pandemic [89, 90], and a large proportion is mixed with conventional waste especially in the developing countries [79]. Thus, an AI-based automated system is established by [79], which provides an integrated solution for more accurate sorting of COVID-19 related medical waste streams from other waste types to support data-driven recycling planning.

4.3 Smart Remanufacturing and Recycling

From cloud-based systems to digital twins [7], Industry 4.0 paves the way for a data-driven smart remanufacturing process. The high uncertainty related to the quality, quantity, and the time and locations of return of EOL products, e.g., WEEE, used vehicles, etc., are the most significant hindrance in a traditional remanufacturing process. To tackle this, a product-based digital twin that integrates IoT and cloud technologies enables smart data collection and condition monitoring throughout the whole product life cycle [7]. Besides, consumers can also easily provide relevant product-related information via several digital platforms, e.g., smartphone apps, websites, etc. Based on the generic architecture proposed by Wang and Wang [7], a personalized digital twin can be developed for tracking the relevant data of specific products, which will be used for better identification, classification, and sorting for further processing.

Big data analytics can help to maximize the value recovery of EOL products through better information on specific production times and options in reverse logistics [71]. Using the real-time product information and system data as the dynamic inputs to the optimization models can maximize the effectiveness and resource utilization through improved and more flexible production planning for remanufacturing [70]. Besides, a data-driven intelligent dismantling may also reduce the damage during product dissembling and improve the quality and predictability of remanufactured products [91]. In addition, some other technologies can also help to improve the remanufacturing and recycling operations. For example, the quality and effectiveness of the maintenance service and functionality restoration in remanufacturing can be improved through intuitive step-by-step AR guidance to human operators in a product disassembling process [74]. Besides, the use of UAVs can assist in monitoring the remanufacturing process. Additive manufacturing provides a more flexible and cost-efficient way to restore the functionalities of EOL products and dissembled components [13]. At the system level, computer-based simulation can provide deep and visualized insights into the system behaviors in a smart remanufacturing process. In this regard, hybrid simulation techniques, i.e., system dynamics, discrete event simulation, and agent-based modeling are used to investigate the impact of smart technologies as well as the economic viability of remanufacturing [75].

4.4 Smart Transportation and Distribution

The effective sharing of information and resources is one of the most important features of Industry 4.0, and this provides different stakeholders in a reverse logistics system with the opportunities to better utilize their resources. IoT-based smart platforms have been used for dynamic optimization of demand allocation and routing of transport vehicles [6]. The real-time vehicle data is collected from GIS, IoT sensors, 4G/5G devices, RFID, and GPS devices, which are then processed to match the task data from different companies. Finally, the assignments and routing decisions are optimized to achieve the most efficient use of available vehicles for multiple assignments from different companies. The system can be further optimized with real-time traffic data for dynamic routing to minimize fuel consumption, greenhouse gas (GHG) emissions, and traffic congestion. A web-based information sharing system is developed by Gebresenbet, Bosona [66] for the reverse logistics management of agricultural biomass. The real-time information is collected via both smart devices and end-users, through which the demands and the supplies can be better matched to achieve a high level of inter-company resource utilization. The improved traceability can help to reduce product losses and logistics costs, while at the same time, improving market opportunity and product quality [66]. In addition, by connecting cameras, smart sensors, and radar equipment to the network of AI-enabled onboard computers, self-driving trucks have shown a great potential to realize autonomous driving [82]. In some tasks, smart AI has already overtaken human competence levels, and with the continuous maturity of autonomous vehicle technology, the paradigm of reverse logistics will also be largely changed in the near future [83].

4.5 Smart Disposal

The problem of waste disposal is not only related to dealing with the disposal of waste in the proper place but is also associated with reducing the volume of waste disposal [92], safety issues, and cleanliness [93]. Even though an increasing amount of EOL products are recycled, incineration plants and landfills are still the final destinations of the non-recyclables in reverse logistics systems, where smart robots can be used to replace human workers in harsh working environments. IoT-enabled smart systems can help to monitor the key performance indicators and remotely control different operations [64, 65]. The landfill of solid waste generates landfill gas and high-density hazardous liquid, called leachate, both of which have significant environmental impacts and need thus to be properly treated. To better manage the leachate problems, a cloud-based IoT system can play an important role in connecting the relevant field data with respective mathematical models to analyze several key parameters, i.e., turbidity, suspended solids, dissolved oxygen, etc., for smart disposal [73]. Besides, the smart bin is a solution for convenient waste disposal without the need to touch the lid, which avoids the spread of disease especially during the pandemic [93].

5 A Future Research Agenda

By analyzing the potential impacts of Industry 4.0 technologies on reverse logistics processes, Table 7 illustrates the architecture that enables the smart and sustainable transformation in *Reverse Logistics 4.0*. The smart and sustainable reverse logistics transformation concisely presents the union of both physical and digital value chains. On the one hand, a physical value chain illustrates the application and impacts of these disruptive technologies at both inter-and intra-organizational levels. On the other hand, a digital value chain assesses the long-term impacts on value-adding and value recovery patterns from a technological standpoint [94]. The proposed architecture explicitly links reverse logistics activities, Industry 4.0-enabled cyber-physical connection and interaction, and technological enablers for the smart transformation of collection, sorting and process management, remanufacturing and recycling, transportation and distribution, and waste disposal. It is noteworthy that the targeted sustainability goals are centered on the architecture of smart reverse logistics transformation, which further reflects the ultimate goal of *Reverse Logistics 4.0* is not to adopt technology but to improve sustainability through service and operation transformation by using technology, as shown in Figure 6. In this regard, Industry 4.0 technologies can provide more data, more connectivity, more intelligence, more flexible automation, and better resource sharing, through which the sustainable goals can be better archived through the improvement of various reverse logistics activities and processes. In addition, based on the analysis of reported research and cases in the literature, Figure 7 illustrates a mapping between the smart reverse logistics transformation and the proper Industry 4.0 enablers.

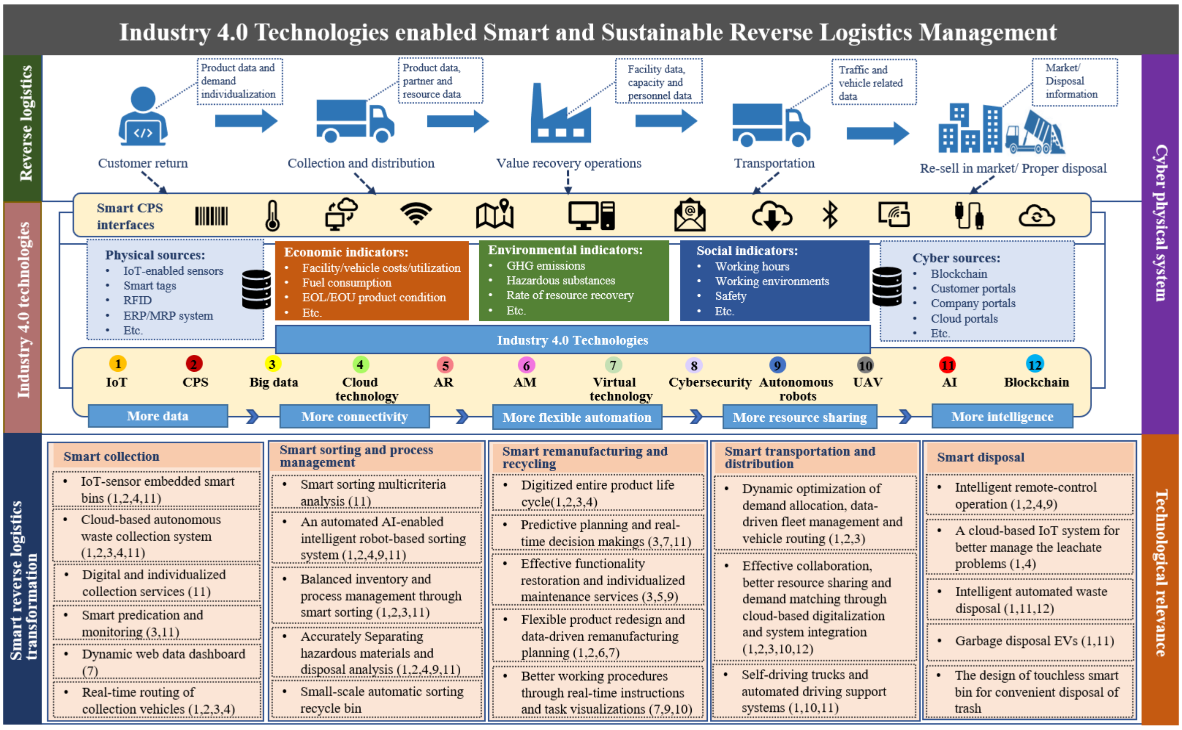

Figure 7 The architecture of the smart reverse logistics system enabled by Industry 4.0.

Even though recent research efforts have been increasingly given to Industry 4.0-enabled smart and sustainable reverse logistics [58, 59], there are still several gaps, e.g., a lack of comprehension and understanding of Industry 4.0 [95], unclear benefits and lack of quantitative approach for performance evaluation [54], etc., need to be filled. Thus, we identified four directions for guiding future research:

- ***Smart and Innovative Reverse Logistics Services***: Service innovation is the most important driver for the paradigm shift in *Reverse Logistics 4.0* to better meet the sustainability goals. However, the current research puts a predominant focus on the smart operations of isolated reverse logistics activities but not on the service innovation, which consequently hinders the real-world adoption of Industry 4.0 technologies due to the unclear benefits on customer value. Furthermore, the role of customers in the smart reverse logistics transformation has not been well investigated. Even though digital platforms are widely used today for better information sharing between customers and collection companies, for example, on the collection schedules of different types of EOL products and waste, they are mainly a one-way information flow and customers cannot require individualized collection service based on their actual needs. Thus, research needs to be carried out to better understand how Industry 4.0 technologies can be used to effectively and efficiently meet individualized demands in reverse logistics, which opens several research possibilities, e.g., demand/data-driven collection service systems, new business models and pricing strategies for the value proposition through demand individualization and service diversification, etc. In addition, a cloud-based system can provide a platform for end-users to register the relevant information of the returned EOL products, but the supporting policies and mechanisms have not been well in place to promote the customers' active participation in reverse logistics. In this regard, future research is invited to focus on service innovation, smartness, as well as the customers' role and active involvement in *Reverse Logistics 4.0*, through which the "*service-based individualization*" can be better interpreted to show clearer customer value and benefits to the companies. It will eventually help to promote the smart and sustainable transformation of *Reverse Logistics 4.0*.

- ***Quantitative Models for Smart and Sustainable Reverse Logistics Management***: The Industry 4.0-enabled smart reverse logistics services will lead to a transformation of traditional reverse logistics operations by increasing connectivity, smartness, and autonomous operations. Thus, there is a need for new quantitative models or new ways of using and integrating existing models to deal with new challenges, e.g., predictive operational planning with AI, real-time data integration, etc., and to better support strategic, tactical, and operational decisions for smart and sustainable reverse logistics management. For example, Reverse logistics network design is one of the most important strategic designs, which may yield long-term impacts on sustainable performance. The smart transformation in *Reverse Logistics 4.0* may dramatically change the operations and the key parameters within the planning horizon, which makes the initial network design becoming much more complex. In addition, implementing Industry 4.0 technologies to reduce internal operating costs through digital end-to-end integration are complex and requires a large initial investment [8], so a holistic analysis is needed to understand the long-term impacts of this smart transformation. In this regard, new quantitative models and methods are needed for better decision-support and comprehensive scenario analyses of the potential impact of smart reverse logistics transformation in the strategic network design, which can provide holistic insights to the decision-makers.

- ***Digital Reverse Logistics Twin***: As shown in Figure 7, the combination of the physical world and the cyber world in a smart digital twin is a promising research direction in *Reverse Logistics 4.0*, where, for example, AI-enabled data prediction and real-time data collected from both cyber and physical sources can be collaboratively used with mathematical models and computer-based simulation to better predict the key parameters or the parameter distributions for the quantitative decision-support models, which will help to minimize the impact of uncertainty in the reverse flows and to yield robust decisions e.g., scheduling and vehicle routing, [70]. The high-quality visualization of the reverse logistics system can help decision-makers to better analyze different operations. Furthermore, developing bi-directional control and interactions of the smart digital twin provides opportunities for autonomous reverse logistics operations. A smart digital reverse logistics twin requires an in-depth methodological integration and a high-level system integration, where various smart robots and devices, software, data, analytical models, visualization tools, etc., need to be effectively and seamlessly connected and interacted [96]. Furthermore, due to the complex flows and the involvement of several stakeholders, the system boundary of the smart transformation needs to be clearly defined, which helps to better interact with different reverse logistics players. In addition, multiple sustainability indicators need to be measured with both cyber and physical sources and be accounted for in the quantitative models for decision support. For example, the real-time routing may be dynamically optimized considering several objectives to balance economic costs, truck utilization, GHG emissions, and driver's working time.

- ***Human-centricity and Reverse Logistics 5.0***: Even though the opportunities for improving sustainability and circular economy have been discussed, Industry 4.0 is primarily a technology-driven paradigm shift. The recently proposed concept of Industry 5.0 has led to a changing focus from technology to human-centricity, resilience, and sustainability in the transition of many sectors [97, 98], which may result in new research directions for smart reverse logistics transformation. For instance, Industry 4.0 focuses on the development of autonomous solutions to replace human workers. However, on the other hand, Industry 5.0 emphasizes the harmony between humans and technology, where technologies are used not to replace humans but to better help human workers and create new job opportunities [97]. In this regard, future research is invited to further investigate the human-centric, resilient, and sustainable transformation of *Reverse Logistics 5.0*. Some specific topics are, for example, the updated sustainability goals in *Reverse Logistics 5.0*, especially from the social and environmental perspectives, human-machine collaboration in reverse logistics, the use of AR and collaborative robots (Cobot) for various operations, and so forth.

Table 3 presents several promising topics to better guide future research in each direction.

Table 3 Future research agenda.

Research directions	Specific topics
Smart and innovative reverse logistics services	• Demand/data-driven waste collection service • New business models for value proposition through individualized and diversified services • Pricing strategies for individualized collection service

	• Customers'role in smart and sustainable reverse logistics transformation • Supporting mechanisms for promoting end users' participation in reverse logistics
Quantitative models for smart and sustainable reverse logistics management	• Quantitative methods for evaluating the impacts of Industry 4.0 technologies, e.g., IoT, AI, additive manufacturing, smart robots, etc., on smart reverse logistics operations • Smart and sustainable reverse logistics network design • Data-driven proactive reverse logistics operational planning with AI and optimization (e.g., remanufacturing and recycling) • Data-driven dynamic and real-time vehicle routing for collection and transportation of EOL products (traffic data, fill level, etc.)
Digital reverse logistics twin	• Product-based digital twin with IoT and cloud technologies for data collection in the EOL stage • Methodological integration (predictive analytics, prescriptive analytics, and descriptive analytics) • Cyber-physical system integration (IoT sensors, smart devices, data, analytical models, and algorithms) • Real-time decision support and optimization under multiple sustainability goals
Human-centricity and *Reverse Logistics 5.0*	• Definition and conceptualization of the human-centric smart transformation of *Reverse Logistics 5.0* and the updated sustainability goals • The role of humans in the paradigm transition of reverse logistics • The development and use of collaborative technologies in smart reverse logistics systems • The impacts of adopting collaborative technologies in smart reverse logistics service and operations

6 Conclusion

Today, Industry 4.0 provides new opportunities and solutions to combine physical elements and data, autonomous technologies, internet- and cloud-based connectivity, data-driven analytics, and model-based analytics in highly digitalized and smart reverse logistics systems. However, there is still a lack of a systematic conceptualization to guide the paradigm transition of reverse logistics in Industry 4.0. Therefore, based on the reported research and case studies from the literature, this paper aims at contributing to the definition and conceptual development of *Reverse Logistics 4.0* and providing a general framework of the smart reverse logistics transformation to better achieve the sustainability goals in the triple-bottom-line by answering the three research questions:

- To answer ***RQ1***, the theoretical and practical evolvement of the concept of reverse logistics is discussed in comparison with the four Industrial Revolutions in history. *Reverse Logistics 4.0* is then defined based on the paradigm shift brought by Industry 4.0.

- To answer ***RQ2***, the general conceptual framework for the smart reverse logistics transformation is proposed considering technological enablers, smart service transformation, smart operation transformation, and sustainability goals. Moreover, the implications of adopting Industry 4.0 technologies in smart collection, smart sorting and process management, smart remanufacturing and recycling, smart transportation and distribution, and smart disposal are thoroughly analyzed.

- To answer ***RQ3***, a research agenda with four research directions is given to show the roadmap towards *Reverse Logistics 4.0* through the smart and sustainable transformation, and several specific topics are also suggested for each research direction.

Research implications. This paper provides a systematic definition, conceptualization, and research agenda of *Reverse Logistics 4.0* to thoroughly link the Industry 4.0, reverse logistics, and sustainability goals in the smart paradigm transition. Furthermore, research opportunities are clearly identified to guide future theoretical and methodological developments related to smart reverse logistics service innovation, quantitative models for smart and sustainable reverse logistics management, digital reverse logistics twin, and human-centricity and *Reverse Logistics 5.0*.

Managerial implications. This paper provides a conceptual framework that can help decision-makers and practitioners to understand how these sustainability goals can be better met through the technology-driven smart service and operation transformations of a reverse logistics system. Furthermore, it also presents a mapping between the technological enablers in Industry 4.0 and the smart transformation of different reverse logistics processes, and this provides a guide for the technology adoption of reverse logistics companies.

Future works. Even though research efforts have been spent to develop smart reverse logistics planning, especially with the application of real-time data in several operations. There is still a need for a better understanding of service innovation, customer participation, the role of humans, as well as other key influencing factors in *Reverse Logistics 4.0*. The impacts of smart reverse logistics transformation need to be holistically and comprehensively taken into account in the initial planning stage, e.g., network design. Besides, increased methodological integration and system integration are needed to realize the concept of a highly integrated and intelligent digital reverse logistics twin. Future research is thus invited to tackle these challenges.

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Authors' contributions:

- Xu Sun and Hao Yu contributed to the study conception and design.
- Data collection and analysis were performed by Xu Sun.
- The research was supervised by Wei Deng Solvang.
- The first draft of the manuscript was written by Xu Sun and all authors commented on previous versions of the manuscript.
- All authors read and approved the final manuscript.

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PAPER 3

A Two-Level Decision-Support Framework for Smart and Sustainable Reverse Logistics Network Design

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Submitted manuscript

Author's Contribution

Xu Sun is the main contribution of conceptualization, methodology, data curation, formal analysis, writhing-original draft of the paper, and writing-review and editing of the paper

A Two-Level Decision-Support Framework for Smart and Sustainable Reverse Logistics Network Design

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Abstract: Reverse logistics aims at the value recovery from end-of-life (EOL) products through reuse, repair, refabrication, remanufacturing, and recycling. However, reverse logistics network design is a complex decision-making problem, which needs to balance the tradeoff among different objectives. Besides, the cutting-edge technologies in Industry 4.0 provide opportunities for technological upgrades and smart transformation within the planning horizon, which further complicates the initial network design problem. In this paper, a two-level decision-support framework is proposed for smart and sustainable reverse logistics network design. While optimization models dominate this field, the combination with simulation methods remains still under-explored. Thus, with a two-level structure, the behavior of the optimized networks can be comprehensively evaluated by dynamic simulation models that incorporate both discrete events and Monte Carlo simulation. The results of a real-world case study in Norway show that the two-level decision-support framework can yield robust strategic decisions and holistic performance analyses under dynamic, realistic, and uncertain environments.

Keywords: reverse logistics, network design, decision support system, simulation, smart technology, waste electrical and electronic equipment (WEEE)

1 Introduction

Today, technological innovations have not only improved people's living standards and changed consumption patterns, but also significantly shortened product lifecycles and therefore accelerated the generation of end-of-life (EOL) products. The generation of waste electrical and electronic equipment (WEEE) has become one of the fastest-growing waste streams in Europe [1]. According to Eurostat [2], the annual generation of end-of-life vehicles (ELVs) in the EU-27 countries has increased by 22% from 5.54 million tons in 2011 to 6.732 million tons in 2018. To tackle this challenge from the increasing EOL products, much attention has been given to the development of effective regional and international reverse logistics systems, with the special aim of increased value recovery from EOL products. Reverse logistics refers to activities of planning, operating, and managing the reverse material, information, and capital flows starting from the end-customers toward the initial manufacturers and suppliers [3]. Effective reverse logistics is considered a crucial countermeasure for sustainable development and circular economy [4]. Network design is the first step in managing reverse logistics and is considered the most important strategic decision that affects the system's long-term performance [5]. Compared with forward logistics networks, a reverse logistics network has embedded intricates due to its inhomogeneous items and complex flows with high uncertainties. Adding on the involvement of many more different types of stakeholders with often contradictive objectives, reverse logistics network design is a complex decision-making problem that needs advanced decision-support methods to properly manage the interactions among various influencing factors. During the last two decades, extensive research efforts have been given to the development of analytical methods for reverse logistics network design [6] to improve economic effectiveness and reduce carbon emissions while complying with stricter environmental legislation and social development.

Recently, with the rapid development of disruptive technologies in the Fourth Industrial Revolution, namely, Industry 4.0, logistics performances have been improved with better data analytics, autonomous and intelligent robots, virtual technologies, and additive manufacturing [7]. In parallel, the paradigm of traditional reverse logistics has inevitably been shifting [8], and the increasing use of Industry 4.0 technologies, i.e., internet of things (IoT), cyber-physical systems (CPS), artificial intelligence (AI), smart robots, etc., provides new opportunities for a smart and sustainable reverse logistics transformation. Smart transformation refers to a paradigm shift driven by innovation and the increasing use of smart technologies in reverse logistics, which may lead to a higher level of predictiveness, intelligence, autonomousity, and sustainability, as shown in Figure 1. Compared with traditional operations, one notable feature of a smart reverse logistics system is that the tactical and operational uncertainties can be drastically reduced with AI- and big data-enabled predictive analytics [9] and IoT-enabled real-time data. For example, a product-based digital twin can be used to monitor the product information through its whole lifecycle [10]. When a product comes to the EOL phase, its information can be captured via a cloud-based system and be shared with the companies in reverse logistics. Besides, the end-users can also be easily involved via digital platforms, e.g., mobile apps, to provide information of the quality level and the time and location of return of their EOL products. The data collected from both cyber and physical environments can help companies to effectively achieve proactive planning and real-time decision making in various reverse logistics operations, i.e., vehicle routing and remanufacturing scheduling [11, 12].

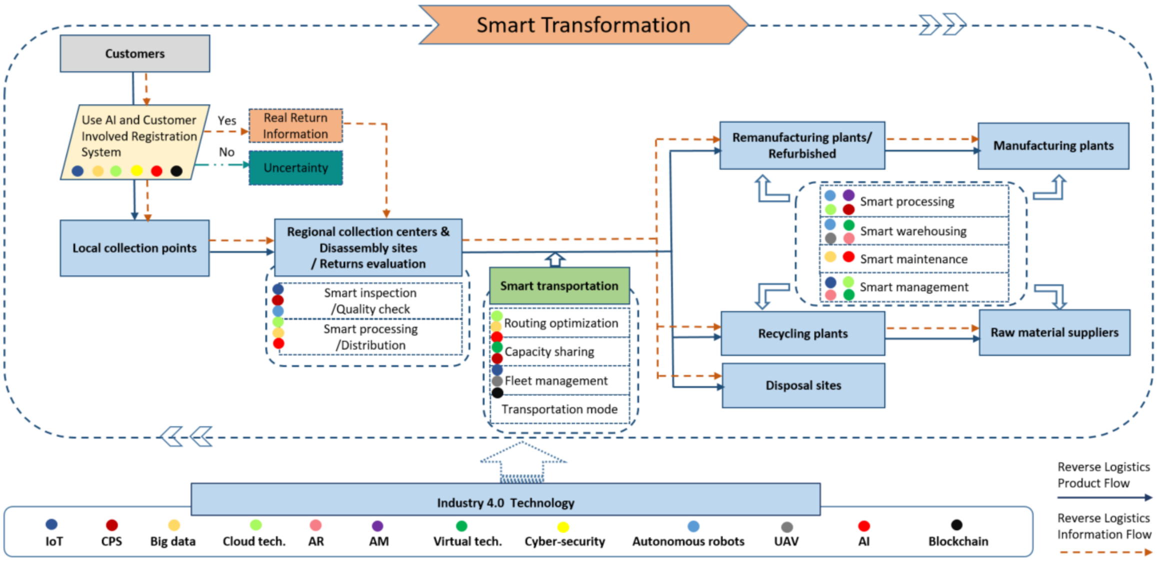


Figure 1 Smart reverse logistics transformation.

From the planning perspective, the value of data and information are predominately emphasized in smart reverse logistics systems to minimize the impact of uncertainty. On the other hand, various reverse logistics operations can become autonomous, which may reduce operating costs, environmental impacts, and safety concerns. For instance, AI-enabled robots can be used to perform an initial inspection and sorting at regional collection/disassembly centers, which may improve efficiency and replace human workers from the harsh working environment. Besides, additive manufacturing is also considered one of the most attractive solutions for remanufacturing. In addition, the increasing use of cleaner fuel and energy helps to reduce the carbon emissions of different reverse logistics activities.

However, the smart transformation by gradual but steady adoption of these new technologies will change the operational conditions over different periods and thus introduce new challenges to reverse logistics network design. In this regard, not only the uncertainty from the external environment but also the configurational change within the lifespan of a reverse logistics system and the disruption during the facility upgrades need to be holistically considered. To solve the planning challenges related to these uncertainties, a two-level decision-support framework combining both mathematical optimization and dynamic simulation is proposed for smart and sustainable reverse logistics network design. Through this approach, the impact of the smart transformation with highly intelligent and effective reverse logistics operations can be evaluated to better analyze the system behaviors of different network alternatives. A bi-objective optimization model is first used to determine a set of candidate network configurations for the reverse logistics system considering both economic and environmental performances. Then, the selected candidate networks are evaluated by a dynamic simulation model using both discrete events and Monte Carlo simulation. This decision-support framework uses the strengths of both optimization and simulation, and the analytical results are obtained under realistic environments with a dynamic planning horizon, stochastic parameters, real-world GIS, practical operational policies, and technological upgrades. Through the quantitative analysis of a case study in Norway, we aim at answering the following research questions:

RQ1: How to design a smart and sustainable reverse logistics system considering dynamic configurations under realistic environments?

RQ2: What are the impacts of smart transformation on the reverse logistics network design?

The rest of the paper is organized as follows. Section 2 presents a literature review and identifies the research gaps and contributions of this research. Section 3 describes the problem under investigation. The two-level decision-support framework is introduced in Section 4. Sections 5 and 6 present the case study and discuss the experimental results. Finally, conclusions are given in Section 7.

2 Literature Review

Reverse logistics network design has been focused on since the beginning of the 2000s [13]. In connection with the focus of this paper, we reviewed relevant quantitative models in three groups: (1) mathematical optimization; (2) simulation; and (3) smart reverse logistics.

2.1 Mathematical Optimization

Mathematical optimization is the most extensively used method for reverse logistics network design [14]. Using mixed-integer program (MIP), both strategic facility location and tactical demand allocation can be determined in either cost minimization or profit maximization manner [15]. During the last decade, extensive research efforts have been spent to model multiple objectives and tackle the uncertainty and computational issues.

2.2.1 Multi-Objective Optimization

The sustainability of reverse logistics network design has been increasingly modeled by using multi-objective optimization [16]. Carbon emissions and other environmental impacts were considered holistically alongside the economic objective [17, 18]. Different carbon policies, e.g., carbon tax [19], carbon cap [20], were formulated by multi-objective models. Recently, the triple bottom line has been increasingly incorporated in reverse logistics network design [21, 22], which aims at balancing the tradeoff among economic, environmental, and social sustainability. To model the social sustainability, various performance indicators, e.g., job creation [21], working conditions [23], GDP level [22], and hybrid social indicators [24], etc., were employed. Several operational indicators have also been considered. Zarbakhshnia, Soleimani [25] maximized the number of machines in reverse logistics operations. Xiao, Sun [26] modeled the facility utilization rate as an objective function. Yu and Solvang [27] focused on the impact of network flexibility in the reverse logistics system. Considering the integration of product recovery into the existing supply chain, Gao and Cao [28] investigated a multi-objective reverse logistics network redesign problem.

2.2.2 Uncertainty

Uncertainty is a crucial factor. If uncertainty is not considered in the initial design stage, it will be difficult to impose major changes without excessive resources when the network is implemented. Many parameters cannot be predicted accurately over the entire planning horizon, and various modeling techniques have been applied to manage the uncertainty. To deal with randomness, stochastic programming has been extensively applied in reverse logistics network design [29]. Trochu, Chaabane [30] developed a two-stage stochastic program to design a reverse logistics system under uncertainty. Rahimi and Ghezavati [24] proposed a multi-period stochastic model for sustainable management of construction waste, where the conditional value at risk (CVaR) was employed for risk aversion. To reduce the high data-dependency of stochastic models, fuzzy programming and robust optimization have been increasingly used. Kuşakcı, Ayvaz [31] investigated a fuzzy MIP to minimize the total costs of end-of-life vehicles (ELVs) recycling in Turkey. Govindan, Paam [23] proposed a fuzzy multi-objective model for reverse logistics network design considering the balance among costs, environmental impacts, and social responsibility. Tosarkani, Amin [32] developed a robust probabilistic optimization model for designing a sustainable WEEE reverse logistics system in Canada. Recently, the research focus has been given to the model development with hybrid techniques, i.e., robust-stochastic programming [33], fuzzy-stochastic programming [34], fuzzy-robust programming [35], and robust-fuzzy-stochastic programming [36], to tackle mixed uncertainty.

2.2.3 Computational Efficiency

The inclusion of multiple objectives and uncertain parameters has led to increased computational complexity. The computational issues were tackled by developing approximation methods, e.g., heuristics and metaheuristics, to find near-optimal solutions. The most extensively used metaheuristics include genetic algorithm (GA), swarm intelligence (SI), relaxation and decomposition methods. For instance, Afra and Behnamian [37] investigated a Lagrangian relaxation method to effectively solve a multi-product production-routing problem in the reverse logistics system considering both costs and environmental impacts. Roudbari, Ghomi [38] developed a hybrid algorithm combining both GA and branch-and-cut to improve the computational efficiency of reverse logistics network design. Zarbakhshnia, Kannan [39] Investigated a sustainable network design problem for an integrated forward/reverse logistics system under uncertainty, where a non-dominated sorting genetic algorithm (NSGA-II) was used to solve the complex optimization problem.

2.2 Simulation

Computer-based simulation has gained increasing momentum in reverse logistics due to its capability to model uncertainties, system complexity, and dynamic features. Simulation can reproduce the operations of real-world systems and can help to compare several what-if scenarios [40]. Simulation has been used for the performance evaluation of reverse logistics operations [41]. For example, Elia, Gnoni [42] developed a simulation model to evaluate three different schemes for WEEE collection, i.e., the fixed schedule, the pure dynamic schedule, and the mixed schedule. Ghisolfi, Chaves [43] studied the impacts of the legal incentives and the bargaining power obtained by waste collection volume on a reverse logistics system of EOL PCs and laptops. The simulation methods used for logistics planning include discrete event simulation, Monte Carlo simulation, and simulation-based optimization.

2.2.1 Discrete event simulation

Discrete event simulation depicts a system and its behavior with a series of discrete events sequentially organized, and these events trigger the change of the system's states autonomously over a dynamic test horizon. With minimum simplifications, it is a powerful tool to model the real-world features of reverse logistics systems. Gonçalves, Fagundes [44] investigated a discrete event simulation to evaluate 11 scenarios of a reverse logistics system for recycling EOL tires in Brazil. de Oliveira, Fagundes [45] developed a discrete event simulation in ProModel. With three waste disposal options, i.e., landfills, recycling, and incineration with energy recovery, 16 scenarios were evaluated to promote sustainability and eco-efficiency in municipal solid waste (MSW) management. Alamerew and Brissaud [46] developed a simulation model for a revere logistics system of battery recovery from e-vehicles, which explored the interplay among the main pillars of the circular economy. Elia, Gnoni [47] investigated a discrete event simulation for the sustainable WEEE collection in Italy. Their results reveal that the hub-and-spoke network has better economic and environmental performances than the traditional WEEE collection system.

2.2.2 Simulation-based Optimization and Monte Carlo Simulation

Simulation-based optimization has been focused on in reverse logistics, where simulation is used as a part of the optimization algorithm to either accelerate the converging speed toward the near-optimal solutions or validate the solutions in stochastic environments. Fu, Fu [48] defined simulation-based optimization is essentially an optimization problem with stochastic features in either parameters or solution procedures, e.g., a two-stage stochastic optimization with recourse decisions. In this regard, Monte Carlo simulation has been extensively used to incorporate with an optimization model. Monte Carlo simulation is a wide category of numerical methods that calculate results through repeatedly solving a large number of random samples [49], which aims at ensuring a high level of statistical stability of a stochastic process.

Ameli, Mansour [50] proposed a simulation-based optimization model to evaluate the performance of manufacturers by considering both product design alternatives and EOL options, where simulation was used to reduce the computational complexity. Yang and Chen [51] performed a Monte Carlo simulation to approximate the robustness of a regional reverse logistics system for construction and demolition wastes. Yu, Sun [52] investigated a two-stage stochastic optimization model for the reverse logistics network design of hazardous materials, where a Monte Carlo simulation-based sampling method was used to analyze the impact of uncertainty.

2.3 Smart Reverse Logistics

The implementation of Industry 4.0 technologies provides new opportunities for smart and sustainable reverse logistics by the increasing use of data analytics and autonomous technologies [8]. For example, big data supported logistics [9], cloud-based and 3D printing-assisted remanufacturing [53, 54], IoT-based data-driven transportation planning [11], and digital twin for product recovery [10], have been increasingly investigated. These features may yield great impacts on reverse logistics operations. From the strategic network design perspective, these may change the parameter settings of decision-support models. In this regard, Govindan and Gholizadeh [55] recently proposed a scenario-based robust optimization model for the network design of a sustainable and resilient reverse logistics system by considering the big data's 3V features (volume, velocity, and variety), which were represented by the uncertainty related to some key input parameters of the model, e.g., return volume, quality, etc. A cross-entropy algorithm was developed to solve the optimization problem.

2.4 Literature gaps

While mathematical optimization dominates the research in logistics network design, the combination of both optimization and simulation, especially discrete event simulation, remains still under-explored in both forward and reverse logistics channels [56]. Table 1 compares the relevant studies. Most research employs a single method either mathematical optimization or simulation. Even though several mathematical models employ Monte Carlo simulation to validate uncertain parameters and scenarios [32], they can only deal with the parametric uncertainty and find the statistically optimum with a static and oversimplified representation of real-world problems [57]. To tackle this, discrete event simulation is capable of thoroughly depicting the dynamic features and analyzing different operational scenarios of a complex reverse logistics system. Due to this reason, combing mathematical optimization with discrete event simulation has recently been emphasized in forward logistics network design [57, 58]. However, as shown in Table 1, discrete event simulation is only used as a single method to compare predefined configurations and strategies, and it has not been combined with mathematical optimization in reverse logistics network design due to several reasons, e.g., the complexity of building respective models, the requirement of different software, the conversion of data with different levels of aggregation, the setting up of realistic operational policies, and so forth. Besides, none of the previous research considers both sustainability and the potential impacts of smart transformation on reverse logistics network design under a dynamic environment with real-world case studies.

Table 1 Overview of relevant literature.

Authors	Sustainability	Smartness	Uncertainty		Method				Experiment
			Technique	Type	Optimization		Simulation		
					Objectives	Solution	Discrete event	Monte Carlo	
Pishvaee, Kianfar [15]	-	-	-	-	Single	Approximation	-	-	Numerical
Kannan, Diabat [17]	√	-	-	-	Single	Exact	-	-	Numerical
Ramos, Gomes [18]	√	-	-	-	Multiple	Exact	-	-	Case
Govindan, Paam [23]	√	-	Fuzzy	Dynamic	Multiple	Exact and approximation	-	-	Numerical
Rahimi and Ghezavati [24]	√	-	-	-	Multiple	Exact	-	-	Numerical
Yu and Solvang [27]	√	-	Stochastic	Static	Multiple	Exact	-	-	Numerical
Farrokh, Azar [36]	-	-	Robust-fuzzy-stochastic	Dynamic	Single	Exact	-	-	Numerical
Wang, Goh [59]	-	-	-	-	-	-	√	-	Numerical
Xiao, Sun [26]	√	-	-	-	Single	Exact	-	-	Case
Trochu, Chaabane [30]	-	-	Stochastic	Dynamic	Single	Approximation	-	√	Case
Zarbakhshnia, Soleimani [25]	√	-	-	-	Multiple	Approximation	-	-	Numerical
Kuşakcı, Ayvaz [31]	-	-	Fuzzy	Static	Single	Exact	-	-	Case
Gonçalves, Fagundes [44]	√	-	-	-	-	-	√	-	Case
de Oliveira, Fagundes [45]	√	-	-	-	-	-	√	-	Case
Elia, Gnoni [47]	√	-	-	-	-	-	√	-	Case

Ameli, Mansour [50]	√	-	Simulation	Static	Multiple	Approximation	-	√	Case
Safdar, Khalid [21]	√	-	-	-	Multiple	Exact	-	-	Numerical
Budak [22]	√	-	-	-	Multiple	Exact	-	-	Case
Gao and Cao [28]	√	-	Stochastic	Static	Multiple	Exact	-	-	Numerical
Tosarkani, Amin [32]	√	-	Robust	Dynamic	Multiple	Exact	-	√	Case
Yu and Solvang [34]	√	-	Fuzzy-stochastic	Static	Multiple	Approximation	-	√	Numerical
Nayeri, Paydar [35]	√	-	Fuzzy-robust	Static	Multiple	Exact	-	-	Case
Zarbakhshnia, Kannan [39]	√	-	-	-	Multiple	Approximation	-	-	Numerical
Yang and Chen [51]	-	-	Robust	Static	Single	Exact	-	√	Case
Yu, Sun [52]	-	-	Stochastic	Static	Multiple	Approximation	-	√	Numerical and case
Shahparvari, Soleimani [33]	√	-	Stochastic	Static	Single	Approximation	-	-	Numerical and case
Afra and Behnamian [37]	-	-	-	-	Single	Approximation	-	-	Numerical
Roudbari, Ghomi [38]	-	-	Stochastic	Static	Single	Approximation	-	-	Case
Che, Lei [14]	-	-	-	-	Single	Approximation	-	-	Case
Govindan and Gholizadeh [55]	√	√	Fuzzy-robust	Dynamic	Single	Approximation	-	-	Numerical
This paper	√	√	Simulation	Dynamic	Multiple	Exact	√	√	Case

2.5 Contributions

This paper aims at filling the research gaps by developing a two-level decision-support framework combining both optimization models and dynamic simulation for smart and sustainable reverse logistics network design. Herein, ***dynamic simulation*** refers to the combination of both discrete events and Monte Carlo simulation to depict the dynamic features of a reverse logistics system.

Specifically, we aim at bringing the following contributions:

- Methodologically, we illustrate how multi-objective optimization, discrete event simulation, and Monte Carlo simulation can be effectively combined to better model the practical features and analyze the dynamic system behaviors of a reverse logistics system.

- We provide a decision-support framework with holistic supports for reverse logistics network design with high visualization and comprehensive performance analyses for smart technological upgrades through the entire planning horizon.

- We demonstrate the practical relevance and applicability of the proposed method with a real-world case study in Norway to discuss the impacts of the smart transformation through scenario analyses of various operational parameters, configuration changes, and disruptions.

3 Problem Description

A reverse logistics network consists of different facilities, i.e., local collection points, regional collection/disassembly centers, remanufacturing plants, recycling plants, and disposal sites. The EOL products are first collected at local collection points and then transported to regional collection centers, where these EOL products are inspected and disassembled to different components. At the regional collection center, the disassembled components can be categorized into three classes based on their product residual value (PRV), namely, high-PRV, low-PRV, and non-recyclable. The high-PRV components will be distributed to remanufacturing plants for refurbishing and function restoration based on the type of products. After that, they can be sold to manufacturers at lower prices [60]. The Low-PRV components are sent to recycling plants, where they are degraded into new materials and then sold to the suppliers. The non-recyclable components and hazardous materials are sent for proper disposal.

Reverse logistics network design is a strategic decision that has long-term impacts on the system performance. The smart transformation in Industry 4.0 may affect the reverse logistics operations and some key parameters over the planning horizon. For example, the low-carbon equipment and transport vehicles will likely become cheaper with technological advancement and be increasingly used in reverse logistics operations, but the adoption of new technologies is a dynamic process, and the change of system configurations occurs gradually over several periods. Thus, we aim at providing a decision-support framework to help with strategic decisions and evaluate the impacts of smart transformation on reverse logistics network design. On the other hand, the methodological integration between mathematical optimization and dynamic simulation forms the initial step of a highly intelligent, visualized, and interactive digital reverse logistics twin [61].

4 Methodology

A two-level decision-support framework is developed, as shown in Figure 2. First, the candidate network configurations are determined by a bi-objective MIP. The augmented ε-constraint method is used to solve the optimization problem and generate a set of efficient Pareto optimal solutions. Then, dynamic simulation is used to further evaluate the selected network configurations in a more complex and realistic environment [62, 63]. In this step, discrete event simulation models are built upon the selected networks to depict the dynamic features, operations, and upgrades of facilities and transportation over the planning horizon. Due to the stochastic nature of the simulation process, Monte Carlo simulation is performed to ensure a high level of confidence in the analytical results. This means the experiment needs to be executed for several repetitions. The purpose is to guarantee that the outputs of the simulation model are stable and are not affected by the scenario generation process. Finally, the performance indicators need to be measured to rank the selected networks and output the analytical results. In case of pre-defined performance indicators are used, new candidate network configurations and/or new operational policies may be tested to ensure all the performance indicators are met.

The combination of simulation and optimization in a two-level decision-support framework can explore the strengths of both methods [57]. For example, in a simulation-optimization cycle, simulation can provide predictions of some critical inputs for optimization models. On the other hand, in an optimization-simulation cycle, simulation can be used to better evaluate the solutions obtained from the mathematical model [57]. More detailed introductions of the respective optimization and simulation processes in this two-level decision-support framework are given in the following subsections.

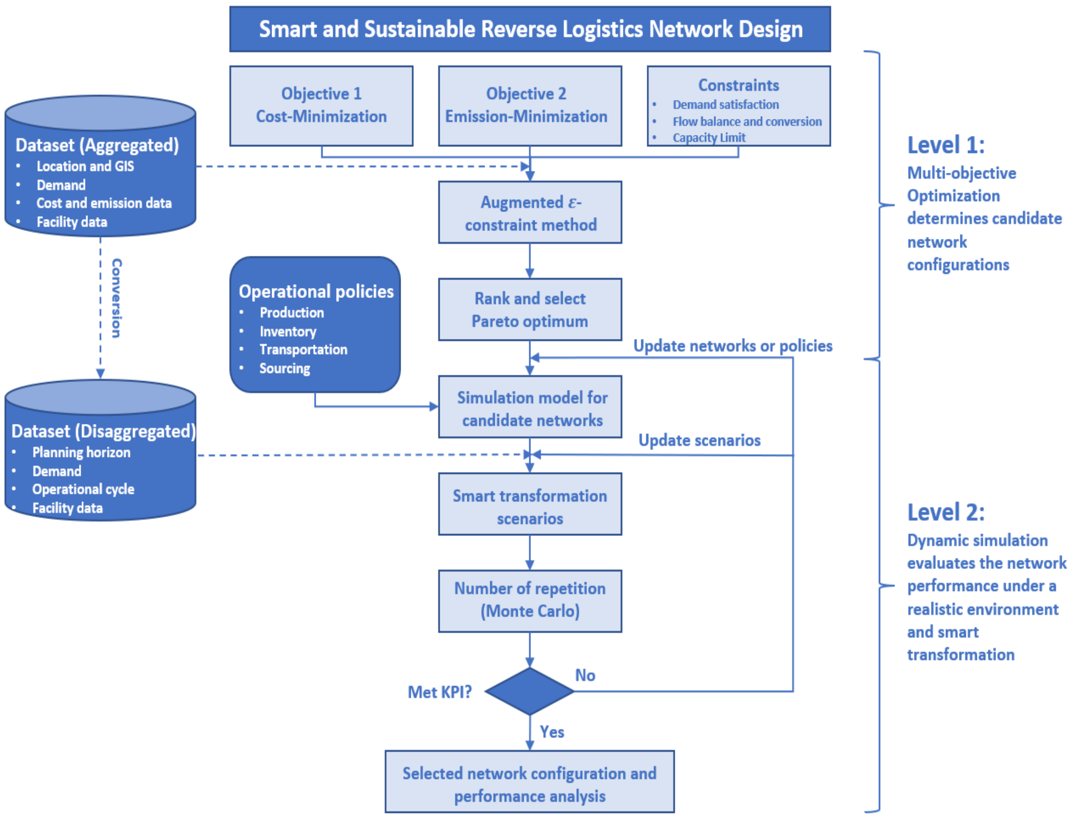


Figure 2 The two-level decision-support framework.

4.1 Mathematical Model

In this paper, we consider the selection and operations of the regional collection centers, remanufacturing plants, recycling plants, and disposal sites, as well as the transportation of EOL products and disassembled components among these facilities. A bi-objective MIP model is formulated considering both cost-effectiveness and carbon emissions, and the model has the following assumptions:

- The demand and locations of the generation points of EOL products are known.
- The candidate locations and planned capacities of the respective facilities for regional collection, remanufacturing, recycling, and disposal are known.
- The relevant cost and emission parameters are known.

The sets, parameters, and variables are first given as follows:

Sets	
P	Set of EOL product *p*
Q	Set of disassembled component *q*
E	Set of local collection center *e*
R	Set of potential location for regional collection center *r*
I	Set of potential location for remanufacturing/refurbishing plant *i*
J	Set of potential location for recycling plant *j*
K	Set of potential location for disposal site *k*
Parameters	
Fxr_r	Fixed opening and operating cost of regional collection center opened at *r*
Fxi_i	Fixed opening and operating cost of remanufacturing plant opened at *i*
Fxj_j	Fixed opening and operating cost of recycling plant opened at *j*
Fxk_k	Fixed opening and operating cost of disposal site opened at *k*
OCr_{rp}	Unit processing cost of EOL product *p* at regional collection center *r*
OCi_{iq}	Unit remanufacturing cost of component *q* at *i*
OCj_{jq}	Unit material recycling cost of component *q* at *j*
OCk_k	Unit disposal cost of unrecyclable at *k*
TCa_{erp}	Unit transportation cost of EOL product *p* on arc(*e*, *r*)
TCb_{riq}	Unit transportation cost of component *q* on arc(*r*, *i*)
TCc_{rjq}	Unit transportation cost of component *q* on arc(*r*, *j*)
TCd_{rkq}	Unit transportation cost of component *q* on arc(*r*, *k*)
$Flex_{ep}$	Unit flexible capacity cost
Esr_{rp}	Unit carbon emissions of EOL product *p* processed at *r*
Esi_{iq}	Unit carbon emissions of component *q* remanufactured at *i*
Esj_{jq}	Unit carbon emissions of component *q* recycled at *j*
Esk_k	Unit carbon emissions at disposal site *k*
$TEsa_{erp}$	Unit carbon emissions of EOL product *p* transported on arc(*e*, *r*)
$TEsb_{riq}$	Unit carbon emissions of component *q* transported on arc(*r*, *i*)

$TEsc_{rjq}$	Unit carbon emissions of component *q* transported on arc(*r, j*)
$TEsd_{rkq}$	Unit carbon emissions of component *q* transported on arc(*r, k*)
$Fles_{ep}$	Unit carbon emissions of flexible capacity
EOL_{ep}	Amount of EOL product *p* collected at location *e*
CRM_{pq}	Conversion rate from EOL product *p* to component *q* for remanufacturing
CRC_{pq}	Conversion rate from EOL product *p* to component *q* for material recycling
CDP_{pq}	Conversion rate from EOL product *p* to component *q* for disposal
$Capr_{rp}$	Capacity of regional collection plant *r* for EOL product *p*
$Capi_{iq}$	Capacity of remanufacturing plant *i* for component *q*
$Capj_{jq}$	Capacity of recycling plant *j* for component *q*
$Capk_{k}$	Capacity of disposal site *k*
$UPFLX_{p}$	Upper limit of flexible capacity for EOL product *p*
Variables	
Dr_{r}	$\begin{cases} Dr_r=1 \text{ Potential location for regional collection center } r \text{ is selected} \\ Dr_r=0 \text{ Otherwise} \end{cases}$
Di_{i}	$\begin{cases} Di_i=1 \text{ Potential location for remanufacturing plant } i \text{ is selected} \\ Di_i=0 \text{ Otherwise} \end{cases}$
Dj_{j}	$\begin{cases} Dj_j=1 \text{ Potential location from recycling plant } j \text{ is selected} \\ Dj_j=0 \text{ Otherwise} \end{cases}$
Dk_{k}	$\begin{cases} Dk_k=1 \text{ Potential location for disposal site } k \text{ is selected} \\ Dk_k=0 \text{ Otherwise} \end{cases}$
Ur_{rp}	Amount of EOL product *p* processed at *r*
Ui_{iq}	Amount of component *q* remanufactured at *i*
Uj_{jq}	Amount of component *q* recycled at *j*
Uk_{k}	Amount of disposed component at *k*
UTa_{erp}	Amount of EOL product *p* transported via arc(*e, r*) for collection, inspection, and disassembly
UTb_{riq}	Amount of component *q* transported via arc(*r, i*) for remanufacturing
UTc_{rjq}	Amount of component *q* transported via arc(*r, j*) for material recycling
UTd_{rkq}	Amount of component *q* transported via arc(*r, k*) for disposal
UF_{ep}	Amount of EOL product *p* sent for flexible options from location *e*
URM_{rq}	Amount of disassembled component *q* for remanufacturing from regional collection center *r*
URC_{rq}	Amount of disassembled component *q* for material recycling from regional collection center *r*
UDP_{rP}	Amount of EOL product sent for disposal from regional collection center *r*

The mathematical model consists of two objectives. The first objective Eq. (1) minimizes the total costs for operating this reverse logistics system, which includes fixed facility cost FX, facility operating cost OX, transportation cost TX, and flexible capacity cost FLX. It is noteworthy that the inclusion of FLX is considered a soft constraint to allow a small violation of the capacity constraints, which improves the model's flexibility and helps to yield robust strategic decisions. In practice, it means the excessive customer demands can be fulfilled by various temporary solutions, i.e., outsourcing, seasonal workers, etc. These flexible solutions are usually more expensive, but they can effectively avoid redundant facility configurations at the strategic level and improve long-term sustainability [34].

$$\text{Min } Z1 = FX + OX + TX + FLX \tag{1}$$

The respective cost components in the objective function are calculated by Eqs. (2-5).

$$FX = \sum_{r\in R} Fxr_r\, Dr_r + \sum_{i\in I} Fxi_i\, Di_i + \sum_{j\in J} Fxj_j\, Dj_j + \sum_{k\in K} Fxk_k\, Dk_k \tag{2}$$

$$OX = \sum_{r\in R}\sum_{p\in P} OCr_{rp}Ur_{rp} + \sum_{i\in I}\sum_{q\in Q} OCi_{iq}Ui_{iq} + \sum_{j\in J}\sum_{q\in Q} OCj_{jq}Uj_{jq} + \sum_{k\in K} DCk_k Uk_k \tag{3}$$

$$TX = \sum_{e\in E}\sum_{r\in R}\sum_{p\in P} TCa_{erp}UTa_{erp} + \sum_{r\in R}\sum_{i\in I}\sum_{q\in Q} TCb_{riq}UTb_{riq} + \sum_{r\in R}\sum_{j\in J}\sum_{q\in Q} TCc_{rjq}UTc_{rjq} + \sum_{r\in R}\sum_{k\in K}\sum_{q\in Q} TCd_{rkq}UTd_{rkq} \tag{4}$$

$$FLX = \sum_{e\in E}\sum_{p\in P} Flex_{ep}\, UF_{ep} \tag{5}$$

The second objective Eq. (6) minimizes the carbon emissions of the reverse logistics system, which consists of the carbon emissions related to facility operation FES, transportation TES, and flexible capacity FLES.

$$\text{Min } Z2 = FES + TES + FLES \tag{6}$$

Eqs. (7-9) calculate the respective carbon emissions.

$$FES = \sum_{r\in R}\sum_{p\in P} Esr_{rp}Ur_{rp} + \sum_{i\in I}\sum_{q\in Q} Esi_{iq}Ui_{iq} + \sum_{j\in J}\sum_{q\in Q} Esj_{jq}Uj_{jq} + \sum_{k\in K} Esk_k Uk_k \tag{7}$$

$$TES = \sum_{e\in E}\sum_{r\in R}\sum_{p\in P} TEsa_{erp}UTa_{erp} + \sum_{r\in R}\sum_{i\in I}\sum_{q\in Q} TEsb_{riq}UTb_{riq} + \sum_{r\in R}\sum_{j\in J}\sum_{q\in Q} TEsc_{rjq}UTc_{rjq} + \sum_{r\in R}\sum_{k\in K}\sum_{q\in Q} TEsd_{rkq}UTd_{rkq} \tag{8}$$

$$FLES = \sum_{e\in E}\sum_{p\in P} Fles_{ep}\, UF_{ep} \tag{9}$$

The model has six sets of constraints to satisfy the logistical flow requirements associated with the facilities and the transportation. The first set of constraints depicts the relationship between local collection and regional collection. Constraint (10) ensures that all the local collection points will be served by the regional collection centers or by the flexible capacity. Constraint (11) calculates the types and the number of EOL products received by each regional collection center.

$$EOL_{ep} \leq \sum_{r \in R} UTa_{erp} + UF_{ep}, \forall e \in E, p \in P \tag{10}$$

$$\sum_{e \in E} UTa_{erp} = Ur_{rp}, \forall r \in R, p \in P \tag{11}$$

Based on the composition and the quality level of different EOL products, constraints (12-14) convert the EOL products to respective components for remanufacturing/refurbish, material recycling, and waste disposal, respectively. Herein, the sum of the conversation rates CRM_{pq}, CRC_{pq} and CDP_{pq} for one EOL product equals to 1.

$$\sum_{p \in P} Ur_{rp} CRM_{pq} = URM_{rq}, \forall r \in R, q \in Q \tag{12}$$

$$\sum_{p \in P} Ur_{rp} CRC_{pq} = URC_{rq}, \forall r \in R, q \in Q \tag{13}$$

$$\sum_{p \in P} Ur_{rp} CDP_{pq} = UDP_{rq}, \forall r \in R, q \in Q \tag{14}$$

Constraints (15-17) calculate the output flows of different EOL products from regional collection centers to remanufacturing plants, recycling plants, and disposal sites.

$$URM_{rq} = \sum_{i \in I} UTb_{riq}, \forall r \in R, q \in Q \tag{15}$$

$$URC_{rq} = \sum_{j \in J} UTc_{rjq}, \forall r \in R, q \in Q \tag{16}$$

$$UDP_{rq} = \sum_{k \in K} UTd_{rkq}, \forall r \in R, q \in Q \tag{17}$$

Constraints (18) and (19) calculate the types and the number of components received at remanufacturing plants and at recycling plants. Constraint (20) calculates the total amount of different unrecyclable received at each disposal site.

$$\sum_{r \in R} UTb_{riq} = Ui_{iq}, \forall i \in I, q \in Q \tag{18}$$

$$\sum_{r \in R} UTc_{rjq} = Uj_{jq}, \forall j \in J, q \in Q \tag{19}$$

$$\sum_{r \in R} \sum_{q \in Q} UTd_{rkq} = Uk_k, \forall k \in K \tag{20}$$

Constraints (21-24) set up the maximal capacity of respective facilities. Meanwhile, the use of un-selected facilities is also restricted by this set of constraints.

$$Ur_{rp} \leq Capr_{rp} Dr_r, \forall r \in R, p \in P \tag{21}$$

$$Ui_{iq} \leq Capi_{iq} Di_i, \forall i \in I, q \in Q \tag{22}$$

$$Uj_{jq} \leq Capj_{jq} Dj_j, \forall j \in J, q \in Q \tag{23}$$

$$Uk_k \leq Capk_k Dk_k, \forall k \in K \tag{24}$$

Constraint (25) is the upper limit of flexible capacity allowed in the reverse logistics system. In addition, the decision variables for facility locations need to fulfill the binary requirements, and the continuous variables need to be non-negative.

$$\sum\nolimits_{e \in E} UF_{ep} \leq UPFLX_{ep}, \forall \mathrm{e} \in \mathrm{E}, p \in P \tag{25}$$

4.2 Solution approach

The augmented ε-constraint method is used to solve this bi-objective MIP, and it can solve the pitfalls of the traditional ε-constraint method by employing a lexicographic method in determining the payoff matrix. Besides, compared with other scalarization methods for multi-objective optimization, e.g., weighted sum, it has a much better chance to yield evenly distributed Pareto Optimal solutions. For more details, Mavrotas [64] can be referred to.

Based on our model, the algorithmic procedures are described as follows.

Algorithmic procedures		
Step 1	***The priority level*** of the objective functions is determined based on the inputs of decision-makers. For example, in this model, $Z1$ has a higher priority level.	
Step 2	***The payoff matrix*** is calculated with the Lexicographic method.	
	2.1	Calculate the individual optimal solutions $Z1_{opt}$ and $Z2_{opt}$ by solving the single objective functions $Z1$ and $Z2$.
	2.2	Calculate the nadir values of the two objective functions $Z1_{nad}$ and $Z2_{nad}$ with the lexicographic method. For example, optimize $Z2$ by adding an additional constraint $Z1 \leq Z1_{opt}$.
Step 3	***The ranges*** of the objective functions can be calculated by $Z1_{nad} - Z1_{opt}$ and $Z2_{nad} - Z2_{opt}$.	
Step 4	***The value of $\boldsymbol{\varepsilon}$*** is determined based on the priority level and the number of divided grids (NG). For example, $Z1$ has a higher priority, and Z2 can be converted to a set of additional constraints with $\Delta\varepsilon_{Z2} = {Z2_{nad} - Z2_{opt}}/{NG}$	
Step 5	***Conversion*** of the multi-objective optimization problem into a single-objective optimization problem based on the priority level and the value of ε. For example, the proposed model can be converted to: $$\min\ (Z1(\boldsymbol{x}) + eps \times s_{Z2})$$ S.t. $$Z2(\boldsymbol{x}) + s_{Z2} = \varepsilon_{Z2}$$ $$\boldsymbol{x} \in X \text{ and } \varepsilon_{Z2} \in \mathbb{R}^+$$ Herein, s_{Z2} is a slack variable and *eps* is a sufficiently small adjustment parameter ranging normally from 10^{-6} to 10^{-3} [64]	
Step 6	***Optimization*** of the single-objective problem and generating a set of efficient Pareto solutions	

4.3 Dynamic Simulation

Due to the limitation of mathematical optimization, e.g., over-simplified real-world problems, many assumptions, etc, the analytical results from the bi-objective MIP may be significantly compromised. Thus, these optimal solutions cannot be automatically converted into managerial decisions. Instead, they need to be further evaluated with management expertise and be better interpreted through the analysis of different alternatives. Thus, in the second level, a dynamic simulation that combines with both discrete event and Monte Carlo simulation is needed to provide a comprehensive performance analysis of the candidate networks considering realistic operations, parametric uncertainties, and scenario analyses of the impact from smart transformation.

To perform the dynamic simulation, a state-of-the-art simulation package called anyLogistix is used, which can effectively set up and perform experiments related to multi-stage logistics networks, production control, inventory control, transportation and shipping control, and sourcing analysis [58, 65]. To build the simulation model, the planning horizon is first decided, and the selected networks are used to configure the reverse logistics systems. Discrete events need to be specified to create the operations of both facilities and transportation, and the operational parameters are converted to a lower level of data aggregation. Stochastic parameters can be used to provide insights into the key parameters concerning random uncertainty. Besides, simulation explores the system performance in a more detailed manner, so the operational policies and conditions over different periods need to be determined by the decision-makers to better model the real-world behaviors of a reverse logistics system. The following operational policies can be configurated:

- Demand generation: Stochastic demands can be set up in both local collection points and the markets for recovered products. Periodic demands can be placed on customer-defined intervals, e.g., weekly or monthly. Besides, seasonal factors may be added if needed [58].

- Inventory policy: Different inventory control policies, e.g., periodic review, continuous review, etc., can be implemented to control the inventory level. A backorder policy is allowed so that the order is pending until the required amount is available for delivery.

- Production policy: Individual BOMs and different production policies, e.g., simple production, partial production, etc., can be used in different facilities. Stochastic and dynamic parameters can be set up to evaluate the influences from smart transformation.

- Sourcing policy: Different sourcing policies, e.g., closest source, multiple sources, fixed source, etc., can be defined at different stages of the reverse logistics system.

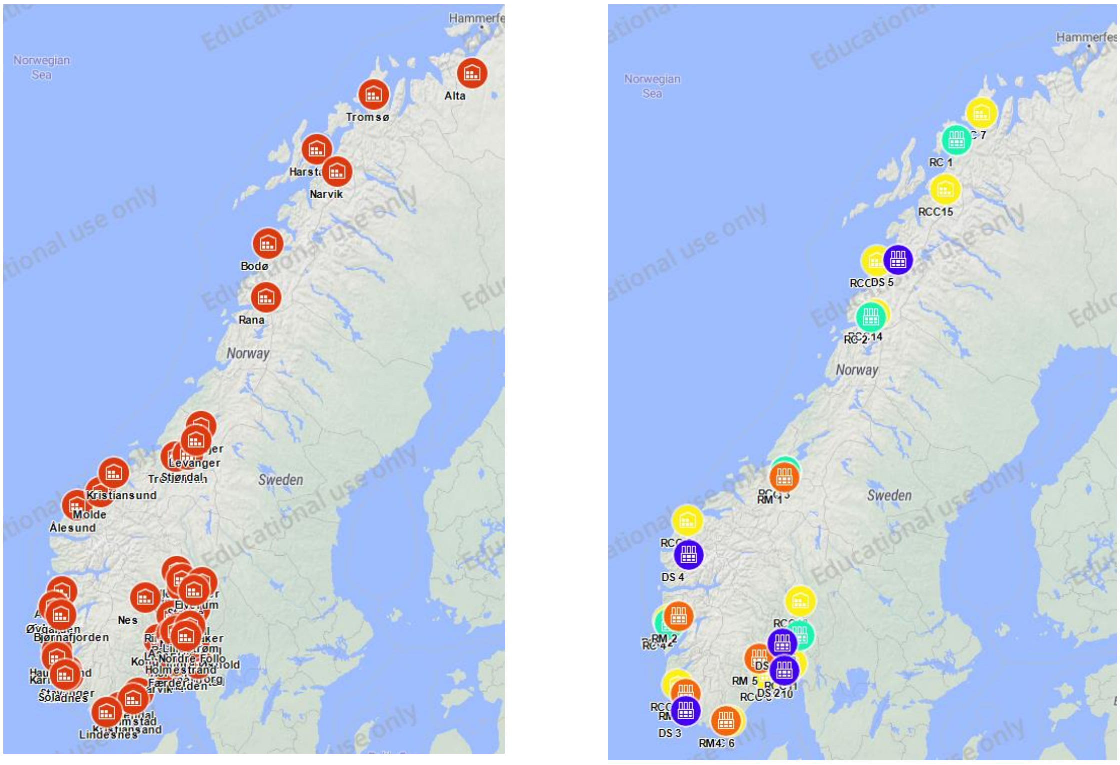
- Transportation policy: Various operational parameters, e.g., vehicle type, vehicle capacity, speed, loading policy, etc., can be defined to model the real-life situation.

In addition, discrete event simulation can also be used to test the impacts of operational uncertainty, configuration upgrades over different periods, and network disruption. For example, the temporary closure or capacity reduction during the facility upgrades, the improvement of productivity and environmental performance after the upgrades, and so forth. These test scenarios can be set up in this stage, and the possible impacts and strategies can be evaluated. Finally, the number of repetitions of the simulation experiment needs to be defined.

5 Case Study

Considering the smart transformation during the planning horizon, we investigated a reverse logistics network design problem for sustainable WEEE management in Norway. With a population density of 15 people/km^2, Norway is one of the most sparsely populated countries in Europe. The low population density and the geographically dispersed municipalities result in complex logistics planning problems to simultaneously balance the economic performance, environmental impact, and service level, due to the loss of economy of scale. Thus, the use of new technological solutions becomes attractive and needs to be considered in long-term strategic planning. With a focus on sustainable development and a low-carbon economy, Norway has a long history in the reuse and recycling of WEEE [66]. The first regulatory system for WEEE management in Norway was implemented in 1999. The relevant WEEE regulations require that all the manufacturers of EEE joining in the collective compliance systems for the EOL recovery of their products, which are operated by third parties. The European Recycling Platform [67] Norway is a nationwide compliance scheme, which ensures the environmentally friendly treatment of WEEE. As a part of the regulatory system, the two major ERP service providers (El-Retur and RENAS) take 94% of the total share of the WEEE collection and recycling in Norway. In addition, there is another smaller compliance scheme called Eurovironment, which is operated by 14 manufacturers of IT equipment [68]. Even though the relevant regulations for WEEE recovery have been well formulated and implemented in Norway, the reverse logistics system has, however, not been optimized since most of the facilities are located near Oslo. This requires frequent and long-distance transportations of WEEE from the northern parts to the southern parts of the country [66], which results in increased transportation costs and carbon emissions. Thus, the optimization of the WEEE reverse logistics network is investigated.

In Norway, the total collection rate of WEEE, the households collection rate of WEEE, and the collection rate of large household appliances in 2018 are 18.16 kg/capita/year, 11.32 kg/capita/year, and 8.45 kg/capita/year, respectively [69]. The EU Directive [70] categorizes ten types of EEE, i.e., large household appliances, small household appliances, IT and telecommunications equipment, consumer equipment and photovoltaic panels, lighting equipment, etc., where the large household appliances account for 47% of the total WEEE in Norway [69]. In this experiment, we selected 7 types of large household appliances based on the EU Directive [70], which were then divided into three groups, namely, refrigerators/freezers (P1), washing machines/dishwashers/clothes dryers (P2), and stoves/cookers (P3). These three groups constitute approximately 80% of the total large household appliances [71]. The proportions of the WEEE generation of P1, P2, and P3 were assumed to be 40%, 40%, and 20%. The collection and recovery of the three groups of WEEE from the 60 largest municipalities in Norway were considered, and the name, the number, and the population of these municipalities are given in Appendix A. The WEEE generation was assumed to be proportional to the population of the municipalities, obtained from Statistics Norway [72]. The average generation per capita was obtained from the database of the European Commission [69].



Local collection point

Remanufacturing plant

Disposal plant

Regional collection center

Recycling plant

Figure 3 The locations of the local collection centers and the candidate locations of respective facilities.

To improve the effectiveness and efficiency of the reverse logistics system, 15 candidate locations were selected for opening the regional collection centers, which are Oslo (R1), Bergen (R2), Trondheim (R3), Stavanger (R4), Drammen (R5), Kristiansand (R6), Tromsø (R7), Skien (R8), Ålesund (R9), Tønsberg (R10), Moss (R11), Bodø (R12), Hamar (R13), Rana (R14), and Narvik (R15). Several candidate locations for the EOL recovery were chosen considering the fair geographical access. In total, the candidate locations for remanufacturing plants, recycling plants, and disposal sites are 5, 5, and 5, respectively. Figure 3 illustrates the locations of the municipalities and the candidate locations for respective facilities. Table 2 shows the disassembly BOMs of P1, P2, and P3. The main components are compressors (q1), metal components (q2), plastics (q3), pump/motor components (q4), and non-recyclables (qw), where q1 and q4 can be remanufactured and q2 and q3 are for material recycling.

Table 2 The disassembly BOMs of the selected WEEE groups.

	CRM_{pq}		CRC_{pq}		CRD_{pq}
BOM	q1	q4	q2	q3	qw
P1	0.0947	0	0.7895	0.0737	0.0421
P2	0	0.0500	0.5750	0.1000	0.2750
P3	0	0	0.9500	0.0357	0.0143

Table 3 Parameter generation intervals of respective facilities.

Facility	Fixed cost (10^3NOK/Year)	Product/Components	Variable cost (NOK/kg)	Carbon emissions (kg/kg)	Capacity (10^3 kg)
Regional collection center	[21400, 21800]	P1	[13, 16]	[0.16, 0.17]	[2000,
		P2	[13, 16]	[0.161, 0.17]	[2000,
		P3	[13, 16]	[0.163, 0.17]	[820, 950]
Remanufacturin g plant	[38200, 40160]	q1	[9, 11]	[1.161, 1.165]	[875, 900]
		q4	[13, 14]	[1.16, 1.169]	[580, 610]
Recycling plant	[26107, 21800]	q2	[4, 5]	[0.161, 0.169]	[810, 950]
		q3	[9, 10]	[0.16, 0.17]	[850, 900]
Disposal plant	[18595, 20475]	qw	[10, 12]	[0.243, 0.25]	[1395,

Based on relevant research, the fixed facility operating costs [73, 74], the capacities of different facilities, the unit processing costs of EOL products or components [75], the unit carbon emissions [76-79] were estimated. Considering the generality, we randomly generated these parameters from the respective parameter intervals, as shown in Table 3. The transportation costs and carbon emissions are directly proportional to the travel distances. Thus, the distance matrixes of the respective links between two locations were first established. In this experiment, we considered two types of vehicles with truckloads of 6.3 tons and 13.4 tons [80]. The first type is used for transportation from the local collection centers to the regional collection centers, and the second type is used for transportation from the regional collection centers to the other facilities. Besides, the unit transportation cost and unit carbon emissions are also affected by the loading rate of the vehicles. The loading rates of the transportation at the first and the second stages of the reverse logistics were generated from the intervals [0.7, 0.75] and [0.8, 0.85], respectively. The unit transportation costs were estimated based on Delgado, Rodríguez [81], and the unit carbon emissions were given based on the report of freight transportation and logistics from the European Automobile Manufacturer Association [80]. Table 4 presents the unit transportation costs and carbon emissions.

Table 4 Unit transportation costs and carbon emissions between different facilities.

Links	Product/Components	Transportation cost (NOK/km/kg)	Carbon emissions (kg/km/kg)
LCP → RCC	P1	0.014286	0.000159
	P2	0.012444	0.000148
	P3	0.012037	0.000154
RCC → RM	q1	0.008750	0.000081
	q4	0.008000	0.000081
RCC → RC	q2	0.008235	0.000076
	q3	0.008000	0.000081
RCC → DS	qw	0.011765	0.000076

Finally, to avoid facility redundancy from the decision model, the costs and unit carbon emissions for using flexible capacities were set for approximately 1.5 times higher than using an opened facility [34], and the upper limit of flexible capacity was set to 10% of the total generation of EOL products at each municipality. The full set of the parameters in the experiment is given in Appendix B.

6 Experiments, Results, and Discussions

6.1 Optimization experiment

The optimization problems with changing values of ε were first solved to generate a set of Pareto optimal solutions. The optimization problems were solved by Lingo 19.0, and the maximum computational time was approximately 3 minutes. Figure 4 illustrates the Pareto optimal frontier formed by 11 points. The points 1 and 11 are the cost-minimization solution and the emission-minimization solution, and the ranges of the two objectives are [761,527,290 NOK, 1,253,751,898 NOK] and [9,839,252 kg, 9,234,054 kg], respectively.

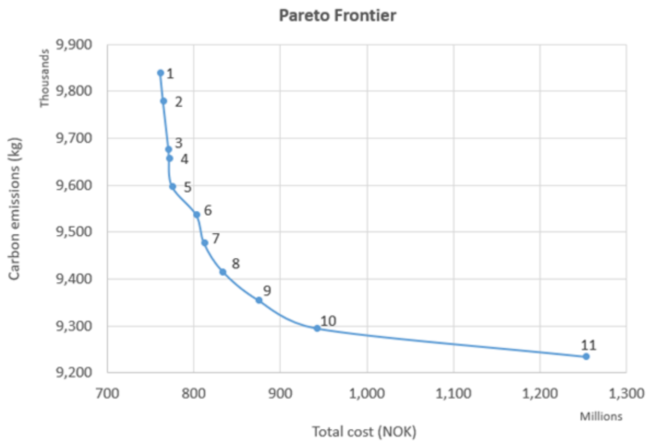


Figure 4 Pareto Frontier.

For comparison purposes, the Pareto frontier is divided into 10 segments. For example, segment 1 is between points 1 and 2. The cost increments and the carbon emission decrements of each segment between two adjacent Pareto optimal solutions can be calculated by $Cost\ increments_n^x = Cost_{n+1}^x - Cost_n^x$ and $Emission\ decrements_n^x = Emission_n^x - Emission_{n+1}^x$, where $x \in \{Total, Facility, Transportation\}$ and $n \in \{1, \ldots, 10\}$. Figure 5 compares the cost increments and the emission increments related to facility operations and transportation. The facility operations predominantly determine the overall system costs. Even though the transportation costs vary drastically with the change of the network configurations, the impacts on the overall system costs are relatively insignificant compared with that incurred from facility operations. However, facility operations yield relatively small impacts on total carbon emissions, and the reduction is primarily led by the reduced carbon emissions from transportation. Therefore, the minimum number of facilities were opened in points 1 and 2 to minimize the total system costs, and the exceeded EOL generations were treated using flexible capacities. On the other hand, more facilities were opened when the emphasis was given to the minimization of carbon emissions to shorten the overall transportation distance in the reverse logistics network.

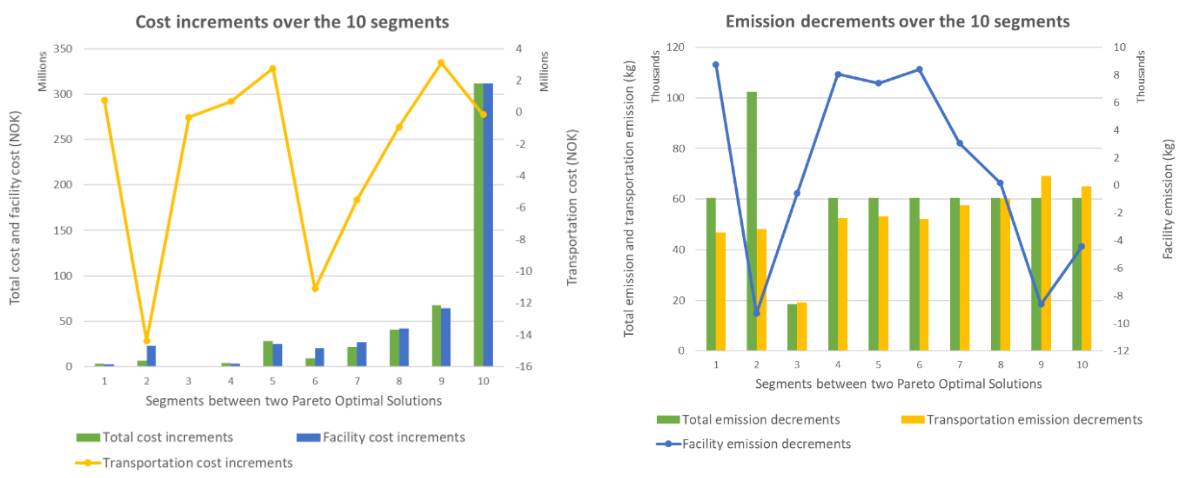


Figure 5 Comparison of the cost increments and the emission decrements over the 10 segments.

Table 5 The facility selections in the five chosen Pareto optimal solutions.

Scenario	Regional collection center	Remanufacturing plant	Recycling plant	Disposal plant
1	(1), (2), (3), (5), (8)	(5)	(4), (5)	(1), (4)
2	(1), (2), (3), (5), (8)	(5)	(4), (5)	(1), (2)
4	(1), (2), (3), (5), (8)	(5)	(3), (4), (5)	(1), (4)
5	(1), (2), (3), (5), (8)	(5)	(3), (4), (5)	(1), (2)
7	(1), (2), (3), (5), (6), (13), (15)	(5)	(3), (4), (5)	(1), (2)

It is noteworthy that the cost increments for reducing one unit of carbon emissions at each Pareto optimal solution are by no means identical. Based on this, five candidate Pareto optimal solutions were chosen for the simulation experiment. Exempt from the cost-minimization solution, the selected solutions are points 2, 4, 5, and 7, which show better cost-effectiveness in the carbon emission reduction. The respective reverse logistics network configurations are given in Table 5. In the first four networks, five regional collection centers are opened in Oslo, Bergen, Trondheim, Drammen, and Skien. While in network 7, instead of opening the regional collection center in Skien, another three candidate locations in Kristiansand, Hamar, and Narvik are selected. Besides, remanufacturing plant 5, recycling plants 4 and 5, and disposal site 1 are selected in all solutions.

6.2 Simulation experiment

6.2.1 Parameter conversion

The five selected network configurations were used to build dynamic simulation models. Based on the same dataset, the relevant simulation parameters were generated. The simulation time was set to 10 years, and the number of repetitions of the experiments was set to 50. It is noteworthy that several parameters need to be converted due to the practical requirements of dynamic simulation. For example, the annual generations of WEEE were disaggregated into shorter periods. Besides, the facility capacity constraint was converted into the production time and was restricted by the annual working hours. The purpose of the reverse logistics system is to manage the WEEE generated in each period. The periodic demands for remanufactured products q1 and q4 and for recycled materials q2 and q3 were thus calculated based on the generation of WEEE. The collection cycle of WEEE at the regional collection centers was set to 15 days, and the customer ordering cycle for recovered items was set to 7—10 days.

In addition, stochastic parameters were used to evaluate the impacts of uncertainty from the key parameters. We considered two sources of uncertainty, namely, the quantity and the quality of WEEE. The quality levels of different EOL products vary significantly, which leads to stochastic facility capacity due to the variation of the processing time. The two stochastic parameters were assumed to follow a uniform distribution. The lower and upper bounds of the uniform distribution can be calculated by $[p_d(1-\sigma), p_d(1+\sigma)]$, where p_d is the respective deterministic value and σ is the deviational adjustment in [0, 1] [82]. In this experiment, σ was set to 10% for the generation of WEEE and 20% for the processing time [83].

6.2.2 Operational policies

Inventory policy is important. We considered different production and inventory policies at different facilities to fulfill the demands and operate the reverse logistics system. For example, the continuous review (R, Q) policy was used by the remanufacturer to replenish the components q1 and q4 from regional collection centers. With this policy, an order quantity at (Q) is sent when the inventory level reaches the reordering point (R). The reordering point and reordering quantity can be calculated by the following equations [84]:

$$R = \mu_D \mu_L + z_\alpha \sqrt{\mu_L \sigma_D^2 + \mu_D^2 \sigma_L^2}$$

$$Q = \sqrt{\frac{2\mu_D c_0}{c_h}}$$

Whereas:

μ_D	Average weekly demand
σ_D	Weekly standard deviation
μ_L	Average lead time
σ_L	Standard deviation of average lead time
c_0	Fixed ordering cost
c_h	Weekly inventory holding cost per unit
z_α	Value from the standard normal distribution table

We used the same method given by Gianesello, Ivanov [85] to set up the inventory levels. First, the (R, Q) values were assumed, and the values of inventory were then projected backward along with the reverse logistics network to ensure the production capability and the available material inventory. To determine the inventory levels of the new products and new materials at the remanufacturing plant and the recycling plant, we used a Min-max policy with safety stock (s, S). The (s, S) policy requires periodic checks and replenish the inventory at discrete intervals. Based on Gianesello, Ivanov [85], the safety stock (ss) was assumed to be equal to the mean weekly demand σd, and the Min (s) and the Max (S) inventory levels were then calculated by the following equations, where LT is the lead time.

$$s = ss + (\sigma d * LT)$$

$$S = 2 * s$$

For the other facilities, the (R, Q) policy was implemented, and the full set of inventory policies and parameters is given in Appendix 3. Production policy is another important factor that is closely linked to the inventory policy and sourcing policy. In this paper, a simple manufacturing strategy is implemented, where the production pattern is driven by the requirements of replenished products defined by the inventory policy. In addition, stochastic production times were defined in the remanufacturing, recycling, and disposal processes to analyze the uncertainty related to the quality of WEEE. A fixed sourcing strategy was used in the first-level transportation, which means a fixed cluster of municipalities is served by a given regional collection center. On the other hand, multiple sourcing strategies were implemented by the remanufacturers and the recycling plants to optimize the recourse decisions over the planning horizon. Finally, to improve the service level, a partial shipment policy was used in the experiments, and two types of vehicles were defined accordingly with stochastic speeds.

6.2.3 Smart transformation

Next, we considered the smart transformation during the planning horizon. At the system level, the implementation of new technologies will influence the operating parameters. For example, the use of AI-based robots may increase the productivity in many industries by 30% by 2025, while cutting labor costs by 18-33% [86]. Adopting AR may achieve up to 25% improvement in operator productivity while providing a safe working environment [86, 87]. Recent research shows that using IoT-enabled smart regulate temperature technology may reduce 20% of carbon emissions and energy consumption on a manufacturing floor [88]. In reverse logistics, the digital twin tracks the quality level of EOL products through a cloud-based system, so remanufacturing can be better planned to minimize the stochasticity related to the processing time. Besides, technological advancement will also yield significant impacts on transportation through the increased use of cleaner energy and improved fuel efficiency [89]. The use of intelligent transport systems and truck platooning has the potential to reduce CO_2 emissions by 10-25% [89, 90]. In addition, the increased use of electric vehicles, hydrogen vehicles, and hybrid trucks may lead to a 10-15% reduction of CO_2 emissions per vehicle basis [89].

Table 6 Test scenarios for technological upgrades and smart transformation.

Scenario	Period	Facility upgrade plan	Expected impacts on facility				Expected impacts on transportation	
			Average production time/unit	Uniform distribution of processing time	Production cost/unit	CO_2 emissions from the facility	Expected CO_2 reduction/unit	Potential cost impact/unit
S1	Year 4	RM for q1, q4 RC for q3	-10%	[95%, 105%]	-10%	-15%	-10%	

	Year 6	RC for q2	-15%	[95%, 105%]	-15%	-15%	-20%	
S2	Year 4	RM for q1, q4	-10%	[95%, 105%]	-10%	-15%	-10%	
	Year 6	RC for q2, q3	-15%	[95%, 105%]	-15%	-15%	-20%	
S3	Year 6	RM for q1, q4 RC for q3	-10%	[95%, 105%]	-10%	-15%	-10%	
	Year 8	RC for q2	-15%	[95%, 105%]	-15%	-15%	-20%	
S4	Year 6	RM for q1, q4 RC for q3	-15%	[95%, 105%]	-15%	-18%	-15%	
	Year 8	RC for q2	-25%	[95%, 105%]	-20%	-18%	-25%	
S5	Year 8	RM for q1, q4 RC for q2,q3	-25%	[95%, 105%]	-20%	-18%	-25%	
S6	Year 8	RM for q1, q4 RC for q2,q3	-25%	[95%, 105%]	-25%	-20%	-25%	
S7	Year 4	RM for q1, q4 RC for q3	-10%	[95%, 105%]	-10%	-15%	-10%	-8%
	Year 6	RC for q2	-15%	[95%, 105%]	-15%	-15%	-20%	-15%
S8	Year 6	RM for q1, q4 RC for q3	-10%	[95%, 105%]	-10%	-15%	-10%	-8%
	Year 8	RC for q2	-15%	[95%, 105%]	-15%	-15%	-20%	-15%
S9	Year 8	RM for q1, q4 RC for q2,q3	-25%	[95%, 105%]	-25%	-20%	-25%	-22%

In this experiment, we tested 10 scenarios. S0 is the basic scenario without technological upgrades, and S1-S6 are scenarios with different plans for technological upgrades of remanufacturing process, recycling process, and transportation. Besides, S7-S9 are counterpart scenarios of S1, S3, and S6 considering potential cost impacts on transportation. Table 6 shows the schedule and the expected influence on the operating parameters of the planned upgrades. The investment for facility upgrades was set to 2 million NOK each. The required time was set to 2 months for each facility upgrade, during which period the respective facility was temporarily closed.

6.2.4 Simulation results

Computer-based simulation can provide powerful visualization of the analytical results. Figure 6 shows an established reverse logistics network, and the key performance indicators (KPIs), e.g., costs, emissions, service levels, etc., at both the facility level and system level can be graphically presented and easily outputted for further analysis.

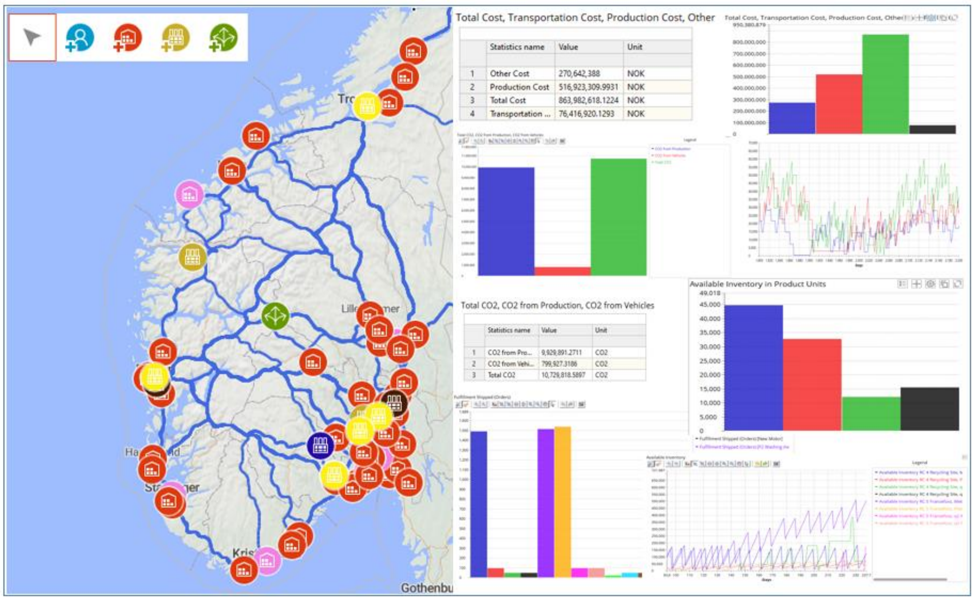
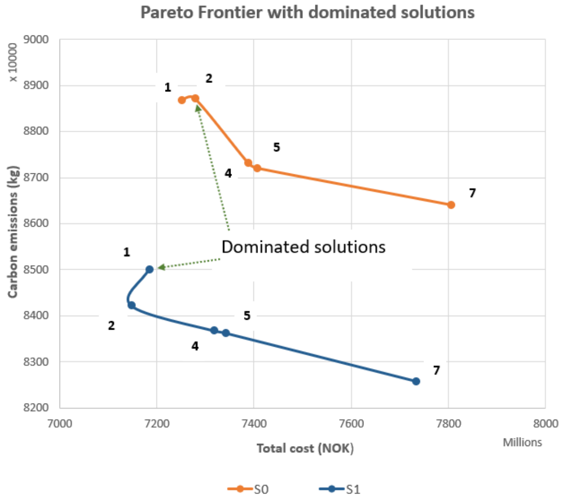
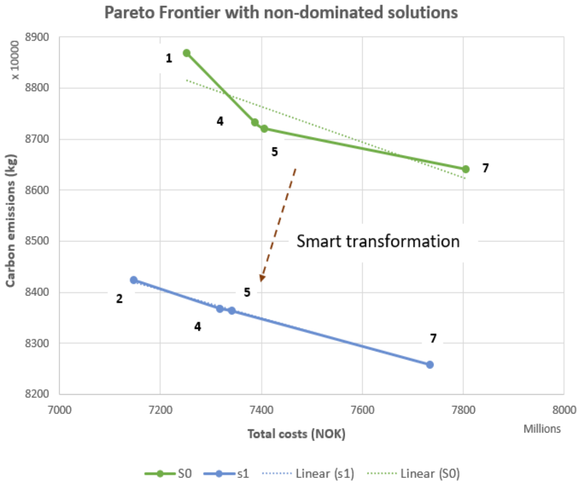


Figure 6 Result visualization.

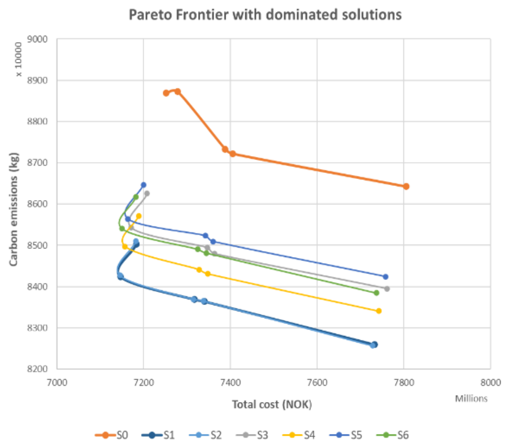
We first considered two scenarios: (1) the basic scenario without facility upgrade (S0); and (2) the facility upgrade scenario (S1). As shown in Figure 7(A), there are two dominated or near dominated solutions in the simulation results. In S0, network 2 is a dominated solution by network 1. In S1, network 1 is a dominated solution. This result reveals that, by incorporating uncertainty, dynamic operational policies, and smart transformation, the performance of the optimal solutions obtained by the mathematical model may be drastically affected, which shows the impacts of including more real-world conditions on reverse logistics network design. In the simulation experiment, dominated and near dominated solutions may be observed, and the Pareto frontier may thus be changed. Figure 7(B) illustrates the non-dominated Pareto Frontiers of the two scenarios. First, it is observed that, by adopting new technologies in S1, both economic effectiveness and environmental performance can be dramatically improved. For example, in network 4, the mid-term facility upgrades will help to reduce the total system operating costs by 70,042,629 NOK and the total carbon emissions by 3,646,539 kg within the planning horizon. This shows the value of the smart transformation for the selected network under the given upgrade plan. Second, it is also observed that the Pareto Frontier in S1 becomes flatter compared with that in the basic scenario. This result implies that the difference of the carbon reductions per unit cost in the Pareto Frontier becomes smaller, and the network structure yields less impact on emission reductions. Therefore, opening more facilities for carbon reductions in S1, e.g., network 7, becomes less attractive. In this scenario, the carbon emissions of networks 2 and 4 can be reduced to better balance the tradeoff between economic and environmental sustainability by technological upgrades and smart transformation.



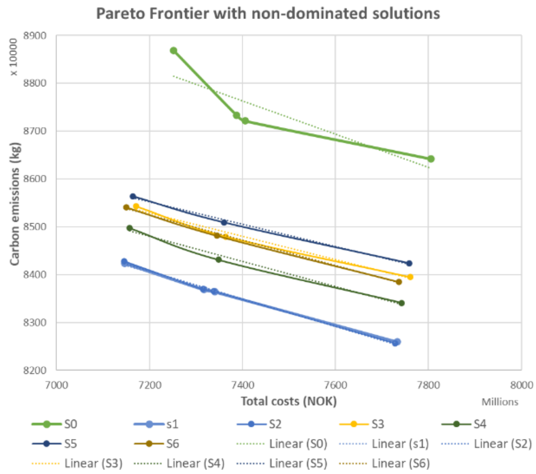
(A) Pareto Frontiers with dominated solutions of S0 and S1.



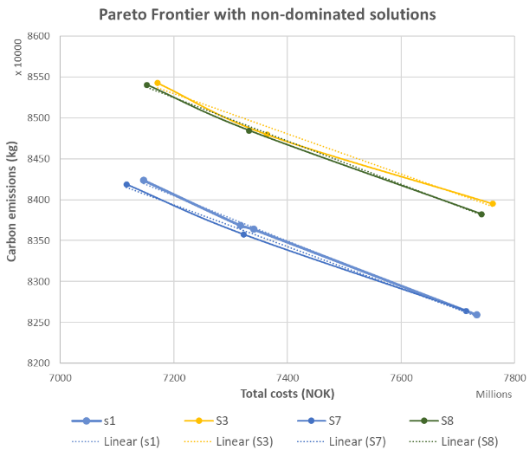
(B) Pareto Frontiers with non-dominated solutions of S0 and S1.



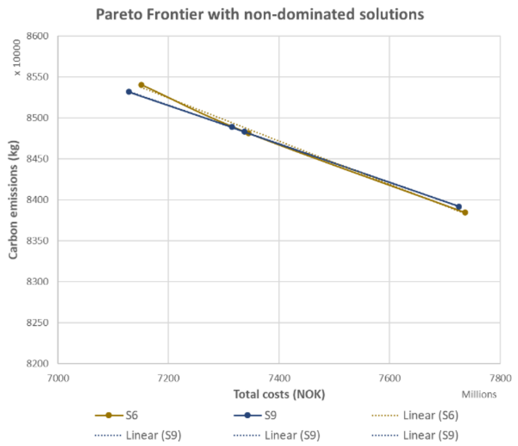
(C) Pareto Frontiers with dominated solutions of S0, S1, S2, S3, S4, S5, and S6.



(D) Pareto Frontiers with non-dominated solutions of S0, S1, S2, S3, S4, S5, and S6.



(E) Pareto Frontiers with non-dominated solutions of S1 vs. S7 and S3 vs. S8.



(F) Pareto Frontiers with non-dominated solutions of S6 vs. S9.

Figure 7 Simulation results.

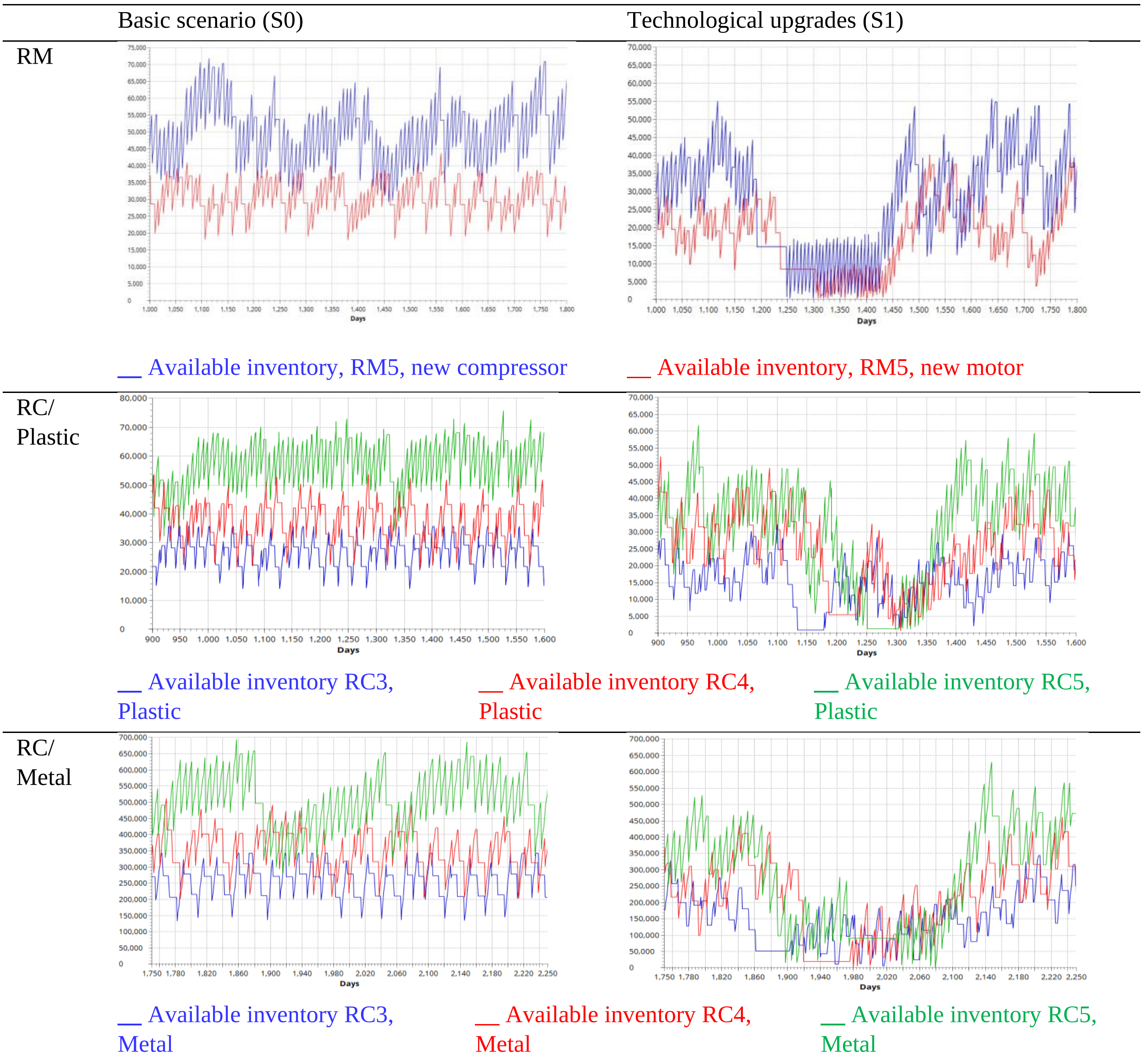


Figure 8 The change of inventory level during facility upgrades of network 4.

Next, we compared scenarios 1-6 with different plans for technological upgrades of facilities and transportation in Figures 7(C) and 7(D). As shown, both the schedule and the expected impacts yield significant impacts on the performance of the reverse logistics networks. For instance, if the planned technological upgrades for respective facilities and transportation are delayed by 2 years from S1 to S3, the total costs of networks 2 and 5 will increase by 24,248,178 NOK and 22,722,489 NOK, while the carbon emissions of these two networks will increase by 1,191,348 kg and 1,162,535 kg, respectively. However, the impacts from the schedule of technological upgrades may be compensated by the expected impacts on operational parameters. For example, compared with S3, even though the upgrades of facilities and transportation in S6 are delayed, the difference between the Pareto frontier in these two scenarios is extremely insignificant due to a higher performance improvement is expected in S6. Figures 7(E) and 7(F) compares the scenarios with expected cost impacts on transportation. For the test scenarios, the improvement in cost efficiency of transportation leads to better performance of the selected networks, but the impacts are insignificant due to its small proportion in the total costs. The results show that the schedule and expected impacts of smart transformation may dramatically affect the performance of a reverse logistics system and need thus to be holistically considered in the network design.

Table 7 Comparison of the service levels of network 4.

Product	Order fulfillment rate		Late order	
	S0	S1	S0	S1
q1 (Compressor)	94.4%	90%	3	15
q2 (Metal)	98.8%	97.7%	6	13
q3 (Plastic)	98.2%	97.8%	10	9
q4 (Motor)	96.7%	90.4%	2	13

Finally, we observed the inventory change during the facility upgrades. Figure 8 depicts the change of inventory level at respective facilities of network 4 in S1. Due to the production line being temporarily closed during the period of facility upgrades, this disruption led to a reduction of the available inventory of new products. At the remanufacturing plant, it needed to take nearly 6 months after the facility upgrades to restore the normal inventory level of the new motor, and for the new compressor, the recovery time of the inventory level was approximately 10 months. At the recycling plants, the inventory levels of the recycled plastic began to drop when the disruption had occurred, and the recycling plants 3 and 4 took a short time to restore their normal inventory level, while nearly 4 months were needed for recycling plant 5. For metal recycling, the recovery time of inventory level at all plants was approximately 8 months. These disruptions at the remanufacturing plant and the recycling plants may cause a ripple effect throughout the reverse logistics system, which may further cause the backlogs of customer orders and excessive inventory at regional collection centers. Thus, the service level of the reverse logistics system will be drastically influenced. For example, as shown in Table 7, the smart transformation in S1 may yield more significant impacts on the remanufacturing process, which leads to 4.4% and 6.3% reductions on the overall order fulfillment rates of q1 and q4. Meanwhile, the late orders of these two remanufactured products increase by 400% and 550%, respectively.

6.3 Discussions

The results illustrate that the behavior and performance of a reverse logistics network can be better analyzed with the proposed two-level decision-support framework. Based on the case study in Norway, we provide discussions to answer the proposed research questions:

RQ1: By using the strengths of multi-objective optimization, discrete event simulation, and Monte Carlo simulation in a two-level decision-support framework, the technological transformation, uncertainties, and practical operational policies can be better modeled and analyzed in smart and sustainable reverse logistics network design. The case study illustrates that a mathematically optimal solution may become a dominated or near dominated solution under realistic and dynamic environments. In this regard, the dynamic simulation model is an enhanced approach for effectively eliminating these dominated Pareto optimal solutions, which can help to yield more robust strategic network decisions and comprehensive performance analyses.

RQ2: Smart transformation may affect both the economic and environmental performances of a reverse logistics system. As shown from the case study, the trend of the Pareto Frontier may be changed by adopting new technologies, and opening more facilities for emission reduction in the initial optimal solutions may become less attractive from a long-term perspective. Moreover, the schedule and the expected influence of technological upgrades may have significant impacts on the system performance. In addition, the temporary facility closure may yield a ripple effect and lead to a reduced service level for both the EOL product collection and the supply of recovered products and materials. Due to these reasons, technological upgrades need to be planned in a smart and coordinated way to maximize performance improvement while minimizing the disruption of the reverse flows.

7 Conclusions

In this paper, a two-level decision-support framework is proposed for smart and sustainable reverse logistics network design. A bi-objective MIP is first used to calculate a set of Pareto optimal solutions balancing both total operating costs and carbon emissions, which are considered candidate reverse logistics networks. In the second level, dynamic simulation models combining both discrete events and Monte Carlo simulation are built with stochastic parameters, dynamic features, operational policies, technological upgrades, and a realistic planning horizon. The application of the proposed decision-support framework is shown through a case study of WEEE reverse logistics in Norway.

The experimental results of the case study show that smart transformation within the planning horizon may affect both the economic and environmental performances of a reverse logistics system, and the carbon emissions from a more economically efficient network may be largely reduced by technological upgrades in the later stage at a much lower cost. Besides, the incorporation of dynamic simulation models can well complement the shortcomings of mathematical optimization models and can help to yield better performance analyses of various scenarios and robust strategic decisions under realistic environments.

Managerial implications. This paper provides a hands-on decision-support framework to combine mathematical models and dynamic simulation, which allows policymakers, supply chain managers, companies in reverse logistics, etc., to optimize the strategic network decisions and to evaluate new technologies and new operational policies holistically. With the help of dynamic simulation, the system behavior and performance, e.g., inventory, service level, etc., can be analyzed more thoroughly. Furthermore, the analysis of the real-world case study of sustainable WEEE management in Norway may provide some practical insights into the smart transformation of reverse logistics systems.

Research implications. This paper provides new methodological integration for inspiring researchers in reverse logistics network design, which is dominated by using a single method today. From the system integration perspective, the effective combination of both mathematical models and advanced computer-based simulation is still at the beginning stage due to several technological challenges, e.g., database conversion, software flexibility, etc., this paper provides a generic structure for the next generation decision-support system that potentially integrates predictive analytics, prescriptive analytics, and descriptive analytics in a smart digital reverse logistics twin [61].

Limitations and Future Research. This paper has three main limitations. First, the parametric uncertainty is not considered in the bi-objective MIP model but is assessed by the dynamic simulation. However, uncertainty may affect the strategic location decisions in reverse logistics network design. Second, validating the method with a single case study may be incapable of fully demonstrating the impacts of smart transformation on reverse logistics network design, particularly considering the sparsely populated nature of Norway, and different insights may be obtained from other regions. Third, several assumptions are used due to data unavailability, e.g., quantitative data related to smart transformation.

Therefore, future research is suggested to tackle these limitations. For example, the mathematical optimization model can be enhanced with uncertain parameters and constraints, e.g., robust optimization, chance-constraint stochastic optimization, etc., to ensure more reliable strategic decisions. Besides, the application and validation of the proposed method in other regions and with more comprehensive datasets are expected.

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Appendices

Appendices A, B, and C provide supplementary data for the numerical results, and they can be accessed on: https://uitno.box.com/s/wvypouuz6pdadpfaak9xji8m202s4w4a

Data Availability Statement

Data is available on request from the authors.

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PAPER 4

System Integration for Smart Reverse Logistics Management

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Author's Contribution

Xu Sun is the main contribution of conceptualization, methodology, data curation, formal analysis, writhing-original draft, and writing-review and editing of the paper.

System Integration for Smart Reverse Logistics Management

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Abstract: To maximize the value and material recovery from waste products, smart reverse logistics aims at managing the complex flows of physical items, cash, data, and information. The effective management of these flows requires optimal decision making at strategic, tactical, and operational levels. To support the decision making, predictive, prescriptive, and descriptive analytics have been proved to be valuable at all three levels. However, because these analytical tools require different software packages, different coding languages, and different structures of data, the decision support for complex problems combining various analytical methods is usually an ad-hoc process and requires thus significant efforts. There is a lack of standardized solutions that comprise all the necessary modules for smart reverse logistics management. Thus, this paper proposes a conceptual framework with the purpose of guiding the next-generation system integration for smart reverse logistics management. It goes further with the design of six criteria for evaluating the integration maturity of a system. The initial concept is shown with existing software solutions through a case study in Norway, and several challenges are identified for future improvements

Keywords: decision making; reverse logistics; system integration; data models

1 Introduction

Today, the rapid pace of technological innovation and the ever-changing consumer demands have led to higher requirements of customization with shortened product lifecycles. This further leads to largely increased waste generation. In 2019, the volume of waste electrical and electronic equipment (WEEE) generation has reached a record high level of 53.6 million metric tons which represented an increase of 21% in five years [1]. This trend is expected to continue with an estimated 30% increase by 2030 [2]. Sustainable management of this rapidly increasing waste has become a global challenge. With the focuses on function restoring and material recovery from discarded products, some regional and international reverse logistics systems have been developed [3].

Reverse logistics refers to a set of activities with the aim of the value recovery from waste products through repair, reuse, refabrication, remanufacturing, recycling, and energy recovery as well as proper disposal of non-recyclables [4, 5]. To achieve sustainable competitiveness in today's market, reverse logistics has become a strategic focus area for most companies due to, i.e., the growing environmental awareness among the general public, stricter legislation, and imposed corporate social responsibility. Effective decision support at strategic, tactical, and operational levels is therefore of essential importance for designing and operating a competitive and sustainable reverse logistics system. To do so, it is necessary to balance complex material and information flows, work with various stakeholders, and make important decisions under uncertainty. To support different decision making in reverse logistics management, predictive, prescriptive, and descriptive analytics must be combined to solve complex problems.

The use of these analytical tools requires different data sources, software packages, different coding languages, and different structures as well as aggregation of data. The combination of several analytical methods to solve a complex decision-making problem in reverse logistics management is, at present, an ad-hoc process, and often requires significant efforts to engage different tools when a new scenario turns up. How to develop an integrated system that can connect different analytic models, data, tools, and other relevant elements for providing efficient decision support is, therefore, a novel question. In this paper, considering the technological innovations in Industry 4.0, we propose a conceptual framework for the next generation of system integration methods for smart and sustainable reverse logistics management. The initial proof-of-concept is applied to a case study design for WEEE management in Norway. In this model, the prescriptive and the descriptive analytics are connected through establishing a shared database structure.

The rest of the paper is organized as follows. Section II explores reverse logistics management with an emphasis on relevant decisions and methods. Section III presents a conceptual framework for the system integration of smart and sustainable reverse logistics management. In sections IV, we demonstrate an application of this framework through a case study, and the problems of the existing software solutions are also discussed. Finally, the conclusions are given in Section V.

2 Reverse Logistics Management

2.1 Reverse logistics management

Reverse logistics focuses on the value recovery activities of waste products, when combining it into the forward logistics system, a closed-loop supply chain can be formed. As shown in Figure 1, the material flow in a reverse logistics system starts from the local collection of waste products from the end-users. The collected waste products will then be disassembled, inspected, and sorted at central collection centers. Based on the remaining values of the dismantled parts, they are sent for further treatment at different facilities. The ones with high remaining values will be sent either for repair and re-sell at second-hand markets or for remanufacturing and refurbishing for function restoration. The remanufactured and refurbished components can be sold to the manufacturers at lower prices. The other components with low remaining values can be sent to recycling plants, where they are degraded into new materials and then sold to the raw material suppliers. The non-recyclable components can be sent either for energy recovery or for proper disposal.

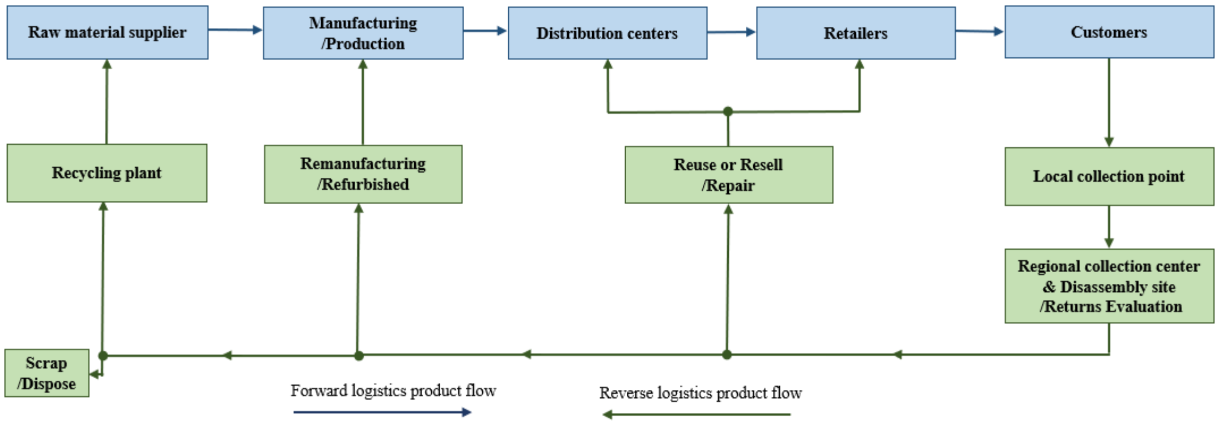

Figure 1 Reverse logistics system

Reverse logistics management refers to orchestrating complex flows (product, capital, and information) among multi-layered and non-homogeneous stakeholders in a highly uncertain environment. Table I shows the key decisions for reverse logistics management at the strategic, tactical, and operational levels. Strategic decisions have long-term impacts on a reverse logistics system since they are difficult or extremely expensive to change. Reverse logistics network design is the most important strategic decision [6]. Several factors and decisions are affecting the performance of a reverse logistics network, i.e., the number and locations of potential facilities, capacity planning, remanufacturing and recycling technologies, transportation strategy, and the establishment of distribution and collaboration channels for recovery products and materials [7, 8]. At the tactical level, the reverse logistics system is governed by a set of medium-term decisions, usually from one month to one year, made under the constraints set by the strategic planning [9]. The formulation of production policy, inventory policy, vehicle routing as well as fleet management are considered tactical decisions. At the lowest level, the short-term operational decisions are made for the dynamic control of product recovery operations, dynamic inventory control, real-time vehicle routing and scheduling problems, and risk analysis, etc.

Table 1 Key decisions for reverse logistics management

Level	**Key decisions**
Strategic level	• Target market situation analysis and evaluation (coordination of reverse logistic network, market size, product, etc.) • Reverse logistic network design • (the number and location of facilities, capacity planning and designing of the remanufacturing/recycling systems) • Transportation strategy • New technology adoption
Tactical level	• Reverse logistics network re-optimization • Vehicle routing • Production planning • Inventory planning • Fleet management

Level	Key decisions
Operational level	• Production control • Inventory control • Vehicle planning and scheduling • Risk analysis • Recovery analysis • Resilience analysis

2.2 Methods for Decision Supports

To support decision making in reverse logistics management, three advanced analytical methods: predictive, prescriptive, and descriptive analytics, are applied.

Predictive analytics is a category of applying advanced methods to predict future trends based on historical data and/or real-time data. It aims to perform an exploratory analysis using several analytical tools. Typical techniques are, e.g., artificial intelligence (AI), data mining, machine learning (ML), modeling, and statistics to estimate, predict, detect future patterns [10]. Decision trees, linear/logistic regressions, and neural networks are the most common predictive models, which can help to clean the data quality for analysis [11]. In terms of reverse logistics management, predictive analytics has been used to reduce the impact of uncertainty so that a better prediction of reverse flows can be achieved. Tuylu and Eroğlu [12] used ML to estimate the product return rate in reverse logistics. In this case, better prediction and planning were achieved by using consumer information so that unnecessary production and transportation were avoided. Lickert, Wewer [13] implemented a ML method to inspect whether the quality levels and conditions of returned products were suitable for remanufacturing.

Prescriptive analytics is to select the constrained and time-dependent optimal solutions with the help of model-based analytics, e.g., mathematical programming (linear/non-linear programming, mixed integer programming, multi-objective programming, etc.), evolutionary computation (genetic algorithm, greedy algorithm, particle swarm optimization, etc.), probabilistic models (Markov decision process, etc.), logic-based models (benchmark rules, fuzzy rules, etc.) [14]. Thus, prescriptive analytics aims at suggesting the best decision options under some preconditions [15], whose results are given, in many cases, based on the outputs from model-based analytics [14]. Prescriptive analytics is the most widely used decision-support method in reverse logistic management at different levels. For example, extensive research efforts have been given to develop mathematical models for sustainable reverse logistic network design [5, 16, 17], profit maximization [18, 19], routing optimization of recycling vehicles [20].

In logistics and supply chain management, descriptive analytics is used to depict the system's behavior and to uncover the meaningful patterns from analyzing the system performance, and simulation is considered the most important descriptive tool. Simulation can be used to capture the randomness, dynamic system behaviors, and disruptions, which are more closed to real-world conditions. In reverse logistics management, simulation has become a powerful tool for decision-makers to investigate the system performance with a set of what-if scenarios. Pandian and Abdul-Kader [21] developed an agent-based simulation model for the performance evaluation of a cell phone remanufacturing system. Gianesello, Ivanov [22] simulated a closed-loop supply chain with disruption considerations. This simulation model provided better illustrations of the recovery decisions. Longo [23] used a simulation method to compare different inventory control policies in reverse logistics so that an optimal solution is ready to be chosen when certain pre-set conditions are met.

Despite the huge advantages the predictive, prescriptive, and descriptive analytics have, the combination of these methods/theories, which can benefit the multi-objective decision-making approach, has not been well developed. Today's rapid advancement of information and communication technology (ICT) in Industry 4.0 has provided new opportunities for reverse logistics management to become more smart, sustainable, and simplified. On the one hand, the wide adaptation of IoT embedded devices, smart sensors, and radio frequency identification (RFID) have provided effective ways for real-time data collection and processing. On the other hand, the significant development of AI and optimization algorithms has improved computational effectiveness and efficiency, which drives the increasing use of data-driven prediction, optimization, and decision-making. However, the effective use of these new technologies in reverse logistics management requires a high level of system integration in a cyber-physical environment.

In the next session, we will propose a framework for system integration purposing smart reverse logistics management.

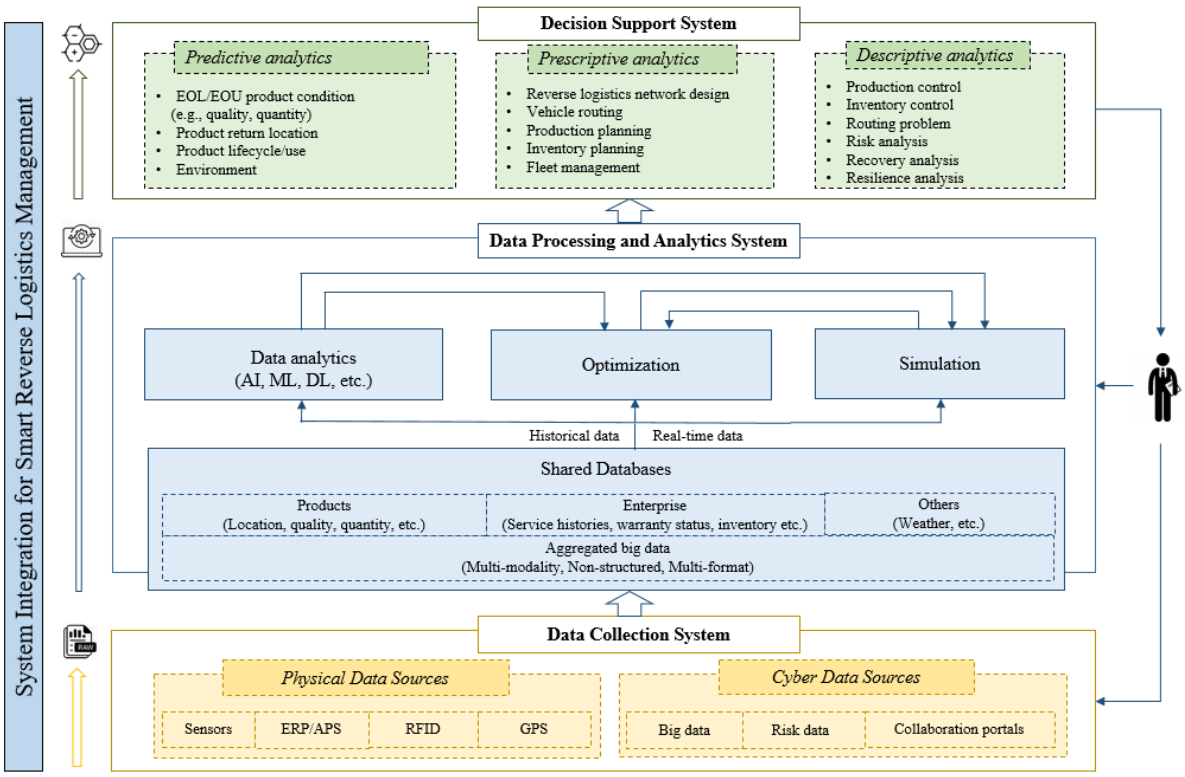

Figure 2 System integration for smart reverse logistics management

3 A Framework for System Integration

System integration is the process that links and integrates several physical and cyber components so that they can work together as a whole [24]. The most significant challenge of the system integration for reverse logistics management is related to the use of several analytical tools and the inclusion of a large amount of data from different sources and stakeholders. However, selecting the right analytical tools and right data to solve specific reverse logistics management problems requires domain expertise. Thus, this conceptual framework is proposed to explore the opportunities for the next generation of system integration for smart reverse logistics management. As shown in Figure 2, the integrated system combines various AI algorithms, optimization models, and simulations to support strategic, tactical, and operational decisions, and these elements form three layers, namely, data collection, data processing and analytics, and decision support. At the lowest data collection layer, the data can be collected from both physical sources, e.g., enterprise resource planning (ERP)/ advanced planning & scheduling (APS), smart sensors, and geographic information system (GIS), etc., and cyber sources, e.g., the information from the online collaboration portals, the online data from track and trace systems, and the product-based digital twin [25], etc. The reliability of a decision-support system depends heavily on the quality, completeness, validity, consistency, timeliness, and availability of data [26]. The raw data collected from these multiple sources can be sent and stored on a cloud-based database and be cleaned. The next step is the core of the system integration, which is the data processing, analysis, and preparation. Depending on the types of decisions to be made for reverse logistics management, the respective AI and/or optimization models and/or simulation models need to be selected and combined, and the data needs thus to be prepared accordingly in order to feed these models. For example, in the proactive planning of a waste product collection system, the historical data can be used with AI, e.g., deep learning, to provide accurate predictions of the waste generation and the maintenance periods required for the waste collection vehicles. The prediction results can be visualized and be directly converted to the inputs of the respective optimization models for routing the vehicles and scheduling the waste collection activities and vehicle maintenance. Besides, the optimization results and relevant parameters can be converted seamlessly to the simulation environment to analyze the system dynamics under different scenarios, evaluate the impacts of disruption, and test and formulate different reactive strategies. Besides, the prediction needs to be dynamically updated with the real-time data collected from various smart devices and information portals, e.g., traffic condition, vehicle utilization, etc., and the optimization and simulation models need to be re-activated accordingly to update the respective analytical results and suggestions. In making short-term operational decisions, real-time data places a more important role in the optimization of reactive decisions. Smart reverse logistics management emphasizes the importance of effective proactive planning and reactive decisions driven by both historical data and real-time data. However, in some cases, the datasets are not available or not large enough for data analytics to generate a reliable prediction. In this regard, simulation can be used at the first stage to yield the initial scenarios for a data-driven learning process [27] and the parameter estimation for optimization. For instance, a simulation method combined with a patient allocation heuristics was used to estimate the system dynamics of the medical waste generation during the early stage of the COVID-19 pandemic in Wuhan, China, whose results were then used as the inputs to a multi-objective mixed integer program to optimize the locations of temporary waste incinerators [28].

This system integration combines AI, optimization models, and computer-based simulation, which can support important decisions and test several alternatives in a risk-free environment [27]. The main features of the next generation of system integration and software development for smart reverse logistics management are discussed as follows:

- *Cyber-physical structure*: At the lowest level, the system integration needs to enable effective data collection from both physical and cyber sources.

- *Cloud-based system*: The important data and analytical models need to be stored in a cloud-based platform so that they can be easily accessed from decentralized locations.

- *Shared database and data conversion*: The parameters for different analytical models are generated from the same database and can be easily converted to feed different models with different requirements on data structure and aggregation.

- *Flexible network structure*: For different problems in reverse logistics management, the numbers of echelons and actors involved are by no means identical, so the integrated system needs to be flexible enough to adapt to different reverse logistics network structures.

- *Large model database*: The model database needs to be broad to tackle a wide range of decision-making problems at strategic, tactical, and operational levels.

- *Flexible model modification*: The model can be easily modified to adapt to the change of system requirements in the decision-making.

- *User-friendly interface*: The digital interface should be designed in a user-friendly way for practitioners and non-expert users.

4 Maturity Evaluation of Existing Solutions

With existing software solutions, we first present the initial proof of concept with a case study of the reverse logistics network design for WEEE management. Then, three existing solutions are compared to evaluate the maturity of system integration for smart reverse logistics management. To optimize the WEEE recycling network in Norway, an analysis combining with both optimization and simulation is given, and the data flow needs to be converted between optimization models and simulation models due to their different requirements. The anyLogistix, which is a cutting-edge combined optimization-simulation software package has the functionality to convert data between the two methods in forward logistics. However, due to the difference of reverse logistics flows and the requirement to consider the carbon emission objective in decision-making, it cannot be used directly to solve this problem. Figure 3 illustrates the data flow of the decision-support process for this reverse logistics network design problem. First, the data input files need to be established in Microsoft Excel. Based on the input data, a bi-objective optimization problem considering the balance of both costs and carbon emissions is solved with a professional optimization solver, whose results are written in the output file. The input parameters need to be converted to feed the simulation model, and a set of Pareto optimal solutions suggested by the optimization model are considered several candidate network configurations. Based on this information, the performance indicators, e.g., cost, carbon emissions, periodic inventory level, etc., can be obtained under a dynamic and stochastic environment. The analytical results can then be easily visualized for better decision supports. As can be seen, to formulate the reverse logistics flows and ensure the model's flexibility, the existing software solutions cannot realize a streamlined data flow conversion between different analytical models in reverse logistics.

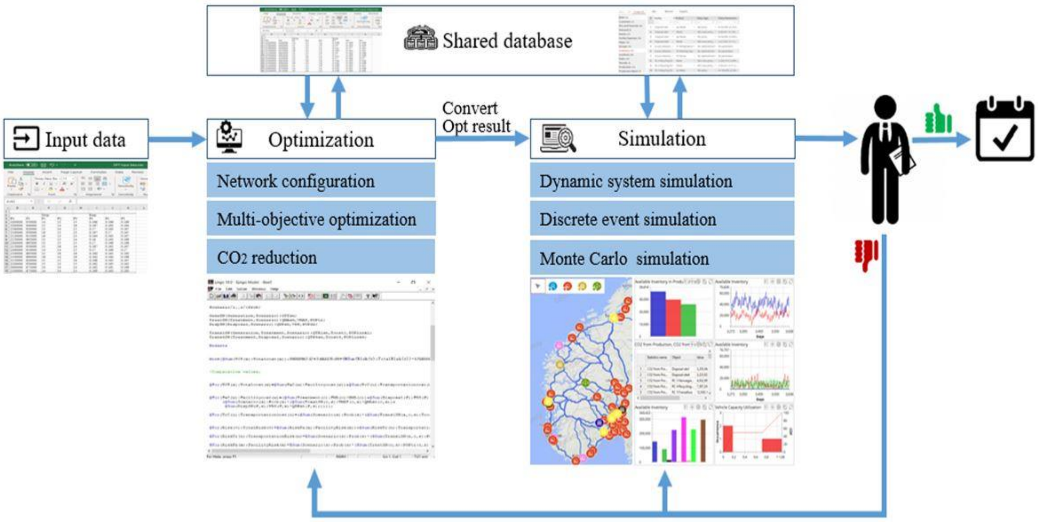

Figure 3 Data flow through the decision-support system.

To identify the gaps related to the system integration for smart reverse logistics management, three existing software solutions i.e., SAP, Optimity, and anyLogistix are compared with respect to the general features given in the previous section. In Table II, three levels of system integration maturity for smart reverse logistics are defined as follows:

- 3 is the highest maturity level, in which the process is standardized and the functionality can be well achieved for smart reverse logistics management.
- 2 means the functionality has been established at the basic level, but significant efforts need to be done to solve reverse logistics management problems.
- 1 is the lowest maturity level, which means the functionality has not been well established for reverse logistics management.

Table 2 Evaluation of system integration

Main features	**Three existing software solutions**		
	SAP	***Optimity***	***anyLogistix***
Cyber-physical structure	3	2	2
Cloud-based system	3	3	3
Shared database and data conversion	3	3	3
Flexible network structure	1	1	1
Large model database	1	2	2
Flexible model modification	1	1	2
User-friendly interface	3	3	3

SAP (System Analysis Program Development) is the world's leading software provider of business process management, data processing, and information flow solutions across organizations. The SAP system has been adopted by a large number of companies in many industries. The SAP’s EPR solution is a comprehensive system including various modules for finance, administration, logistics, etc., with which a high level of cross-functional integration and cross-organizational coordination can be achieved. SAP is a mature system to integrate and process data from different sources and to convert data for different purposes via a cloud-based system. In logistics planning, SAP offers a set of embedded models and algorithms to solve a wide range of problems, e.g., vehicle routing problems (VRP). However, there is a lack of standardized solution modules and models for reverse logistics management problems, e.g., network design. Besides, as a commercial system, it suffers from flexibility issues.

Both Optimity and anyLogistix focus on providing the next generation of software solutions and digital twin for managing logistics systems and supply chains. Optimity emphasizes data-driven optimization combined with both ML and a set of optimization models for better prediction and better decision support. On the other hand, anyLogistix focuses on the combination of mathematical optimization and computer-based simulation to provide solutions and analytical insights under a dynamic and realistic environment, and the data flow conversion between optimization models and simulation models is thus well developed. However, since both software packages are developed with a primary focus on forward logistics systems and supply chains, the network structure is not well adapted for modeling the material flows in the reverse logistics system, as shown in Figure 3. Besides, even though they offer model adjustment by adding and subtracting some elements, e.g., carbon cost, penalty, etc., the flexibility is extremely limited to adapt different modeling requirements, e.g., multi-objective optimization, stochastic programming, etc. Thus, there is still a long way to go in order to achieve the next generation of system integration for smart reverse logistics management.

5 Conclusion

The emergence and increasing use of several Industry 4.0 technologies have provided new opportunities for improved connectivity and intelligence of a system. The combination of both data-driven analytics and model-based methods is driving the paradigm change toward smart reverse logistics management. However, different tools and models need to be used to solve different decision-making problems, and these tools and models need different software packages, different inputs, and different structures and levels of aggregation of data. Thus, it is usually an ad-hoc process to combine different data sources and different models to solve complex decision-making problems in reverse logistics management, and there is a lack of standardized solution and software package that contains a comprehensive network structure and a large model collection to solve a wide range of reverse logistics management problems.

In this paper, from the user’s perspective of reverse logistics management, we propose a conceptual framework for the next generation of system integration for smart reverse logistics management. Six primary parameters, i.e., cyber-physical structure, cloud-based system, shared database and data conversion, flexible network structure, large model database, flexible model modification, and user-friendly interface, are given to evaluate the maturity of system integration of smart reverse logistics management. The initial proof of concept is given by a case study in Norway. Besides, three existing software solutions, i.e., SAP, Optimity, and anyLogistix, are compared to identify the current problems and challenges of system integration. The proposed six parameters for the maturity evaluation of system integration are considered the general guidelines for the next generation of software development in order to realize smart reverse logistics management.

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PAPER 5

A Digital Reverse Logistics Twin for Improving Sustainability in Industry 5.0

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Submitted manuscript

Author's Contribution

Xu Sun is the main contribution of conceptualization, methodology, data curation, formal analysis, writhing-original draft of the paper, and writing-review and editing of the paper.

A Digital Reverse Logistics Twin for Improving Sustainability in Industry 5.0

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Abstract: The rapid advancement of information and communication technology (ICT) and digitalization in the Industry 5.0 era have opened up new opportunities for re-verse logistics management to become digitalized, smarter, more sustainable, and simplified by incorporating disruptive technologies, e.g., Internet-of-things (IoT), artificial intelligence (AI), big data analysis, simulation, blockchain, etc. Digital twin is one of the most promising concepts in Industry 5.0, which can re-create a physical object or system in the digital world. In this paper, different from the widely practiced product-based definitions, we extend this concept to a system-oriented digital reverse logistics twin. Based on a conceptual framework allowing for a high level of system integration, we present the key enabling elements for a digital reverse logistics twin that can support decisions in a complex and uncer-tain environment. Through an illustrative example of a remanufacturing network design problem in Norway, the initial proof-of-concept illustrates how different systems and models can be combined in a digital reverse logistics twin in order to support different decisions.

Keywords: reverse logistics, digital twin, Industry 5.0, decision support system, simulation, optimization

1 Introduction

Today, the accelerated pace of technological innovation and development has resulted in an ever-faster pace of product renewal and shortened product life cycles, which, in consequence, leads to an exponential increase in the generation of end-of-life (EOL) and end-of-use (EOU) products [1]. Meanwhile, sustainable logistics and supply chains have been a major research subject in recent decades due to increased global awareness and concerns associated with economic, environmental, and social sustainability in socio-economic activities [2]. To properly manage the increased waste streams, while simultaneously promoting resource recovery from both EOL and EOU products, reverse logistics is considered to be one of the most crucial steps for moving toward sustainable development and circular economy. Due to this reason, as a profitable and sustainable business strategy, reverse logistics has gained increasing attention by worldwide companies and organizations.

The emerging concept of Industry 5.0 has shown a blueprint of the human-centric transition that predominantly focuses on social and environmental dimensions of sustainable development. Several disruptive technologies of Industry 5.0 are driving firms to shift business strategies to be more sustainable. This process requires more information involved and the integration of interconnected smart components, real-time monitoring and control devices across the entire manufacturing network and logistics systems, which potentially enables virtual product and virtual process planning in order to provide better and more comprehensive decision support and system control [3]. As one of the most important enablers of Industry 5.0, digital twin is increasingly focused on by both industrial practitioners and academia.

Even though the concept of digital twin has been widely discussed in the context of different industries and businesses, most of them, especially in reverse logistics, are mainly defined from the product perspective, e.g., a data-intensive digital model that can tract the product conditions and information throughout its entire life cycle [4]. However, reverse logistics is a complex system, and there is a lack of definition and conceptualization of digital reverse logistics twin from the system-oriented perspective. Thus, considering smart reverse logistic features and, in particular, cyber-physical integration for effective system visualization and data-driven decision-making, we provide a systematic conceptual framework of the digital reverse logistics twin to fill the literature gaps. The initial proof-of-concept is provided by an illustrative example of a compressor remanufacturing network design from EOL refrigerators in Norway. The proposed framework aims at showing a clear roadmap for future system integration that allows a high level of interaction between the digital and physical worlds of a smart reverse logistic system, with which various decision-making problems can be better supported.

2 Theoretical Backgrounds

2.1 Reverse Logistics Management

Reverse logistics refers to a set of value recovery operations regarding the process of shipping EOL and EOU products or parts from the consumer point for possible reuse, remanufacturing, recycling, or proper disposal of materials, components, and products [5, 6]. The effective management of these operations is not an easy endeavor due to the complexity of reverse logistics systems that need the participation and collaboration of various stakeholders [7]. Due to the unpredictability and large variations of the EOL and EOU products in the reverse flow, the uncertainty related to reverse logistics operations are substantially larger than that in forward logistics [8], which results in greater impacts on decision-making [9].

Furthermore, reverse logistics operations may be affected by many unpredictive events and disruptions. For example, the COVID-19 pandemic has posed considerable challenges to global logistics systems and supply chains. The border closure, city lockdown, and reduced and limited transportation capacity have severely interrupted goods movements, increased logistics costs, and increased uncertainty of total transit time. In reverse logistics, the transborder movement of EOL and EOU products has been largely affected. Thus, the resilience and flexibility of logistics systems become increasingly important [10]. Furthermore, in an effort to overcome and minimize the negative impacts of logistics operations, the pandemic has also spurred many businesses and companies to adopt new technologies and methods from the latest industrial revolution to increase automation and reduce the need for human resources [11]. Therefore, there is a need to develop new solutions for reverse logistics management considering the emerging sustainable development challenges in the post-pandemic era under a highly uncertain and fluctuating global environment.

2.2 Industry 5.0

The fifth Industrial Revolution, namely, Industry 5.0, has the most potential to substantially optimize logistics in a strategic way [11], which offers new opportunities for smart and sustainable reverse logistics management by building up competitive and innovative business models and better managing the operations. While Industry 4.0 primarily emphasizes the role of automation and digitization through connecting physical objects with the real world to enhance manufacturing productivity, intelligence, and flexibility, Industry 5.0 focuses, however, on the human-centric transformation in the age of augmentation [12, 13]. Enabled and empowered by disruptive technologies, the importance of personalization, environmental sustainability, and human-centric societal transition are simultaneously emphasized [14]. Compared with Industry 4.0, despite smartness, connectivity, digitalization, and autonomy are still the core elements of Industry 5.0, the role of the human becomes most crucial in the transformation, where the potential of both human and technology can be largely exploited in a human-machine collaborative environment [11].

Industry 5.0 empowers human intelligence to work with cognitive computing and intelligent automation [15], which paves the way for enabling smart logistics systems through achieving proactive planning with big data, real-time decision making, responsive communications, better resource allocation, and smoother material flows [16, 17]. However, on the other hand, there are still numerous obstacles related to the implementation of new technologies in reverse logistics [18], e.g., the technological maturity and compatibility, the life-cycle environmental footprint of new technologies [19], etc. Thus, further research is needed to provide comprehensive decision supports to better plan the smart reverse logistics transformation in the Industry 5.0 era.

2.3 Digital Twin

Digital twin is one of the most essential technologies in Industry 5.0 [14]. The terminology was first put forward as a concept practiced in the aerospace and aviation industry in the 1960s [20]. A " twin" concept was developed by NASA to assess and simulate conditions onboard Apollo 13 so that the astronauts and the controlling center can monitor the spaceship's condition remotely and make decisions in the emergency event [21]. Digital twin was depicted as "digital equivalent to a physical product" by Michael Grieves at the University of Michigan in 2003 [22]. Digital twin has become one of the top strategic technology trends since 2017 with the worldwide focus on digitalization. Research activities on digital twin have been dramatically increased by the explosion and rapid development of machine learning, wireless communication, and cloud computing [20, 22, 23]. The digital twin market is predicted to increase with an annual growth rate of 58 percent from USD 3.1 billion in 2020 to USD 48.2 billion by 2026 [24].

The origins of digital twins describe replicating products [3]. One of the key features of digital twin is the capability of transmitting and providing diverse types of data and information in an interoperable and consistent format [23]. Digital twin has various industrial applications at different lifecycle stages including product design, manufacturing, service, and EOL products [22, 25]. Among others, the application of digital twin in manufacturing has gained predominant focuses, which can effectively help with production planning and control, maintenance, and layout planning [3]. It is a fundamental enabler of a highly integrated and collaborative smart manufacturing environment, which can effectively respond to the real-time customer needs and conditions in the factory [26]. For example, a simulation-based digital twin is used to support heat monitoring and predictive maintenance of an automotive braking system in order to make prompt decisions and reduce accidental risks [27]. Digital twin, enabled by intelligent analytical tools, e.g., AI, simulation, optimization, etc., provides new opportunities for processing large volumes of data, achieving data-driven operation, realizing the real-time interaction, communication, and integration between cyber and physical worlds, and diversifying value creation.

3 Digital Reverse Logistics Twin

3.1 Human-centric smart reverse logistics transformation

The increasing adoption of disruptive technologies in Industry 5.0 will eventually lead to a smart reverse logistics transformation in various aspects including the smart collection of EOU and EOL products, smart transportation, smart remanufacturing and recycling, and smart disposal [28]. As illustrated in Figure 1, reverse logistics has experienced paradigm shifts from unstructured isolated activities to today’s highly structured, automated, and connected operations that aim at sustainable value recovery of EOL and EOU products and materials. Enabled by new technologies, e.g., IoT, AI, CPS, etc., the human-centric smart reverse logistics transformation has become the emerging hotspot in the Industry 5.0 era. For example, as an innovative business model, the collection activities of EOL and EOU products can be scheduled based on individual customer demands [29], where real-time truck utilization data and traffic data can be used to optimize routing and resource allocation. Besides, AI-enabled smart robots can be used in the sorting center to relieve human workers from harsh working conditions, where, in a collaborative environment, human workers can help the robots to categorize different types of waste streams. This human-centric smart reverse logistics transformation requires a high level of system integration to connect the physical world with the digital world. In this regard, digital twin plays an essential role.

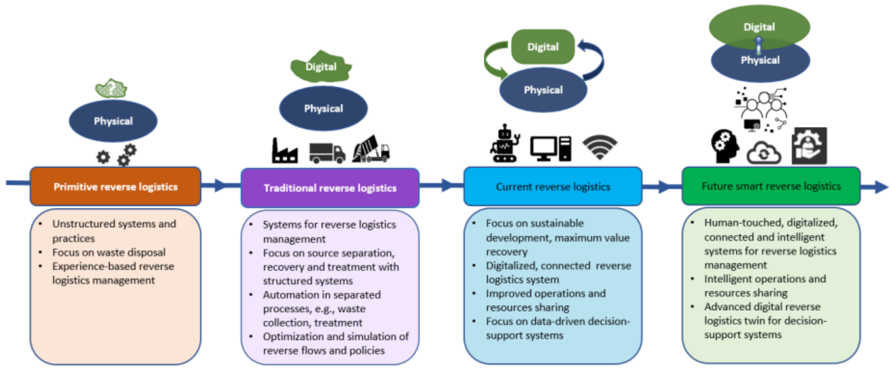

Figure 1 Smart reverse logistics transformation.

3.2 Digital twins for reverse logistics operations

Currently, the application of digital twin is still in the way of exploratory development [30]. Among other reverse logistics activities, remanufacturing has become the most focused area of the adoption of digital twin [30], since it is becoming today's mainstream practice for recovering the EOL components at high value [31]. In remanufacturing, the concept of digital twin is defined from the product- or process-oriented perspective. A product-oriented digital twin tracks the product conditions through its entire lifecycle and provides valuable information for remanufacturing that usually suffers from high uncertainties related to the quantity, quality, and demand of EOL products [32]. In this regard, the primary enablers are to establish a cloud-based automatic data collection and sharing system with IoT, smart sensors, cloud technology, etc., as shown in Table 1.

Table 1. Comparison between the product-oriented digital twin and the system-oriented digital twin in reverse logistics.

	Product-oriented digital twin	System-oriented digital twin
Scope	Management of the entire product lifecycle	Management of the entire reverse logistics system
Data	Product condition throughout the entire lifecycle	System or process information at different locations and routes
Applications	Data and Information supports, e.g., EOL product quality, prediction of equipment failure, etc.	Decision support at strategic, tactical, and operational levels, e.g., real-time routing, proactive maintenance and operational planning, etc.
Key enablers	Connectivity enablers	Both connectivity and intelligence enablers

A process-oriented digital twin is similar to a system-oriented digital but with a smaller scope that focuses on a specific reverse logistics operation or activity, e.g., equipment maintenance, demand forecasting, etc. For example, a big data-driven hierarchical digital twin can be used for predictive remanufacturing planning [33]. Market demand can be predicted using big data analytics so that rapid reconfiguration of sustainable products and remanufacturing processes can be achieved. Ghorbani and Khameneifar [34] developed a digital twin to predict the repair volume in the remanufacturing of damaged aero-engine blades. Simulation is a core element in a process- or system-oriented digital twin [35]. For instance, a simulation-based digital twin can be used to predict maintenance needs and potential equipment failures in remanufacturing operations [36]. Combining real-time data simulation with decision evaluation, a data-driven disassembly process can be achieved [37].

3.3 Digital reverse logistics twin

Even though product- and process-oriented digital twins have been investigated in reverse logistics, there is still a lack of conceptualization of a system-oriented digital reverse logistics twin. Thus, this paper investigates the concept of digital reverse logistics twin from the system perspective. A digital reverse logistics twin is a data-based digital avatar of the entire logistics system, which combines both physical smart devices, i.e., IoT-sensors and intelligent robots, and cyber intelligence, i.e., AI, big data analytics, advanced optimization algorithms, and simulation tools, so it can be considered a high-level of CPS that enables effective system visualization and data-driven decision making with better proactive planning and real-time reactive adjustments. To support decision-making at different levels, data-driven analytics and decision-support models need to be effectively combined [38], which requires a high level of system integration to provide comprehensive decision support in a complex and uncertain environment [39].

A digital reverse logistics twin can be used to simulate dynamic processes or behaviors of reverse logistics operations and comprehensively assess the impact of dynamic situations. AI and big data analytics can be used to build data-driven forecasting systems in the proactive phase before EOL/EOU products enter the value recovery phase, which helps reduce uncertainties and generate adequate and more accurate data as the input for optimization and simulation models for further decision supports, e.g., remanufacturing planning, transportation scheduling, etc. Then, based on the needs of different decisions, a single method or a combination of both optimization and simulation methods will be selected to conduct various data-driven analyses with historical data and real-time data adjustment.

For example, in the proactive planning phase of an EOL product collection system, AI-based data analytics can be used at the initial step for reducing uncertainties based on historical data to accurately predict the generation of EOL products and the required maintenance in each period. The predicted results can be directly converted to the input of the corresponding optimization models for resource assignment, routing, collection schedule, and vehicle maintenance. Furthermore, the optimized setups and decisions can also be automatically converted to the simulation environment for analyzing system dynamics under various scenarios, e.g., traffic congestion, accidents, etc., based on which reactive strategies can be formulated and tested. With the help of the real-time data collected from various smart devices and information portals, the prediction results can be updated and the short-term operational decisions, e.g., routing and collection schedules, can be dynamically optimized to improve the overall system performance in terms of operating costs, fuel consumption, emissions, working hours, and service levels. Thus, based on the discussions above, a generic definition of digital reverse logistics twin is given from the system perspective:

Digital Reverse Logistics Twin is a data-based digital representation of a real-world reverse logistics system, which forms a multi-architecture and high-level integrated information platform by integrating different stakeholders, data, and analytical tools to support various proactive and/or reactive decisions.

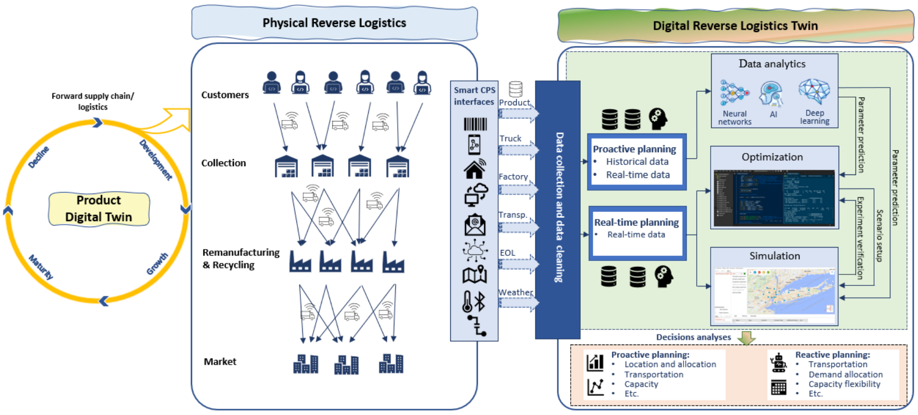

Figure 2 Digital reverse logistics twin.

Figure 2 shows a generic framework of digital reverse logistics twin, which aims to digitize the physical entities and activities of a reverse logistics system into a cloud-based virtual environment, where smart devices, data, and analytical models can be used for proper needs. It requires three layers including the physical system layer, the cyber-physical layer, and the smart analytical layer. The first two layers link the physical world to the cyber world, which allows data collection, treatment, and processing from the physical devices, sensors, and processes, and the third layer supports the critical decisions with AI, optimization, and simulation models in an interactive way. In addition, the product-orient digital twin is also considered a key enabler for this generic framework. For example, these digital twin models established for individual products throughout their entire lifecycle, e.g., electronic products, vehicles, etc., provide key data for various reverse logistics activities. Besides, the end-users can easily provide updated information related to these products via digital platforms, which will be used for a better organization of respective value recovery activities in a sustainable reverse logistics system.

As can be seen, data is the most essential element in the digital reverse logistics twin, which is the bridge connecting the physical world and the cyber world. The accuracy of data represents the fidelity of the digital model. Furthermore, data connects different analytical tools in the smart analytical layer, with which different analytical models can be seamlessly connected and implemented in the decision-making of specific reverse logistics planning problems. However, this is one of the major challenges of system integration since AI, optimization, and simulation are usually performed as ad-hoc processes and implemented in different environments, so further development is needed to promote a high level of system integration in a digital reverse logistics twin [39].

4 Initial Proof-of-Concept

In this section, we use an illustrative example of a remanufacturing network design problem in Norway to show the initial proof-of-concept and potential applications of digital reverse logistics twin. In this example, a compressor remanufacturing network from EOL refrigerators is planned. The compressors are mainly collected from 16 cities in the southern part of Norway, and 3 candidate locations are selected for opening the remanufacturing plant. The un-remanufactured parts and components can be treated by three waste management companies, and Figure 3 shows the locations of respective actors. The experimental data is estimated based on Statistics Norway and the European Commission's database.

A digital reverse logistics twin model is built to optimize the network decisions under various scenarios. Conventionally, formulating such a decision-making problem starts from the establishment of a mathematical model, based on which relevant data is collected and tested. Afterward, these network decisions may further be evaluated with a dynamic simulation model with more realistic operating rules. However, this is usually an ad-hoc process, and the re-use of the analytical models in other scenarios may require large efforts to modify the model's structures, elements, and setups. Furthermore, implementing these models may require different software, programming languages, and data structures [39]. Thus, this is an inefficient process that suffers from a lack of universal applicability.

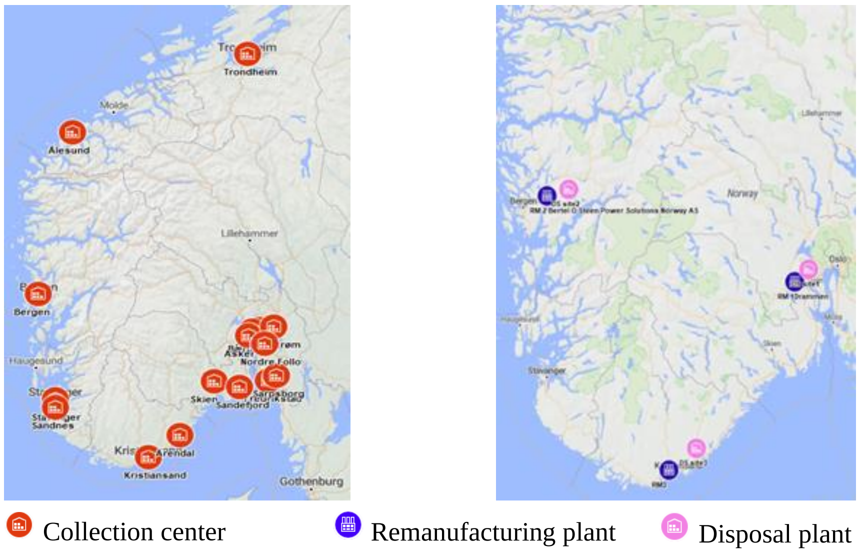

Figure 3 The locations of respective reverse logistics actors.

Establishing a digital reverse logistics twin takes an opposite perspective, where a highly integrated information platform is required to connect the GIS system, AI algorithms, analytical optimization models, dynamic simulation elements, as well as other physical and cyber components to support different decisions. Feeding with real-world data, the physical system can be digitized into the virtual world through combining with different analytical tools, where the level of data accuracy shows the fidelity of the digital reverse logistics twin. As shown in Figure 4, based on the physical remanufacturing network structure, we converted the relevant facility operating data, transportation data, collection data, and market data into a comprehensive data model in anyLogistix, through which the remanufacturing network is digitized through automatically selecting different modeling elements. The analytical optimization and dynamic simulation can then be seamlessly connected and interacted via the automatic data conversion to different levels of required aggregation. For example, the optimized remanufacturing network can be easily evaluated under various operational policies with a realistic planning horizon and lower data aggregation in the simulation environment.

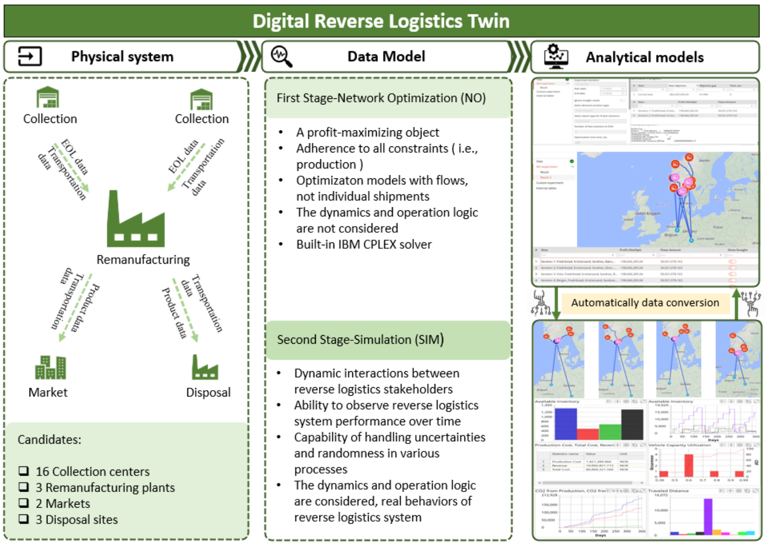

Figure 4 Digital reverse logistics twin for remanufacturing network design.

The successful implementation of a digital reverse logistics twin requires a high level of system integration of both physical and cyber components, whose maturity is evaluated by seven key indicators, namely, cyber-physical structure, cloud-based system, shared database, large model database, user-friendly interface, and flexible models and networks [39]. In this example, the use of digital reverse logistics twin is shown through supporting strategic network decisions, where key implications can be obtained through combining optimization and simulation with historical data. At tactical and operational levels, the data model can be further developed by, for instance, connecting with the company's business intelligence (BI) and smart devices to support real-time operational decisions, e.g., vehicle routing.

5 Conclusion

With the focus of human-centricity and sustainable development in Industry 5.0, technological enablers are increasingly emphasized for promoting a smart digital transition, which will shift the paradigms of many industries and businesses. Digital twin is one of the most promising Industry 5.0 enablers, which has been extensively focused on during the last decade. In reverse logistics management, the concepts of digital twin are mainly studied from the product- and process-oriented perspectives. Thus, in this paper, we extend the scope of this concept and define the digital reverse logistics twin from the system perspective. The generic definition and framework summarize the most essential features of digital reverse logistics twin, which can be adopted to a wider range of applications. For example, the product- and process-oriented digital twin applications can be considered important elements and enablers within this concept.

In a digital reverse logistics twin, data plays the most crucial role to link different physical and cyber elements, with which the system performance can be monitored, and the respective decisions can be dynamically optimized. An initial proof-of-concept is given based on a remanufacturing network design problem in Norway. Through a common and shared data model, the network optimization and dynamic simulation can be seamlessly connected to optimize the reverse logistics network configuration and evaluate the performance under different scenarios. The result shows the effectiveness of integrating different analytical tools via data model in a smart and sustainable digital reverse logistics twin. Future research is needed to provide a higher level of system integration of AI, optimization, and simulation in reverse logistics management.

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